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Paying for Creativity: The Effect of Piece-Rate vs. Time-Rate Compensation on Quality of Work

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Abstract

Incentive-systems theory proposes generally that piece-rate compensation should yield higher quantity of output and, assuming that quality cannot be perfectly monitored, lower quality of output than time-rate compensation. But recent advances in psychology and behavioral economics suggest that such incentive compensation will elicit particularly poor quality results for non-routine tasks for which creative problem-solving is required. Using a unique database from the energy-related home services industry, we explore differences in quantity and quality outcomes between employee technicians who are paid a daily rate and contractor technicians who are paid by the job. Of particular interest, different job types require different levels of creative problem-solving, and calls are assigned to technicians independently of their compensation-scheme status. We find significant evidence that piece-rate workers indeed work faster and complete more jobs, with this advantage especially pronounced for routine jobs. We find mixed evidence regarding quality: piece-rate workers yield comparable quality for routine, low-creativity tasks, while their quality is significantly lower for high-creativity tasks. This study thus helps to reconcile prior results from conflicting theories.

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Paying for Creativity: The Effect of Piece-Rate vs. Time-Rate Compensation on Quality of Work

I. Introduction

A large literature explores the impact of incentive compensation on worker performance (Lazear & Oyer 2012, Shearer 2004, Freeman & Kleiner 2005). A common finding is that piece-rate compensation elicits higher volumes of output from employees than time-based compensation, presumably by eliciting effort to work more rapidly. However, a related question remains unanswered empirically: how does piece-rate compensation affect the quality of the output? Theoretical economic models predict that if quality is monitored less effectively than quantity, then piece-rate compensation should lead workers to sacrifice quality for quantity; hence, the quality of piece-rate-based output should be lower than that of output from time-based compensation (Gibbons 1987).[1] Further, research from other disciplines such as psychology suggests that such compensation is likely to hinder output that depends on non-routine effort (Amabile 1996). It is therefore not clear whether piece-rate compensation will yield higher quality-adjusted productivity than time-based compensation.

Although a growing body of empirical work has found evidence consistent with the predicted effect of piece-rate compensation on output quantity, particularly for routine tasks (Courty & Marschke 2004; Freeman & Kleiner 2005; Bandiera et al. 2007), the empirical research has been largely silent on the issue of output quality. Thus far, it has been difficult to address this issue because, unlike quantity, the quality of output has been difficult to measure in non-experimental settings. Exceptions to this include Fernie & Metcalf's (1999) study of jockeys under varying payment schemes, which does not have sufficient data to support large-scale regression estimation, and Ederer & Manso's (2013) experimental study that finds evidence that incentive pay can be detrimental to output for creative (rather than routine) tasks.

In this paper, we use a novel data set to overcome constraints that have afflicted prior research. Our setting is the energy-related home services industry. A large North American firm

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[1] Quality-shading is one variant of the general problem of the "gaming" of incentive systems by agents. Another example of gaming relates to the timing of effort, e.g. manipulating sales to exploit quarterly targets (Larkin 2014).

agreed to provide confidential access to detailed data on every service call in a specific state/province over two 12-month periods, totaling over 500,000 visits to residences. We call this firm ServCo and the state/province BigState. ServCo uses a mixture of employees who are paid a daily wage and contractors who are paid by the completed job. We are able to measure numerous aspects of each service call including the nature of the call, the time each call takes to complete, the outcome of the call, and whether the customer subsequently calls the company back for follow-up service.

This empirical setting offers two distinct benefits. A common challenge for studies of this type relates to endogeneity: if the assignment of jobs to piece-rate workers and employees is not random, then it is difficult to infer the impact of compensation on performance. Our empirical setting surmounts this problem because ServCo assigns technicians to calls via an automated dispatching system based on proximity to the service-call address; technician compensation mode is not part of the system's decision calculus. In addition, whereas most of the prior literature focuses on uniform, routine tasks such as installing windshields (Lazear 2000), planting trees (Shearer 2004), or typing letters (Dickinson 1999), ServCo technicians encounter jobs requiring different levels of complexity and creativity. We can therefore explore quality and quantity differences between compensation types along the routine/non-routine margin.

We present three results. First, consistent with prior research, we find that piece-rate technicians complete jobs more quickly – and drive more quickly between calls – than time-rate technicians. Second, we find nuanced differences in the quality provided. Consistent with theoretical predictions, piece-rate technicians generate more "defects" – jobs for which the worker claims successful completion, but after which the customer calls ServCo for subsequent service on the same equipment. Third, we find that the above-described quantity and quality differences vary depending on the degree of routineness in a job. Piece-rate technicians have a higher speed advantage and a markedly lower defect disadvantage when performing routine tