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Incentive Pay and Firm Productivity: Evidence from China

Zhangfeng Jin; Shiyuan Pan*

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Abstract

This study examines the causes and consequences of incentive pay adoption among Chinese manufacturing firms. First, we find that a higher degree of labor scarcity encourages firms to adopt more incentive pay. Second, using an instrumental variables approach, we find that a 10 percentage point increase in the intensity of incentive pay results in 38% higher firm productivity. Third, the average productivity differences between SOEs and non-SOEs decrease by about 65% after controlling differences in incentive pay adoption. Therefore, facilitating incentive pay adoption among firms with better labor endowments (e.g. SOEs) increases productivity while reduces resource misallocation in developing countries.

Keywords: Incentive Pay; Firm Productivity; Labor Scarcity; China; Instrumental Variables

JEL Codes: O14; O33; M52; J33; P31

1 Introduction

Differences in technology and productivity are considered as main sources of income differences between developing and developed countries. The origin of productivity differences across countries and firms remains to be explored (Syverson 2011). One strand of literature argues that resource misallocation is an important factor of productivity differences between developing and developed countries (Hsieh and Klenow 2009). A more recent strand of literature reveals that differences in “management technology” account for a large proportion of productivity differences across countries and firms (Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013). While it is firmly established that reducing resource misallocation improves productivity in developing countries, the role of “management technology” in driving productivity growth

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in these countries is not clear. This study investigates the causes and consequences of differences in incentive pay adoption, an important component of “management technology”, among manufacturing firms in developing countries. Specifically, we consider two unanswered questions. First, what determines the differences in incentive pay adoption across manufacturing firms? Second, to what extent does incentive pay adoption affect firm productivity?

Studying incentive pay adoption is important for other reasons. First, while long-standing theoretical literature acknowledges the importance of incentive pay (Stiglitz 1975; Baker 1992; Lazear 2000), not much is known about how incentive pay adoption works in developing countries (Guiteras and Jack 2018). Second, while several prominent studies find that incentive pay adoption (e.g., piece rates) dramatically increases workers’ productivity (Lazear 2000; Shearer 2004)—mostly through field experiments within specific firms—they fail to identify the role of incentive pay adoption in driving productivity differences between firms (e.g., state-owned firms versus non-state-owned firms).¹ Third, while previous studies have explored factors that drive differences in “management technology” adoption across countries and firms (Bloom and Van Reenen 2007; Bloom and Van Reenen 2010; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen 2019), they do not specifically examine what determines the differences in incentive pay adoption across firms, which may differ from overall “management technology” in developing countries. Last but not least, previous studies on consequences of various wage payment systems in China focus on either the agricultural sector (McMillan, Whalley, and Zhu 1989; Lin 1988; Lin 1992), or state-owned firms in the industrial sector (Groves, Hong, McMillan, and Naughton 1994; Groves, Hong, McMillan, and Naughton 1995; Li 1997); little is known about the impact of incentive pay on firm productivity in the presence of non-state-owned firms, which use incentive pay more intensively than state-owned firms and have become the backbone of the Chinese economy in the 2000s.²

National representative survey data with information on incentive pay adoption at the firm level is rare in China and other developing countries, which presents a significant empirical challenge. In reality, firms offer a complex package of incentives in their employment contract, including promotion schemes, bonuses, piece-rate wages etc. It’s challenging to collapse all of that into a single-dimensional vertical measure. To explore the causal relationship between incentive pay adoption and firm productivity, this study resorts to an enterprise survey conducted by the World Bank in 2005, which allows us to capture intensity of incentive pay adoption using employees’ wage components at the firm level. Specifically, we use the ratio of bonuses and piece-rate wages to total compensation among permanent workers to capture incentive pay

¹There are other forms of incentive pay, such as team-based incentives, relative pay (tournament), career incentive (promotion), nonmonetary incentive (intrinsic motivation). A short summary on different forms of incentive pay and consequences on workers’ productivity can be found in (Lazear 2018). Nevertheless, most of these studies are also conducted within a very specific context.

²According to the National Bureau of Statistics of China (2000), the industrial output of state-owned and collective-owned firms accounted for 99% of total industrial output in 1980, which decreased to 63% in 1999. According to China’s industrial census in 2004, the industrial output of state-owned and collective-owned firms accounted for about 21% of total industrial output, while the industrial output of non-state-owned domestic firms accounted for about 48% of total industrial output.

adoption.³ We do not consider temporary workers in the main analysis to reduce the concern that we mix the impact of incentive pay adoption with the impact of contract labor hiring.⁴ Moreover, the impact of managerial pay and non-managerial pay on firm productivity may be quite different. Since we do not have data on non-managerial pay separately, we further resort to additional information on general manager’s performance pay adoption for complementary analysis. Finally, the timing of the survey echoes with the period when China’s manufacturing sector developed rapidly and significantly affected the global economy (David, Dorn, and Hanson 2013; Bloom, Draca, and Van Reenen 2016; Bloom, Handley, Kurmann, and Luck 2019).

Our first research question examines how firms select into the incentive pay adoption. Existing literature does not reach a consensus on whether firms with better labor endowments positively select into incentive pay adoption or not (Acemoglu 2010; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen 2019). We focus our analysis on two different indicators: degree of labor scarcity and human capital of firms. Both indicators capture a firm’s labor endowments to some extent. While it is hard to put a causal interpretation on these exploratory patterns, they are helpful to find an appropriate identification strategy for our next research question.

Our second research question examines whether incentive pay adoption substantially affects firm productivity. Two identification problems need to be solved in order to generate causally interpretable evidence on the effectiveness of incentive pay adoption. The first is that productivity may affect firms’ decisions to adopt incentive pay, resulting in reverse causality problem. For example, firms may not adopt piece-rate wage if they are worried about shirking in other dimensions of work, such as product quality. Thus, the heterogeneity in the use of piece-rate wage may be associated with heterogeneity in firms’ product positioning. Within the same industry, firms specialize in simple/basic versions of the goods will adopt piece-rate wage more than those position themselves at the higher end (and perhaps more productive). The second is that factors such as job differences, production technologies, product market competition and demand shocks differ across firms. These differences are relevant for incentive pay adoption decisions, causing omitted variables problem.

To solve these issues, we implement a variant of the supply-push immigration framework to construct instrumental variables (Card 2001; Kerr and Lincoln 2010; Kerr, Kerr, and Lincoln 2015).⁵ We assume that a higher degree of labor scarcity

³According to the data, bonuses and piece-rate wages account for about 41.6% of total compensation on average among permanent workers, the fraction of which is a bit smaller than that of fixed salary (47%). The percent of bonuses and piece-rate wages is higher for private firms (44%) than state-owned firms (37%). Given the fact that bonuses and piece-rate wages may affect firm productivity quite differently, we will use them separately in the robustness checks. Moreover, permanent workers account for about 77% of total employment on average, and we further consider the remaining temporary workers in the robustness checks.

⁴The fraction of piece-rate wage is highly correlated with the fraction of temporary workers (versus permanent workers) in the firm. Therefore, any impact driven by differential adoption of incentive pay can be due to differential hiring of temporary workers. The latter can both be driven by and directly affect firm productivity. Therefore, considering temporary workers may make it hard to interpret the incentive pay measure as a strict improvement in a firm’s management practice.

⁵When incentive pay adoption is considered as a component of “management technology” (Bloom, Draca, and Van Reenen 2016), our IV approach borrows the idea from previous studies that technical change is biased toward particular factors (Acemoglu 2002; Acemoglu 2010; Hanlon 2015; Dustmann and Glitz 2015).

encourages local firms to adopt more incentive pay, an important component of “management technology”, to utilize existing workforces more effectively and the practices of incentive pay adoption in the past will be transferred to recent firms through technology spill-overs as firms can learn from each other regardless of labor conditions de facto.⁶ In this paper, we construct an indicator of incentive pay adoption to proxy for an important component of “management technology” and test whether shifts in the relative labor scarcity in the past are associated with more incentive pay adoption in recent firms. We resort to two different exogenous variations on labor availability in the past.

The first instrumental variable is institutional migration barriers (also known as *Hukou System*). The strength of institutional migration barriers is measured as ratio of agricultural *Hukou* holders to total local registered population.⁷ The rationale is that *Hukou System* prevents agricultural *Hukou* holders from migrating permanently to the urban areas (Chan and Zhang 1999; Chan and Buckingham 2008). Prefectures with a larger ratio of agricultural *Hukou* holders are associated with fewer workers in the nonagricultural sector because of higher institutional migration barriers on average. Given that labor supply from rural to urban areas is nontrivial, firms in prefectures with higher institutional migration barriers are more likely to suffer from labor shortage through decreased availability of permanent migrants.⁸

Moreover, the *Hukou System* used to be regulated by the central (provincial) government through a restrictive annual quota system and local (prefecture-level) governments had little autonomy to alter migration barriers by themselves, until recently.⁹ Specifically, we construct the indicator of institutional migration barriers using data from 1990, when the *Hukou System* was strictly regulated by the central (provincial) government. As we have discussed before, the institutional migration barriers would affect the pool of “management technology” available to manufacturing firms through labor scarcity. Therefore, the past institutional migration barriers at the prefecture level provide a plausibly exogenous source of variations on the intensity of incentive pay adoption in recent firms.¹⁰

The second instrumental variable is farm size. Farm size is measured as land per capita among agricultural *Hukou* holders. The rationale is that it is easier for agricul-

⁶An important assumption is that labor scarcity and incentive pay adoption are complementary.

⁷A distinctive feature of Chinese *Hukou System* is that local people are registered with either an agricultural *Hukou* or a nonagricultural *Hukou*. Agricultural *Hukou* holders are mainly located in rural areas, while nonagricultural *Hukou* holders are mainly located in urban areas. The *Hukou System* strictly prevents agricultural *Hukou* holders from migrating permanently to the urban areas through an annual quota system.

⁸By the end of 2004, the total urban population was 542.83 million, accounting for 41.76% of total population. By contrast, the number of nonagricultural *Hukou* holders was 391.4 million, accounting for 30.81% of total population, suggesting that the number of people temporarily working in the urban area is nontrivial.

⁹The *Hukou* reform since the late 1990s allowed local authorities to reduce institutional migration barriers based on local social and economic conditions. In particular, some local authorities abolished the legal distinction between agricultural and nonagricultural *Hukou* and allowed people who satisfy certain entry conditions to migrate permanently to the destination (Jin 2018).

¹⁰By contrast, temporary migrants, from the same or other cities, are not restricted by the institutional migration barriers, reducing the concern that the institutional migration barriers leads to labor shortage. In other words, the labor shortage channel would not reject the validity of our IV if factors such as labor demand shocks are independent of institutional migration barriers in the past.

tural *Hukou* holders located in prefectures with a larger farm size to migrate permanently to the urban areas when migration is very costly and incomes from agricultural production reduces liquidity constraints.¹¹ Given that labor supply from rural to urban areas is nontrivial for the industrial sector, firms located in prefectures with a larger farm size are less likely to suffer from labor shortage through increased availability of permanent migrants. Moreover, the household responsibility system that was introduced since the early 1980s distributed farm land evenly among local agricultural *Hukou* holders, suggesting that differences in farm size are largely determined by local natural endowment. Unlike institutional migration barriers, farm size determines agricultural individuals' financial capacity to migrate permanently to urban areas. As we have discussed before, farm size would affect the pool of "management technology" available to manufacturing firms through labor scarcity. Therefore, the past farm size at the prefecture level provides an alternative plausibly exogenous source of variations on the intensity of incentive pay adoption in recent firms.

The main findings of the study are as follows. First, by exploring determinants of incentive pay adoption across firms, we find that firms with better labor endowments are adopting less incentive pay, suggesting that firms negatively select into incentive pay adoption. Second, when examining the impact of incentive pay adoption on firm productivity, the Ordinary Least Squares (OLS) estimate shows no significant relationship between intensity of incentive pay adoption and firm productivity. Using an instrumental variables approach, we find that a 10 percentage point (or 0.3 unit standard deviation) increase in the intensity of incentive pay results in 38% higher firm productivity on average, suggesting that the OLS estimate is biased downward. Third, by controlling incentive pay adoption, we find that productivity differences between state-owned and non-state-owned firms decrease by 65%, which suggests that a large proportion of production differences between state-owned and non-state-owned firms is caused by differences in incentive pay adoption. Therefore, facilitating incentive pay adoption among firms with better labor endowments increases productivity while reduces resource misallocation.

This study contributes to the literature as follows. First, to the best of our knowledge, this is the first study to investigate the causal impact of incentive pay adoption on productivity of Chinese industrial firms with a large and representative firm-level survey data. The larger productivity effect of incentive pay adoption found in this study not only enhances our understanding of consequences of changing wage payment systems in China but also sheds light on incentive pay adoption in developing countries. Second, our study sheds light on the origin of productivity differences between state-owned and non-state-owned firms. Our finding that a large proportion of productivity differences between state-owned and non-state-owned firms is attributable to differences in incentive pay adoption suggests that state-owned firms could be as productive as non-state-owned firms with appropriate "management technology", which adds to the debates on the productivity effect of ownership and socialist system (Lin 1988; Lin 1990; Boardman and Vining 1989; Vining and Boardman 1992; Ehrlich, Gallais-Hamonno,

¹¹ Several studies reveal that a positive income shock significantly increases migration propensity through reduced financial constraints (Chernina, Dower, and Markevich 2014; Angelucci 2015; Bazzi 2017; Cai 2020).

Liu, and Lutter 1994; Dewenter and Malatesta 2001; Brown, Earle, and Telegdy 2006; Estrin, Hanousek, Kocenda, Svejnar, Kočenda, Svejnar, Estrin, Hanousek, Kocenda, and Svejnar 2009). Third, our study sheds light on determinants of differences in “management technology” adoption across firms (Bloom and Van Reenen 2007; Bloom and Van Reenen 2010; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen 2019). Our finding that labor scarcity facilitates incentive pay adoption echoes with previous studies on labor scarcity and technological advances (Acemoglu 2010; Acemoglu and Restrepo 2017), while our finding that firms with better labor endowments are less likely to adopt incentive pay in China is at odds with previous evidence on “management technology” adoption, suggesting that previous findings on determinants on “management technology” adoption may not apply to determinants of incentive pay adoption in developing countries. Finally, our study sheds light on the causes and costs of resource misallocation in developing countries (Restuccia and Rogerson 2017). Our findings show that facilitating incentive pay among firms with better labor endowments increases productivity while reduces resource misallocation.

The rest of the paper is structured as follows. The next section introduces the evolutionary wage payment systems in China and proposes our research hypotheses. Section 3 presents data description and summary statistics. Section 4 investigates some drivers of incentive pay adoption. Section 5 examines the causal impact of incentive pay adoption on firm productivity and Section 6 concludes the paper.

2 Background and Research Hypotheses

China’s economic reforms have achieved unprecedented economic outcomes since 1979. A distinct feature of China’s economic reforms is the gradual transformation from a plan-oriented to a market-oriented economic system (McMillan and Naughton 1992; Lau, Qian, and Roland 2000; Young 2000; Xu 2011), in contrast to the radical economic reforms adopted by Eastern European countries. Starting with the agricultural sector, China’s economic reforms were gradually extended to the industrial sector. This section consists of two parts. Part one describes the evolutionary wage payment systems in China. Part two presents three specific hypotheses for empirical tests.

2.1 Wage Payment Systems in China

The reforms of wage payment systems in China started with the introduction of the Household Responsibility System (HRS) to the agricultural sector. After the massive collective movement in the 1950s, China’s agricultural sector worked under the production team system for about 20 years. Under this system, agricultural workers got work points for the jobs they performed every day. At the end of each year, the net income of production team was distributed based on the work points that each one earned during the year. Although various systems of work points had been adopted to reflect the quality and quantity of work performed by each worker, it is extremely difficult to supervise agricultural work because of the nature of agricultural production. An agricultural worker received fixed work points for a day’s work regardless of his work output. Consequently, the incentive to work was low, and productivity was stagnant (Lin

1988). The HRS was introduced to deal with problems associated with the collective system of the late 1970s. Under the new system, the individual peasant, rather than the production team, became the basic decision-making unit for agricultural production. The HRS involves contracts signed between the production team and each household, which regulate the taxes and delivery quotas payable to the state, and the welfare and investment funds payable to the team. Any production above the delivery quota is retained by the household, which can sell it and receive the proceeds. Some significant studies have assessed the effectiveness of the HRS (McMillan, Whalley, and Zhu 1989; Lin 1988; Lin 1992; Wen 1993). These studies consistently provide evidence that introducing the HRS significantly increases agricultural productivity through changing wage payment systems.

The second stage introduces the “managerial responsibility system” to state-owned firms in the industrial sector, which transferred the responsibility of production decisions from the state to the firm and increased the fraction of profits that the firm could retain. As a result, firm managers respond to these increases in autonomy by strengthening workers’ performance incentives, such as paying more in bonuses and hiring more workers on fixed-term contracts. A number of studies have confirmed that introducing the “managerial responsibility system” significantly increases productivity of the state-owned firms through increased bonuses (Groves, Hong, McMillan, and Naughton 1994; Li 1997).

The third stage is the prevalence of the non-state-owned firms in the industrial sector since the late 1990s. Since non-state-owned firms adopt more flexible wage payment systems than their state-owned counterparts, the increased proportion of non-state-owned firms significantly alters the wage payment systems of the industrial sector. For example, while state-owned firms used to recruit permanent (contract) workers, it is very common for non-state-owned firms to recruit temporary (contract) workers, particularly temporary migrants, who change jobs frequently. As a result, more flexible wage payment systems such as piece rates have been adopted intensively by non-state-owned firms than their state-owned counterparts.

Overall, China’s transformation into a more market-oriented economic system is accompanied with significant changes in wage payment systems. In particular, the prevalence of non-state-owned firms results in more flexible wage payment systems for the industrial sector. Nevertheless, very few empirical studies investigate the extent to which more flexible wage payment systems affect China’s productivity growth.

2.2 Research Hypotheses

Hypothesis one: Firms exposed to a higher degree of labor scarcity are adopting incentive pay more intensively. Existing studies suggest that labor scarcity encourages technological advances when technology is strongly labor-saving (Acemoglu 2010). In addition, incentive pay adoption can be considered as a component of management technology that increases labor productivity (Bloom, Sadun, and Van Reenen 2016). Consequently, firms exposed to a higher degree of labor scarcity are adopting incentive pay more intensively.

Hypothesis two: Adopting incentive pay makes manufacturing firms more productive. Existing economic theory implies that adopting incentive pay affects firm

productivity mainly through two channels. First, incentive pay adoption may increase productivity by inducing employees to work harder. Second, incentive pay adoption may increase productivity by attracting more productive workers. Both channels lead to a positive impact of incentive pay adoption on firm productivity.

Hypothesis three: The productivity gap between state-owned and non-state-owned manufacturing firms narrows down when considering differences in incentive pay adoption. According to previous studies, there are two stylized facts about state-owned firms in China. First, state-owned firms are much less productive than non-state-owned firms on an average. Second, state-owned firms usually adopt an inferior “management technology”, including a more rigid wage payment system and lower intensity of incentive pay, than their non-state-owned counterparts. Consequently, if our second hypothesis holds, the productivity gap between state-owned and non-state-owned firms should be smaller after controlling differences in incentive pay adoption.

3 Data, Variables and Summary Statistics

3.1 Data Sources

Our primary data comes from investment climate survey for firm managers, conducted by the World Bank between July–November, 2005. It covers 12,400 Chinese manufacturing firms in 120 cities, located in all provinces, autonomous regions, and directly administrated cities, with the exception of Tibet. In each city, a random sample of firms stratified along sector and size was chosen. The local sample size was 100 firms each in prefecture-level cities and 200 firms each in other cities directly administered by the central government, like *Beijing*, *Chongqing*, *Shanghai*, and *Tianjin*.¹² The survey covers a broad range of firm-level information including firm age, ownership, industry, employee wage components, financial statement, and labor statistics. While most information above for each firm is only available for 2004, the year prior to the survey year information on financial statement and labor statistics is available for three years (2002–2004).

In addition, we resort to the China City Statistical Yearbook (1991) to construct our instrumental variables in 1990.¹³ For identification reasons, we mainly focus on prefecture-level cities that existed in 1990. Consequently, we drop firms located in seven cities, namely *Beijing*, *Chongqing*, *Shanghai*, *Tianjin*, as well as *Taizhou (Zhejiang)*, *Jingzhou (Hubei)*, and *Huanggang (Hubei)*.¹⁴ Our final sample consists of 11,300 firms.

¹²More information on the survey methodology can be found at <http://www.enterprisesurveys.org/Methodology>.

¹³We will explain the selection of 1990 to calculate our instrumental variables later. We also use an alternative year for robustness check.

¹⁴The first four cities are directly administrated by the central government, while the other three became prefecture-level cities after 1990.

3.2 Variable Definitions

The key variable to be defined is intensity of incentive pay adoption at the firm level. According to the survey, total compensation consists of five different wage types: fixed salary, bonus, piece-rate wage, time wage, and others. Incentive pay is an inherently multidimensional concept, but we focus on a single dimension for this study: the extent to which firms adopt more bonuses and piece-rate wage. Given the wage components of all employees for each firm, we can calculate the percent of bonuses and piece-rate wages to total compensation at the firm level. Consequently, firms with a higher percent of bonuses and piece-rate wages to total compensation are adopting incentive pay more intensively than other firms with a lower percent of bonuses and piece-rate wages to total compensation. Conceptually, the minimum intensity of incentive pay is 0 and the maximum is 100.

Given that the survey provides information on total compensation for permanent and temporary (contract) workers separately, we only focus on incentive pay adoption among permanent workers for each firm. This is because the fraction of piece-rate wage is highly correlated with the fraction of temporary workers (versus permanent workers) in the firm. Therefore, any impact driven by differential adoption of incentive pay can be due to differential hiring of temporary workers. The latter can both be driven by and directly affect firm productivity. Focusing on incentive pay adoption among permanent workers only reduces the concern that the impact of incentive pay adoption is contaminated by contract labor hiring. Nevertheless, we use alternative indicators of incentive pay for robustness checks.

The main outcome variable in the study is firm productivity. Our basic measurement is total sales per worker, which measures labor productivity at the firm level. An alternative measurement is value added per worker. We define value added as value of output minus value of raw materials. Both indicators can be directly calculated using information from 2004. In addition, we calculate total factor productivity (TFP) at the firm level, following (Levinsohn and Petrin 2003; Akerberg, Caves, and Frazer 2015). Specifically, we use data on output, capital, labor (skilled), labor (unskilled), and intermediate inputs from 2002 to 2004 to calculate the TFP indicator.¹⁵ In this study, we use total sales per worker for the benchmark results and alternative indicators of productivity for robustness checks.

3.3 Summary Statistics

Summary statistics of main variables are reported in Table 1. According to the table, the average intensity of incentive pay is 41 (unit) among permanent (contract) workers. We also find that the permanent (contract) workers account for 77% of all employment on an average, suggesting that firms prefer them.

Figure 1 shows the distribution of incentive pay adoption across firms. We find that the intensity of incentive pay is 0 (unit) for 2,136 firms, accounting for 17% of all samples. In addition, there are 2,552 firms with intensity of incentive pay more than 80 (unit), accounting for 21% of all samples. Figure 2 shows the distribution of incentive pay adoption across industries. We find that incentive pay adoption is prevalent in

¹⁵We use STATA code-prodest, to calculate the TFP at the firm level.

Table 1: Summary statistics for main variables

Variables	count	mean	min	max
var_logincome_pc	11035	12.20	5.31	21.30
var_incentive_pw	11035	41.85	0.00	100.00
var_piece_pw	11035	29.38	0.00	100.00
var_bonus_pw	11035	12.47	0.00	100.00
var_fix_pw	11035	47.00	0.00	100.00
var_age	11035	13.83	3.00	140.00
var_state	11035	0.09	0.00	1.00
var_nonstate	11035	0.72	0.00	1.00
var_foreign	11035	0.18	0.00	1.00
var_logemploy	11035	5.60	1.79	13.50
var_logasset	11035	16.31	0.00	25.61
var_logrd	11035	7.32	0.00	22.20
var_export_country	11035	16.49	0.00	100.00
var_export_city	11035	60.37	0.00	100.00
var_high_above	11035	49.36	0.00	100.00
var_college_above	11035	17.96	0.00	100.00
var_master	11035	0.15	0.00	1.00
var_undergraduate	11035	0.43	0.00	1.00
var_college	11035	0.28	0.00	1.00
var_high_	11035	0.14	0.00	1.00
var_permanent_ratio	11035	78.90	0.00	100.00
var_agri_1990	11035	66.37	16.53	89.49
var_land_1990	11035	1.49	0.37	6.62

Source: Enterprise Survey(2005), World Bank.

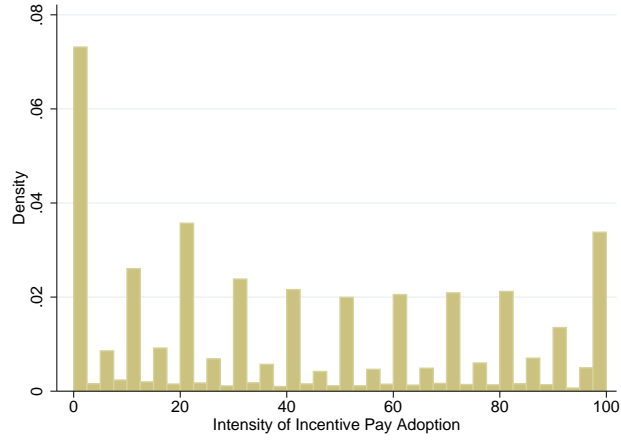


Figure 1: Distribution of incentive pay adoption across firms
Source: Enterprise Survey (2005), World Bank.

most industries at the time of the survey. In particular, incentive pay accounts for more than half of total compensation on an average among firms in industries like textile and garment, shoes and hats. By contrast, incentive pay are adopted much less frequently in industries like manufacturing of communication equipment. Figure 3 shows the overall distribution of the total sales per worker as a log, suggesting that productivity varies significantly across firms. In particular, the sales per worker (log) of top 10 percentile is 13.7 on an average, which is 300% larger than that of bottom 10 percentile.

4 How do Firms Select into Incentive Pay Adoption?

An important question on incentive pay adoption is whether firms positively select into incentive pay adoption or not. Some studies show that firms that use human capital more intensively tend to have much better management practices (Lazear 2000; Bloom and Van Reenen 2010; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen 2019). Other studies argue that labor abundance/endowment deters technical advances (Acemoglu 2010; Acemoglu and Restrepo 2017). Consequently, whether firms positively select into incentive pay adoption or not is an empirical question. In this section, we present some exploratory patterns on the relationship between labor conditions and incentive pay adoption to shed light on this question. Since labor conditions adopted here are self-reported by firms, we do not try to put a causal relationship on these coefficients.

Figure 4 shows the relationship between labor conditions and intensity of incentive pay, without controlling other variables. We find that the average intensity of incentive pay is higher for firms affected by labor scarcity relative to other firms with labor surplus or sufficient labor. We further resort to a linear regression model to examine the impact of these factors on intensity of incentive pay adoption by controlling additional

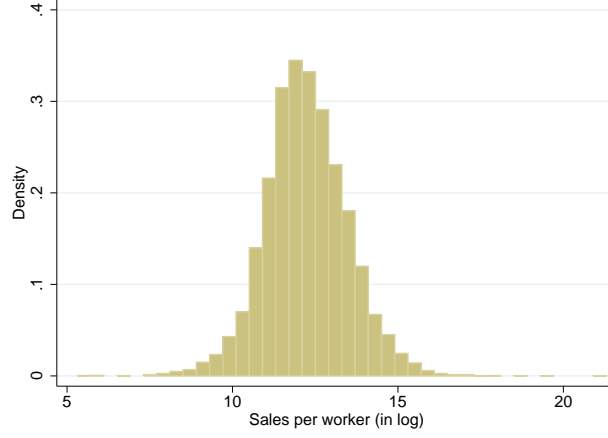


Figure 2: Distribution of sales per worker (in log)
Source: Enterprise Survey (2005), World Bank.

variables.

$$IncentivePay_i = \alpha + \sum \beta_j LaborConditions_{ij} + \sum \gamma_k HumanCapital_{ik} + Z\Psi + \varepsilon_i \quad (1)$$

where $LaborConditions_{ij}$ refers to the j th indicator of labor conditions for firm i . $HumanCapital_{ik}$ refers to the k th indicator of human capital for firm i . Vector Z includes firm characteristics such as firm age, fraction of permanent workers, composition of sales (exports versus non-exports), total employment in log, total capital in log, total R&D in log, ownership dummies, 2-digit industry dummies, and 4-digit region dummies. ε_i is the error term.

Main results are reported in Table 2. Column 1 shows the impact of general labor condition on incentive pay adoption without controlling other variables. The base group refers to firms with sufficient labor. We find that firms with labor shortage are associated with 6.5 unit higher intensity of incentive pay adoption, suggesting that labor scarcity is an important factor that encourages firms to adopt incentive pay more intensively. Column 2 further controls indicators of accessibility to skilled labor. The base group refers to firms with no lack of skilled labor. We find significant evidence that a lack of skilled labor affects incentive pay adoption. Column 3 further controls indicators of human capital of firms. We find evidence that firms with a higher fraction of workers with a college degree or above are less likely to adopt incentive pay. Moreover, firms with less educated general manager are more likely to adopt incentive pay than firms with more educated general manager. Our main results are still robust after controlling other firm-level characteristics as well as city fixed effects (Columns 4-5).

Overall, we find consistent evidence that firms with labor scarcity are adopting incentive pay more intensively compared with other firms with sufficient labor or labor surplus. Since incentive pay adoption can be considered as a component of manage-

Table 2: Drivers of incentive pay adoption

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
	b/se	b/se	b/se	b/se	b/se
LabourShortage	6.530*** (0.894)	6.192*** (0.903)	4.792*** (0.899)	3.319*** (0.895)	3.101*** (0.883)
LabourSurplus	-0.448 (1.003)	-0.660 (1.007)	-0.650 (0.998)	-2.415** (1.007)	-2.538** (0.993)
LowSkillShortage		1.243 (0.851)	1.942** (0.842)	0.643 (0.810)	0.580 (0.809)
ModerateSkillShortage		0.897 (0.879)	1.474* (0.870)	-0.520 (0.840)	-0.076 (0.844)
HighSkillShortage		3.280*** (1.060)	4.045*** (1.048)	1.580 (1.012)	2.206** (1.019)
HighschoolorAbove			-0.007 (0.015)	-0.004 (0.015)	-0.006 (0.015)
CollegeorAbove			-0.249*** (0.024)	-0.240*** (0.024)	-0.199*** (0.024)
GM_undergraduate			0.708 (0.962)	1.464 (0.938)	0.809 (0.923)
GM_college			4.321*** (1.062)	5.027*** (1.065)	3.582*** (1.053)
GM_high			4.246*** (1.277)	5.721*** (1.301)	4.584*** (1.291)
Observations	11042	11042	11040	11035	11035
Adjusted R^2	0.005	0.005	0.029	0.112	0.157
F	28.02	13.17	34.40	29.99	13.87

Notes: This table shows OLS estimates on determinants of incentive pay adoption. Column 1 only considers general labor conditions. The base group is firms with sufficient labor. Column 2 considers skill labor shortage. The base group is firms with no skilled labor shortage. Column 3 considers human capital of firms. Column 4 controls variables such as firm age, ownership and industry dummies, employment, capital, RD expenditures, composition of sales. Column 5 considers city dummies. Standard errors in parentheses.

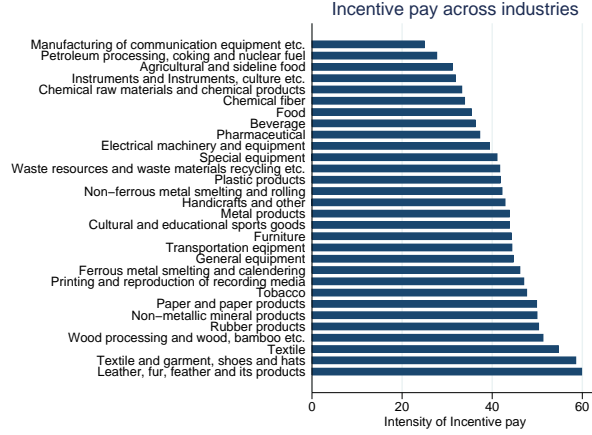


Figure 3: Distribution of incentive pay adoption across industries
Source: Enterprise Survey (2005), World Bank.

ment technology (Bloom, Sadun, and Van Reenen 2016), these findings are consistent with previous argument that labor scarcity encourages technological advances when technology is strongly labor-saving (Acemoglu 2010). Moreover, we find evidence that firms with higher human capital are adopting incentive pay less intensively. All the evidence suggests that firms negatively select into incentive pay adoption.

5 Impact of Incentive Pay on Firm Productivity

In the previous section, we have found evidence that firms with better labor endowments are adopting less incentive pay. In other words, firms negatively select into incentive pay adoption. In this section, we empirically estimate the causal impact of incentive pay adoption on firm productivity. This section consists of three parts. Part one introduces model specification and identification strategy. Part two presents main estimation results. Part three conducts several robustness checks.

5.1 Model Specification and Identification Strategy

To examine the impact of incentive pay adoption on firm productivity, we estimate the following model specification:

$$Y_i = \alpha + \beta IncentivePay_i + X\Phi + \varepsilon_i \quad (2)$$

where Y_i is the total sales per worker in log for each firm i . $IncentivePay_i$ is the (weighted) intensity of incentive pay adopted by firm i . The intensity of incentive pay is defined as the ratio of bonuses and piece-rate wages to total compensation among permanent workers. X refers to firm characteristics such as age, skill composition of workers, education degree of general manager, fraction of dependency on permanent

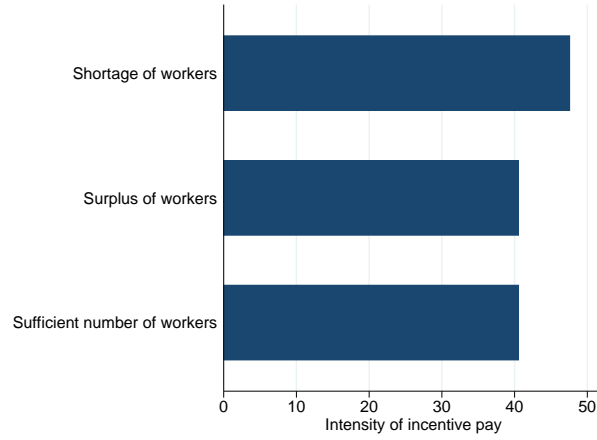


Figure 4: Labor conditions and incentive pay
Source: Enterprise Survey (2005), World Bank.

(contract) workers (versus temporary workers), composition of sales (exports versus non-exports), total employment in log, total capital in log, total R&D expenditures in log, ownership dummies, 2-digit industry dummies, and city-level dummies.¹⁶ ε_i is the error term and β is the parameter of interest, which captures the impact of incentive pay on firm productivity.

Estimating the causal impact of incentive pay adoption on firm productivity presents some empirical challenges. As we have shown before, firms negatively self-select into the incentive pay adoption. Specifically, it is easier for less productive firms to adopt piece-rate wages incentive pay when they are associated with more simple tasks/jobs that can be evaluated separately. By contrast, more productive firms are more likely to be associated with complex tasks/jobs that cannot be evaluated separately, and in turn are less likely to adopt piece-rate wages incentive pay. Consequently, the OLS estimate suffers from reverse causality issues. The OLS estimate will be biased downward when less productive firms are adopting incentive pay more intensively.

In addition, firms differ in production technologies, and if production technologies are associated with intensity of incentive pay adoption, omitting these variables makes the OLS estimate biased and inconsistent. For example, when firms with more advanced production technologies are less likely to adopt piece rates, omitting variables relevant to production technologies will make the OLS estimate biased downward. Firms are also likely to be exposed to different degrees of product market competitionlabor scarcity. When product market competition is positively associated with intensity of incentive pay adoption, omitting variables relevant to product market competition makes the OLS estimate biased upward. Finally, firms are exposed to different

¹⁶Given the fact that our instrumental variables are at the city level, we cannot control city-level fixed effects when estimating our results using the IV approach. We also find evidence that controlling city-level fixed effects does not affect our OLS estimates.

demand shocks, and when demand shocks are positively associated with incentive pay adoption, the OLS estimate is also biased upward. Overall, both the reverse causality and omitted variable problems make the OLS estimate biased and inconsistent.

One potential way to deal with endogenous incentive pay adoption is using a field experiments approach, which has been adopted by several studies to investigate how workers respond to incentive pay within firms (Bandiera, Barankay, and Rasul 2011). An obvious advantage of this approach is that it allows us to design clean treatment and control groups for identification. The disadvantage is that it is usually very difficult to conduct large-scale randomized trials in practice. As a result, most field experiments are restricted to a very specific context and are far less representative.

Our paper resorts to an instrumental variables approach to estimate the causal impact of incentive pay adoption on firm productivity. We use two plausibly exogenous variations on labor scarcity in the past as instrumental variables. Our instrumental variables take advantage of two distinctive supply-push factors of rural-urban permanent migration in China: institutional migration barriers and financial constraints. We test whether shifts in the relative labor scarcity in the past are associated with more incentive pay adoption in recent firms. The intuition is that a higher degree of labor scarcity encourages local firms to adopt more incentive pay, an important component of “management technology”, to utilize existing workforces more effectively. Moreover, the practices of incentive pay adoption in the past will be transferred to recent firms through technology spill-overs regardless of labor conditions *de facto*. In addition, the early shocks on the relative labor scarcity does not directly affect recent labor costs exposed to firms in the presence of large-scale (temporary) migration in the mid-2000s, within and across regions.

Our first instrumental variable is institutional migration barriers (also known as *Hukou System*). The strength of institutional migration barriers is measured as ratio of agricultural *Hukou* holders to total registered population at the prefecture level. The rationale is that *Hukou System* prevents agricultural *Hukou* holders from migrating permanently to the urban areas.¹⁷ Prefectures with a larger ratio of agricultural *Hukou* holders are associated with higher institutional migration barriers. Given that labor supply from rural to urban areas is nontrivial, firms located in regions with higher institutional migration barriers are more likely to suffer from labor shortage.¹⁸ In particular, until the late 1990s, the central government strictly controlled the conversion from an agricultural *Hukou* to a nonagricultural *Hukou* through an annual quota system, and local (prefecture-level) governments had little autonomy to alter migration barriers by themselves.¹⁹ The institutional migration barriers would affect the pool of “management technology” available to manufacturing firms through labor scarcity. Therefore, the past institutional migration barriers at the prefecture level provide an exogenous source of variations on the incentive pay adoption in recent firms, varying

¹⁷Many existing studies have pointed out that the *Hukou System* prevents an agricultural *Hukou* holder from migrating permanently to the nonagricultural sector through restrictive access to local public services as well as employment opportunities (Chan and Zhang 1999; Wang and Zuo 1999; Meng and Zhang 2001; Song 2014; Kinnan, Wang, and Wang 2018).

¹⁸This argument also applies when there are migrants from other cities.

¹⁹The annual quota of *Hukou* conversion was largely determined by previous stocks of nonagricultural individuals.

independently of production technologies, product market competition, and demand shocks.

Our second instrumental variable is farm size. Farm size is measured as land per capita among agricultural *Hukou* holders at the prefecture level. The rationale is that it is easier for agricultural *Hukou* holders located in prefectures with a larger farm size to migrate permanently to the urban areas when migration is very costly and agricultural production provides a main source of income.²⁰ Given that labor supply from rural to the nonagricultural sector is nontrivial, firms located in prefectures with a larger farm size are less likely to suffer from labor shortage. The introduction of the HRS since the early 1980s distributed farm land evenly among local agricultural *Hukou* holders, suggesting that differences in farm size are largely determined by local natural endowment. The farm size would affect the pool of “management technology” available to manufacturing firms through labor scarcity. Therefore, past farm size provides an exogenous source of variation on incentive pay adoption in recent firms. In contrast to institutional migration barriers that determine whether agricultural *Hukou* holders are allowed to migrate permanently to the urban areas, farm size determines whether agricultural *Hukou* holders can afford permanent migration costs.

The instrumental variables approach properly identifies treatment effects if (1) initial institutional migration barriers are made exogenously by the central government and farm size is made exogenously by local natural endowment, and (2) neither of the terms are correlated with omitted factors that also shape firm productivity. Failure of these conditions would again lead to biased estimates. For example, the strength of institutional migration barriers as well as the farm size in the past may be correlated with labor conditions de facto exposed to recent firms. When these instrumental variables affect firm productivity through alternative channels such as labor shortage or labor costs, omitting these variables will again make our estimates biased. Our empirical analysis will thus test for these issues.

We construct both instrumental variables using prefecture-level data from 1990.²¹ First, the *Hukou System* experienced significant changes since the late 1990s. In particular, local governments were granted more autonomy to reform the *Hukou System*. Consequently, the legal distinction between agricultural and nonagricultural *Hukou* was abolished by some local governments, which makes the recent ratio of agricultural *Hukou* holders inappropriate while capturing the strength of institutional migration barriers.²² By contrast, the distinction between agricultural and nonagricultural *Hukou* was still prominent in 1990 when the conversion from an agricultural to a nonagricultural *Hukou* was strictly regulated by the central government through an annual quota system. Second, the Chinese agricultural production system has gradually changed from a production team system to a HRS since the early 1980s. Consequently, agricultural individuals are allowed to retain a large proportion of income from agricultural production, in contrast to “fixed salary” under the production team system. As a result, farm size is closely associated with financial capacity of agricultural *Hukou* holders

²⁰Many existing studies have revealed financial constraint as an important factor determining migration decisions in developing countries (Bryan, Chowdhury, and Mobarak 2014; Angelucci 2015).

²¹We will use alternative earlier data to construct our instrumental variables for robustness checks.

²²In *Hukou* reform cities, local authorities set up different entry barriers after abolishing the legal distinction between agricultural and nonagricultural *Hukou*.

under the HRS. Therefore, it makes sense to construct farm size using data from 1990, when the HRS was adopted nationally.

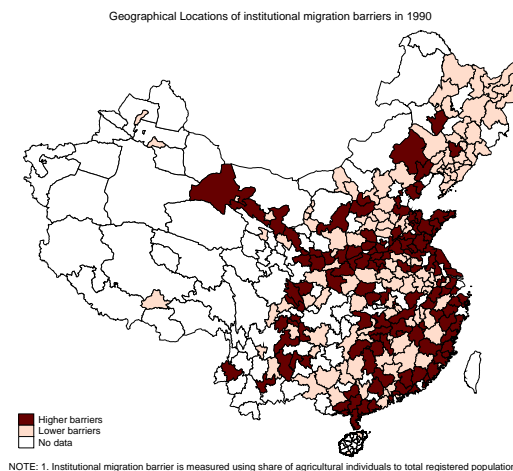


Figure 5: Strength of institutional migration barriers across cities in 1990
Source: China City Statistical Yearbook (1991), NBS.

Figures 5-6 display geographical distribution of institutional migration barriers and farm size across cities in 1990. We find that the strength of institutional migration barriers varies significantly across prefectures. Specifically, the coastal prefectures are more likely to suffer from higher institutional migration barriers than inland and north-east prefectures. This is consistent with the fact that the central government set up a larger number of state-owned firms in inland and northeast China than in coastal China during the 1950s.²³ In other words, the initial strength of institutional migration barriers is largely determined by early investments on state-owned firms that vary across prefectures. Prefectures receiving relatively more investments from the central government are associated with a larger state sector. Since agricultural *Hukou* holders are allowed to convert to a nonagricultural *Hukou* when employed by state-owned firms, a larger state sector is associated with a larger ratio of nonagricultural *Hukou* holders. Unlike institutional migration barriers, there are significant differences in farm size between northern and southern China, which is largely attributable to local natural endowment. Taking prefectures located in northeast China as an example, the larger farm size and lower institutional migration barriers suggest that supply of permanent workers is relatively more abundant there. According to our previous argument, firms located in northeast China should adopt incentive pay less intensively than other regions with a relatively lower ratio of nonagricultural *Hukou* holders and smaller farm size.

²³ According to Bo (1991), military concern is one of the main reasons that the central government made relatively more investments on inland and northeast China relative to coastal China from 1953 to 1957.

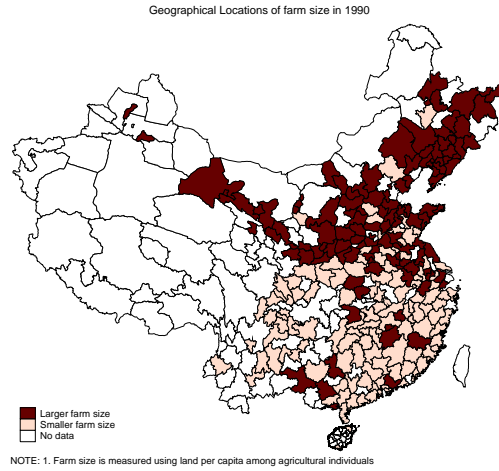


Figure 6: Farm size across cities in 1990
Source: China City Statistical Yearbook (1991), NBS.

5.2 Estimation Results

5.2.1 First stage results

We start with reporting first stage results for our first instrumental variable, institutional migration barriers. Main results are reported in Table 3. Column 1 shows the impact of institutional migration barriers on the intensity of incentive pay adopted by firms. We find that a 10 percentage point (or 0.5 unit standard deviation) increase in the strength of institutional migration barriers is associated with 1.1 unit increase in the intensity of incentive pay. This is consistent with our previous hypothesis that higher institutional migration barriers in the past result in stronger intensity of incentive pay adoption in recent firms.

An important rationale of this instrumental variable is that the early pool of “management technology” will be transferred to recent firms through technology spill-overs. Assuming that the fraction of permanent workers represents recent firms’ dependency on permanent workers, the relationship between the early shock on labor scarcity and current incentive pay adoption should be stronger in firms that are more dependent on permanent workers. Results are reported in Column 2. We find that the impact of institutional migration barriers on incentive pay adoption is larger for firms with a larger fraction of permanent workers, suggesting that availability of better “management technology” encourages recent firms that are more dependent on permanent workers to utilize existing workforces more effectively. However, the estimate is not statistically significant at the conventional level.

We further examine how the impact of institutional migration barriers on intensity of incentive pay adoption varies across firms’ ownership. Given that the *Hukou System* hardly affects state-owned firms’ access to permanent workers (Knight, Song, and Huaibin 1999; Knight and Song 1999; Kamal and Lovely 2012), the impact of institu-

Table 3: Instrumental variable (Migration barrier) and incentive pay

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
	b/se	b/se	b/se	b/se	b/se
IV(Migration barriers)	0.110*** (0.040)	0.015 (0.070)	0.119*** (0.044)	0.109*** (0.040)	0.142*** (0.053)
IVtimesPermanentRatio		0.001 (0.001)			
IVtimesState-owned			-0.081 (0.052)		
IVtimesLaborShortage				0.020 (0.062)	
IVtimesLaborSurplus				-0.022 (0.050)	
IVtimesLowSkillShortage					-0.064 (0.049)
IVtimesModerateSkillShortage					-0.013 (0.050)
IVtimesHighSkillShortage					-0.053 (0.072)
Observations	11035	11035	11035	11035	11035
Adjusted R^2	0.114	0.114	0.114	0.115	0.114
F	33.66	34.25	33.28	33.00	33.90

Notes: This table shows first stage results for the instrument variable of migration barriers. Column 1 shows the overall impact on the intensity of incentive pay adoption. Column 2 considers interaction term between the instrumental variable and fraction of permanent workers. Column 3 considers interaction term between the instrumental variable and firm ownership. Column 4 considers interaction term between the instrumental variable and labor conditions. Control variables include firm age, skill composition of workers, education degree of general manager, fraction of permanent workers (versus temporary workers), composition of sales (exports), total employment in log, total capital in log, total RD expenditures in log, ownership dummies, 2-digit industry dummies. Standard errors are clustered at the city level. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Instrumental variables (Farm size) and incentive pay

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	b/se	b/se	b/se	b/se	b/se	b/se
IV(Farm size)	-2.830*** (0.844)	-6.755*** (1.685)	-3.103** (1.401)	-2.893*** (0.910)	-2.704*** (0.957)	-2.988*** (0.856)
IV2(Farm size squared)		0.731** (0.279)				
IVtimesPermanentRatio			0.003 (0.013)			
IVtimesState-owned				0.574 (1.010)		
IVtimesLaborShortage					0.376 (1.157)	
IVtimesLaborSurplus					-0.857 (0.872)	
IVtimesLowSkillShortage						-0.577 (0.666)
IVtimesModerateSkillShortage						0.494 (0.689)
IVtimesHighSkillShortage						0.904 (0.928)
Observations	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.116	0.117	0.116	0.116	0.117	0.116
F	31.87	31.64	31.26	31.28	36.57	37.41

Notes: This table shows first stage results for the instrument variable of farm size. Column 1 shows the overall impact on the intensity of incentive pay adoption. Column 2 considers farm size squared. Column 3 considers interaction between farm size and fraction of permanent workers. Column 4 considers interaction between farm size and firm ownership. Column 5 considers interaction between farm size and labor conditions. Control variables include firm age, skill composition of workers, education degree of general manager, fraction of permanent workers (versus temporary workers), composition of sales (exports), total employment in log, total capital in log, total RD expenditures in log, ownership dummies, 2-digit industry dummies. Standard errors are clustered at the city level. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

tional migration barriers on firms' incentive pay adoption should be much smaller for state-owned firms than their non-state counterparts. Results are reported in Column 3. We find that institutional migration barriers mainly affect non-state-owned firms.

Finally, we check how the impact of institutional migration barriers on intensity of incentive pay adoption varies across labor conditions. As we have discussed before, an important hypothesis is that the past "management technology" will be transferred to recent firms regardless of recent labor conditions. Results are reported in Column 4. We find that the impact is still very significant for firms with sufficient number of workers, reducing the concern that the institutional migration barriers in the past affect incentive pay adoption in recent firms through labor shortage *de facto*. All these findings above confirm that institutional migration barriers in the past affect recent firms' adoption of incentive pay through the availability of "management technology" to manufacturing firms.

Table 4 reports the first stage results for our second instrumental variable, farm size. Column 1 shows the impact of farm size on the intensity of incentive pay adoption. We find that one unit (or one standard deviation) increase in the farm size is associated with 2.8 unit decrease in the intensity of incentive pay. In other words, farm size is negatively associated with the intensity of incentive pay adoption. This is consistent with our previous hypothesis that larger farm size in the past result in lower intensity of incentive pay adoption in recent firms. Column 2 further considers the quadratic form of farm size. We find that the coefficient of land per capita squared variable is significantly positive, which suggests that the relationship between farm size and intensity of incentive pay is U-shaped. This is consistent with recent studies that a larger farm size decreases the probability of migration when the larger demand for agricultural workers offsets the reductions in financial constraints (Yan, Bauer, and Huo 2014). In other words, our results are consistent with some recent findings that there is a reverse U-shaped relationship between farm size and migration probability. We find that the threshold point is 4.6 (ha), which also suggests that the farm size of most agricultural individuals is below that threshold.

Column 3 shows how the impact changes with the fraction of permanent workers recruited by recent firms. We find that the negative impact is smaller in firms with relatively more permanent workers but not statistically significant at the conventional level. We also examine whether the impact of farm size on intensity of incentive pay adoption varies across firms' ownership. Column 4 shows the estimation results. We find that the impact of farm size on intensity of incentive pay adoption is a bit smaller for state-owned firms relative to non-state-owned firms. However, the coefficient is not statistically significant at the conventional level.

Finally, we check how the impact of farm size on intensity of incentive pay adoption varies across labor conditions. As we have discussed before, an important hypothesis is that the past "management technology" will be transferred to recent firms regardless of recent labor conditions. Results are reported in Column 5. We find that the impact is still very significant for firms with sufficient number of workers, reducing the concern that the farm size in the past affect incentive pay adoption in recent firms through labor shortage. All these findings above confirm that farm size in the past affect recent firms' adoption of incentive pay through the availability of "management technology"

Table 5: Incentive pay and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.038*** (0.007)	0.038*** (0.006)	0.035*** (0.005)	0.038*** (0.005)	0.036*** (0.004)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.382	0.452	-0.584	-0.610	-0.466	-0.600	-0.492
cdf			48.558	70.985	44.661	49.701	39.193
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.248	0.949	0.506

Notes: This table reports the impact of incentive pay adoption on firm productivity. Column 1 reports the OLS estimates without city fixed effects. Column 2 reports the OLS estimates by controlling city fixed effects. Columns 3-7 report IV estimates. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses farm size and farm size squared as instrumental variables together. Column 6 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Main control variables are the same as before. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to manufacturing firms.

Overall, we find consistent evidence that both institutional migration barriers and farm size in the past significantly affect recent firms' intensity of incentive pay adoption. In particular, we find evidence that the relationship still holds in firms that have sufficient number of workers, reducing the concern that these instrumental variables affect firm productivity through alternative channels such as labor shortage.

5.2.2 Impact of incentive pay on firm productivity

This section shows the impact of incentive pay adoption on firm productivity. Main results are reported in Table 5. Column 1 shows the OLS estimates. We find that the coefficient of interest is close to zero and is not statistically significant at the conventional level. Column 2 reports the OLS results by further controlling prefecture-level fixed effects. We still do not find any significant relationship between incentive pay adoption and firm productivity. In other words, adding prefecture-level fixed effects does not significantly affect our OLS estimates. Given that our instrumental variables are at the city level, we do not consider prefecture-level fixed effects when using the instrumental variables (IV) approach.

IV estimates that address potential endogenous issues are reported in Columns 3-7. Column 3 uses institutional migration barriers as an instrumental variable. Column 4 uses farm size as an instrumental variable. We find almost the same coefficient using different instrumental variables, enhancing the reliability of our instrumental variables. Specifically, a 10 percentage point increase in the intensity of incentive pay increases firm productivity by 38% on an average. In other words, the OLS estimate seriously underestimates the actual impact of incentive pay on firm productivity. There are at least two reasons why the OLS estimate is biased downward. First, within the same industry,

Table 6: Incentive pay and labor productivity with city characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV	IV	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	0.041*** (0.006)	0.040*** (0.006)	0.040*** (0.006)	0.038*** (0.006)	0.038*** (0.006)	0.034*** (0.007)	0.034*** (0.007)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	-0.690	-0.613	-0.613	-0.512	-0.530	-0.302	-0.305
cdf	39.653	35.168	31.829	33.332	31.337	23.475	23.403
arfp	0.000	0.000	0.000	0.000	0.000	0.000	0.000
sarganp	0.285	0.367	0.360	0.376	0.397	0.844	0.690

Notes:Notes: This table shows the impact of incentive pay adoption on firm productivity by controlling city characteristics. Column 1 reports OLS estimate. Columns 2-8 report IV estimates using both instrumental variables. Column 2 controls geographical location (coastal versus non-coastal), size of urban population, size of migration (relative to local natives) and GDP per capita. Column 3 further controls industrial structures. Column 4 further controls size of state sector (relative to non-state sector). Column 5 further controls skill ratio (relative to unskilled). Column 6 further controls average labor costs. Column 7 further controls local unemployment rate. Column 8 further controls land price. Other control variables are the same as before. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

firms specialize in simple/basic versions of the goods will adopt piece-rate wage more than those position themselves at the higher end (and perhaps are more productive), resulting in reverse causality issues. Second, firms differ in production technologies and labor endowments, omitting these variables also makes the OLS estimate biased downward.

The bottom rows of Table 5 reports the p-values from the Durbin-Wu-Hausman test, which tests the null hypothesis that the OLS estimator is consistent and efficient against the alternative hypothesis that it is inconsistent for each of the specifications we report. At the 1% level we reject the null hypothesis for all specifications. Further, when incentive pay adoption is instrumented with more than one instrument, we can test for the validity of the instruments. Column 5 uses both farm size and farm size squared as instrumental variables. Column 6 uses institutional migration barriers and farm size as instrumental variables. Column 7 uses all three instrumental variables. Using different model specifications, we find that the impact of incentive pay adoption on firm productivity is almost unchanged. The last row of Table 5 reports the p-value from the Hansen over-identification test. We fail to reject the null hypothesis that the instruments are valid.

As we have shown above, both instrumental variables vary at the city level and thus these IV regressions cannot control for city fixed effects, raising concerns on the plausibility of the IV exclusion restriction. For instance, farm size may affect demand for final goods produced by firms by affecting agricultural incomes, and the institutional migration barriers may affect human capital investments and therefore the quality, not just the quantity of migrants. To reduce the concern that these instrumental variables can be correlated with other city characteristics that affect firm productivity, we further control the following city-level variables. First, we control variables such as geographical location (coastal versus non-coastal), size of urban population, size of migration

Table 7: Incentive pay and labour productivity gap between SOEs and non-SOEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay		-0.000 (0.000)	0.038*** (0.007)	0.038*** (0.006)	0.035*** (0.005)	0.038*** (0.005)	0.036*** (0.004)
State-owned	-0.486*** (0.037)	-0.491*** (0.037)	-0.240*** (0.075)	-0.236*** (0.071)	-0.256*** (0.066)	-0.238*** (0.068)	-0.252*** (0.065)
Observations	11292	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.380	0.382	-0.584	-0.610	-0.466	-0.600	-0.492
cdf			48.558	70.985	44.661	49.701	39.193
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.248	0.949	0.506

Notes:Notes: The table shows how productivity differences between state-owned and non-state-owned firms change when considering incentive pay adoption. Column 1 reports the OLS estimate without considering incentive pay adoption. Column 2 reports the OLS estimate by considering incentive pay adoption. Columns 3-7 report estimates using instrumental variables for incentive pay adoption. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 6 uses farm size and farm size squared as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(relative to local natives) and GDP per capita. Second, we control variables such as industrial structures and size of state sector (relative to non-state sector). Third, we control variables such as skill ratio (relative to unskilled), average labor costs and unemployment rate. Finally, we consider land price. If our instrumental variables are valid, controlling these city characteristics should not significantly affect our estimation results. We use both instrumental variables for the estimation. Main results are reported in Table 6. We find very similar results using different model specifications. For example, after controlling all these city characteristics, the coefficient only decreases slightly from 0.038 to 0.034, suggesting that these alternative channels does not seriously weaken the validity of our instrumental variables. Thus, we use our benchmark model specification for the following analyses.

5.2.3 Incentive pay and productivity differences across firms

We have shown that adopting incentive pay significantly increases firm productivity. So, how do differences in productivity across firms change when accounting for differences in incentive pay adoption across firms? Previous empirical studies on productivity differences across firms with different ownership rarely consider the channel of incentive pay adoption. These studies argue that state-owned firms are much less productive than their non-state-owned firms and privatization improves firm performance (Boardman and Vining 1989; Dewenter and Malatesta 2001; Brown, Earle, and Telegdy 2006). This section further examines the extent to which productivity differences between state-owned and non-state-owned firms are attributable to incentive pay adoption.

Table 7 shows differences in firm productivity between state-owned and non-state-

Table 8: Incentive pay and labor productivity gap between SOEs and non-SOEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay		-0.000 (0.000)	0.040*** (0.008)	0.037*** (0.006)	0.034*** (0.005)	0.038*** (0.005)	0.036*** (0.004)
State-owned	-0.413*** (0.033)	-0.415*** (0.033)	-0.134* (0.076)	-0.153** (0.065)	-0.173*** (0.060)	-0.146** (0.063)	-0.164*** (0.059)
Observations	11292	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.380	0.382	-0.666	-0.531	-0.395	-0.576	-0.457
cdf			44.086	74.660	46.912	49.572	39.392
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.228	0.749	0.413

Notes:Notes: The table shows how productivity differences between state-owned and non-state-owned firms change when considering incentive pay adoption using alternative definition of firm ownership. Column 1 reports the OLS estimate without considering incentive pay adoption. Column 2 reports the OLS estimate by considering incentive pay adoption. Columns 3-7 report estimates using instrumental variables for incentive pay adoption. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 6 uses farm size and farm size squared as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Standard errors in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

owned firms. Column 1 shows the OLS estimate without considering incentive pay adoption. The coefficient of productivity differences is 0.49, suggesting that the average productivity of state-owned firms is 49% lower than that of non-state-owned firms. This is consistent with existing literature that the productivity of state-owned firms is much lower than that of non-state-owned firms. Column 2 further shows the OLS estimate by controlling incentive pay adoption. We find that the coefficient of productivity differences is almost unchanged. In other words, we do not find significant evidence that incentive pay adoption is responsible for the productivity differences between state-owned and non-state-owned firms. One possibility is that the OLS estimate does not fully capture the incentive pay adoption channel because of endogeneity problems, as we have shown before. Columns 3–7 use instrumental variables to deal with endogeneity problems of incentive pay adoption. We find that the coefficient of productivity differences decreases dramatically from 0.49 to 0.24. In other words, the average productivity differences between state-owned and non-state-owned firms decrease by about 51% when accounting for the differences in incentive pay adoption across firms..

Given that distinguishing between state-owned firms and non-state-owned firms based on registration type may be inaccurate, we further resort to ownership structure rather than ownership type to check our results (Dollar and Wei 2007). Main results are presented in Table 8. We find that a 10 percentage point increase in the share owned by the state is associated with 4% lower firm productivity. However, by controlling incentive pay adoption, we find that a 10 percentage point increase in the share owned by the state is associated with 0.14% lower firm productivity but the coefficient is not statistically significant at the conventional level. Therefore, using an alternative

Table 9: Incentive pay and labor productivity for SOEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	0.002*** (0.001)	0.002*** (0.001)	0.023 (0.031)	0.044* (0.023)	0.053** (0.022)	0.040** (0.020)	0.050** (0.020)
Observations	2035	2035	2035	2035	2035	2035	2035
Adjusted R^2	0.443	0.504	0.236	-0.420	-0.840	-0.276	-0.680
cdf			1.604	5.378	3.840	3.000	2.751
arfp			0.391	0.002	0.000	0.010	0.000
sarganp					0.520	0.603	0.668

Notes:Notes: The table shows the impact of incentive pay adoption on firm productivity for state-owned firms. Column 1 reports the OLS estimate without considering incentive pay adoption. Column 2 reports the OLS estimate by considering incentive pay adoption. Columns 3-7 report estimates using instrumental variables for incentive pay adoption. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 6 uses farm size and farm size squared as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

indicator of ownership, we find that productivity differences between state-owned and non-state-owned firms decrease by 65% after considering heterogeneity in incentive pay adoption. To draw the conclusion that a more intense use of incentive pay would close the productivity gap between SOEs and non-SOEs, we further estimate the impact of incentive pay on firm productivity by firm ownership separately. Using the preferred model specification with both instrumental variables, we find very similar impacts of incentive pay on firm productivity regardless of firm ownership. Results are reported in Table 9 and Table 10.

To some extent, our results echo with previous findings that privatization per se does not guarantee improved performance without good management (Estrin, Hanousek, Kocenda, Svejnar, Kočenda, Svejnar, Estrin, Hanousek, Kocenda, and Svejnar 2009). All the findings suggest that a larger proportion of productivity differences between state-owned and non-state-owned are attributed to differences in incentive pay adoption.

5.2.4 Managerial pay

In our previous sections, we do not distinguish between managerial pay and non-managerial pay due to data limitation. To some extent, piece-rate wages are more likely to be involved with non-managerial pay. It is also interesting to look the impact of managerial pay on firm productivity. Although we do not have data on managerial pay separately, we resort to the information on whether general manager's annual income is directly related to the company's performance or not to construct a dummy variable to proxy for incentive pay adoption for the general manager. According to the data, about 66% of firms adopted incentive pay for general managers. Using the same empirical approach, we estimate the impact of managerial pay on firm productivity. Results are reported in Table 11. The OLS estimates show that adopting incentive pay

Table 10: Incentive pay and labor productivity for non-SOEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.001*** (0.000)	-0.001*** (0.000)	0.039*** (0.007)	0.039*** (0.006)	0.034*** (0.005)	0.039*** (0.005)	0.035*** (0.005)
Observations	9000	9000	9000	9000	9000	9000	9000
Adjusted R^2	0.376	0.451	-0.743	-0.729	-0.482	-0.735	-0.545
cdf			44.108	62.639	38.672	44.528	34.636
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.061	0.978	0.166

Notes:Notes: The table shows the impact of incentive pay adoption on firm productivity for non-state-owned firms. Column 1 reports the OLS estimate without considering incentive pay adoption. Column 2 reports the OLS estimate by considering incentive pay adoption. Columns 3-7 report estimates using instrumental variables for incentive pay adoption. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 6 uses farm size and farm size squared as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

for the general manager is associated with 7.8% higher firm productivity on average. We also use instrumental variables to deal with potential endogeneity problems. Our preferred model specification shows that adopting incentive pay for general manager leads to 283% higher productivity. Therefore, adopting incentive pay among managers dramatically increases firm productivity.

5.3 Robustness Checks

In this section, we conduct a number of robustness checks. First, we add more control variables to check whether there are alternative channels that may reject the validity of our instrumental variables approach. Second, we use alternative indicators of incentive pay adoption. Third, we use alternative indicators of firm productivity. Finally, we construct alternative instrumental variables.

5.3.1 Adding more control variables

We have provided evidence that controlling city characteristics does not significantly affect our IV estimation results. Nevertheless, it is still possible that we omit some (firm-level) variables that can be correlated with our instrumental variables. To reduce these concerns, we further control alternative channels such as overall labor scarcity, capital scarcity, product market competition and other management practices using relevant information from the survey. To control for overall labor scarcity, we resort to a variable that indicates the labor situation firms are exposed to (e.g., surplus of workers, shortage of workers). For capital scarcity, we control for the extent to which access to finance and financing costs (interest rates) affect firms' operation and growth. For product market competition, we control for the extent to which local protectionism and anti-competition behaviors by other firms affect firms' operation and growth. For other

Table 11: Managerial incentive pay and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	0.097*** (0.020)	0.079*** (0.019)	7.197** (3.005)	2.886*** (0.451)	2.851*** (0.425)	3.035*** (0.464)	2.983*** (0.436)
Observations	11166	11166	11166	11166	11166	11166	11166
Adjusted R^2	0.379	0.449	-6.482	-0.679	-0.653	-0.795	-0.754
cdf			6.068	60.635	33.649	30.668	22.658
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.803	0.003	0.010

Notes:Notes: This table reports the impact of incentive pay adoption on firm productivity. Columns 1 -2 report the OLS estimates. Columns 3-7 report IV estimates. Columns 3 and 4 use strength of institutional migration barriers and farm size separately as an instrumental variable. Column 5 uses farm size and farm size squared as instrumental variables together. Column 6 uses strength of institutional migration barriers and farm size as instrumental variables together. Column 7 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1990. Main control variables include firm age, skill composition of workers, education degree of general manager, fraction of permanent workers (versus temporary workers), composition of sales (exports), total employment in log, total capital in log, total RD in log, ownership dummies, 2-digit industry dummies. Standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

management practices, we control for the percentage of the employees received formal training, average monthly employee overtime days, demotion of mid-level managers in the past 3 years, and the decision-making power of junior managers/staff. Table 12 shows the impact of incentive pay adoption on firm productivity by controlling alternative channels. We find that the coefficient decreases slightly from 0.038 to 0.037, which is still very significant. Therefore, we do not find significant evidence that controlling other alternative channels would reject our main results.

Table 12: Incentive pay and labor productivity with additional firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.037*** (0.007)	0.036*** (0.006)	0.032*** (0.005)	0.036*** (0.005)	0.033*** (0.004)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.402	0.463	-0.499	-0.459	-0.285	-0.475	-0.339
cdf			47.116	65.449	42.548	46.844	37.732
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.140	0.917	0.308

Notes:Notes: This table shows the impact of incentive pay on productivity by controlling additional variables with respect to labor scarcity, product market competition, access to capital and other management practices. Standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 13: Incentive pay (Bonuses) and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	0.002*** (0.000)	0.002*** (0.000)	0.095*** (0.027)	0.113*** (0.030)	0.087*** (0.018)	0.104*** (0.022)	0.087*** (0.016)
Observations	10402	10402	10402	10402	10402	10402	10402
Adjusted R^2	0.384	0.451	-2.509	-3.745	-2.018	-3.131	-2.070
cdf			14.458	15.659	13.123	12.352	11.656
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.083	0.612	0.227

Notes:Notes: This table shows the impact of incentive pay on firm productivity using bonuses to capture incentive pay adoption. Standard errors in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Alternative definitions of incentive pay adoption

In the previous analyses, we use the ratio of bonuses and piece-rate wages to total compensation among permanent workers to measure the average intensity of incentive pay adoption. We further examine whether using alternative indicators of incentive pay adoption affects our main results. Our first alternative indicator use bonuses separately. In other words, incentive pay is measured using the ratio of bonuses to total compensation (excluding piece-rates) among permanent (contract) workers. According to the data, bonuses account for about 12.9% of total compensation on an average. Our second alternative indicator of incentive pay uses the ratio of piece-rate wages to total compensation (excluding bonuses). According to the data, piece-rate wages account for about 28.7% of total compensation on an average. Our third alternative indicator of incentive pay uses the ratio of fixed salary to total compensation. In contrast to our previous indicators, a higher ratio of fixed salary is associated with lower intensity of incentive pay adoption. According to the data, fixed salary accounts for about 47.2% of total compensation on an average. Our fourth alternative indicator further considers temporary workers but calculates the average intensity of incentive pay simply based on the share of permanent and temporary workers. Our fifth alternative indicator uses the weighted ratio of bonuses and piece-rate wage to total compensation to measure the intensity of incentive pay. Main results are reported in Tables 13-17. We do not find evidence that our main results are rejected using alternative indicators of incentive pay adoption.

5.3.3 Alternative definitions of firm productivity

In the previous analyses, we measured firm productivity as total sales per worker. Here, we examine whether the use of alternative indicators of firm productivity affects our main results. Our first alternative indicator of firm productivity is value added per worker. The value added is calculated by subtracting raw material costs from total sales. Our second alternative indicator of firm productivity is TFP. Main results are reported in Table 18-20. We find that all the results are significant but become smaller than the benchmark results. Nevertheless, even the most conservative estimation shows

Table 14: Incentive pay (Piece rate) and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.001*** (0.000)	-0.001*** (0.000)	0.040*** (0.008)	0.038*** (0.006)	0.035*** (0.005)	0.039*** (0.005)	0.036*** (0.005)
Observations	11019	11019	11019	11019	11019	11019	11019
Adjusted R^2	0.383	0.453	-0.975	-0.826	-0.658	-0.875	-0.731
cdf			36.141	62.074	38.647	40.987	32.363
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.274	0.796	0.493

Notes:Notes: This table shows the impact of incentive pay on firm productivity using piece rate wage alone to capture incentive pay adoption. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

Table 15: Incentive pay (Fixed salary) and labor productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	0.000 (0.000)	0.000 (0.000)	-0.053*** (0.013)	-0.034*** (0.005)	-0.033*** (0.005)	-0.037*** (0.005)	-0.036*** (0.005)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.382	0.452	-1.631	-0.476	-0.427	-0.629	-0.559
cdf			23.314	82.943	48.284	45.931	35.129
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.580	0.070	0.135

Notes:Notes: This table shows the impact of incentive pay on firm productivity using fixed salary to capture incentive pay adoption. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

Table 16: Incentive pay (unweighted with temporary workers) and labour productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.042*** (0.008)	0.041*** (0.006)	0.039*** (0.006)	0.042*** (0.006)	0.040*** (0.005)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.382	0.452	-0.712	-0.682	-0.552	-0.693	-0.590
cdf			43.094	66.542	41.033	45.632	35.547
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.325	0.950	0.597

Notes:Notes: This table shows the impact of incentive pay on firm productivity based on the ratio of bonuses and piece rate to total compensation among all workers, and adopts the unweighted approach. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

Table 17: Incentive pay (weighted with temporary workers) and labour productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.044*** (0.009)	0.041*** (0.006)	0.039*** (0.006)	0.042*** (0.006)	0.040*** (0.005)
Observations	11035	11035	11035	11035	11035	11035	11035
Adjusted R^2	0.382	0.452	-0.822	-0.677	-0.589	-0.724	-0.647
cdf			39.218	67.083	39.944	44.375	33.807
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.477	0.772	0.710

Notes:Notes: This table shows the impact of incentive pay on firm productivity based on the ratio of bonuses and piece rate to total compensation among all workers, and adopts the weighted approach. Standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 18: Incentive pay and labor productivity (Value-added per worker)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.001** (0.000)	-0.001** (0.000)	0.020*** (0.006)	0.021*** (0.005)	0.023*** (0.004)	0.021*** (0.004)	0.022*** (0.004)
Observations	10875	10875	10875	10875	10875	10875	10875
Adjusted R^2	0.309	0.357	0.034	0.011	-0.029	0.020	-0.011
cdf			48.893	69.288	43.524	49.205	38.652
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.514	0.895	0.768

Notes:Notes: This table shows the impact of incentive pay adoption on firm productivity using value added per worker (in log). Standard errors in parentheses.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

that a 10 percentage point (or 0.3 unit standard deviation) increase in the intensity of incentive pay adoption increases firm productivity by more than 10%. Therefore, incentive pay adoption significantly increases firm productivity regardless of productivity definitions.

5.3.4 Alternative definitions of instrumental variables

In the previous analyses, we constructed instrumental variables using data from 1990. An important assumption to justify these instrumental variables is that both land policies and migration policies were strictly regulated by the central government and local governments were granted with little autonomy to change these policies. To further strengthen this argument, we use alternative data from 1986—the earliest data available to us—to construct our instrumental variables. Main results are reported in Table 21. Our main results are still significant. We find that a 10 percentage point increase in the intensity of incentive pay adoption increases firm productivity by about 42%, which is very similar to our benchmark results. These results suggest that using alternative data to construct our instrumental variables does not reject our main results.

Table 19: Incentive pay and labor productivity (TFP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.013** (0.005)	0.012*** (0.004)	0.014*** (0.004)	0.012*** (0.004)	0.014*** (0.003)
Observations	10484	10484	10484	10484	10484	10484	10484
Adjusted R^2	0.054	0.092	-0.115	-0.080	-0.127	-0.093	-0.127
cdf			45.674	68.966	43.633	48.090	38.230
arfp			0.005	0.002	0.000	0.001	0.000
sarganp					0.309	0.799	0.596

Notes:Notes: This table shows the impact of incentive pay adoption on firm productivity using total factor productivity, which is calculated based on the methodology by Levinsohn and Petrin (2003). Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

Table 20: Incentive pay and labor productivity (alternative TFP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.010** (0.005)	0.010** (0.004)	0.013*** (0.004)	0.010*** (0.003)	0.012*** (0.003)
Observations	10484	10484	10484	10484	10484	10484	10484
Adjusted R^2	0.053	0.091	-0.051	-0.048	-0.103	-0.049	-0.090
cdf			45.674	68.966	43.633	48.090	38.230
arfp			0.029	0.008	0.000	0.007	0.000
sarganp					0.183	0.982	0.389

Notes:Notes: This table shows the impact of incentive pay adoption on firm productivity using alternative indicator of total factor productivity, combined with ACF correction. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

Table 21: Incentive pay and labor productivity (IVs in 1986)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	IV	IV	IV	IV	IV
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
IncentivePay	-0.000 (0.000)	-0.000 (0.000)	0.051*** (0.011)	0.039*** (0.006)	0.035*** (0.005)	0.042*** (0.005)	0.038*** (0.004)
Observations	10939	10939	10939	10840	10840	10840	10840
Adjusted R^2	0.386	0.452	-1.381	-0.636	-0.441	-0.811	-0.595
cdf			32.266	77.707	51.190	47.902	39.991
arfp			0.000	0.000	0.000	0.000	0.000
sarganp					0.128	0.208	0.082

Notes:Notes: This table shows the impact of incentive pay adoption on firm productivity using alternative data to construct instrumental variables. Columns 1 and 2 use strictness of the Hukou System and farm size separately as an instrumental variable. Column 3 uses strictness of the Hukou System and farm size as instrumental variables together. Column 4 uses farm size and farm size squared as instrumental variables together. Column 5 uses all three instrumental variables together. All the instrumental variables are constructed using data in 1986. Standard errors in parentheses.* p<0.1, ** p<0.05, *** p<0.01.

6 Conclusion

To the best of our knowledge, this is the first study to examine the causes and consequences of differences in incentive pay adoption among manufacturing firms in China as well as in developing countries. Our findings show that a higher degree of labor scarcity encourages firms to adopt more incentive pay. We also find that incentive pay adoption significantly increases firm productivity. Finally, we find that a large proportion of productivity gap between state-owned and non-state-owned is attributable to differences in incentive pay adoption.

The most important contribution of this study is to clarify the origin of productivity puzzles in China. While recent studies demonstrate that resource misallocation accounts for a large proportion of productivity differences between developing and developed countries such as China and the United States, and the growth effect of re-allocating from less to more productive firms is sizable, our study suggests that an alternative and even competing channel, that is, differences in incentive pay adoption, is important to uncover productivity puzzles in China. According to our results, state-owned firms could be more productive (relative to non-state-owned firms) by adopting appropriate “management technology”. More importantly, facilitating incentive pay adoption among firms with better labor endowments significantly increases productivity and reduces resource misallocation, and failing to consider heterogeneity in incentive pay adoption is likely to overestimate the growth effect of resource misallocation between firms in China.

This paper also sheds light on the origin of differences in incentive pay adoption across firms. Our finding that firms negatively select into incentive pay adoption is at odds with previous studies on “management technology” adoption (Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen 2019), suggesting that these studies do not apply to incentive pay adoption in developing countries. One possibility is that firms with better labor endowments resort to alternative incentive strategies rather than piece rates, which cannot be verified thoroughly in our study because of data limitations. Another possibility is that firms with better labor endowments are exposed to a less competitive product market (e.g., state-owned firms in China), which discourages them from adopting more advanced “management technology”. However, our findings show little evidence that product market competition encourages firms to adopt more incentive pay. Furthermore, our finding that firms exposed to a higher degree of labor scarcity are adopting incentive pay more intensively are consistent with previous arguments that labor scarcity encourages technological advances when technology is strongly labor-saving (Acemoglu 2010).

There are three limitations of this study and further improvements can be made in the future. First, incentive pay in this study mainly refers to bonuses and piece rates because of data limitation, which is naive to some extent. In reality, firms offer a complex package of incentives in their employment contract, including promotion schemes, bonuses, etc. It’s challenging to collapse all of that into a single-dimensional vertical measure as constructed in the paper. Therefore, more precise measurements of incentive pay adoption are especially important for examining their future consequences. Second, we present exploratory patterns on the drivers of incentive pay adoption and it is still hard to put a causal interpretation on these coefficients. The key challenge

is to find a good instrumental variable that both affects the endogenous variable but also satisfies the exclusion restriction. Third, although our study acknowledges the importance of incentive pay adoption for productivity growth, we have not explored the relative importance of resource reallocation and incentive pay adoption on productivity growth in China any further. This remains to be explored in the future studies.

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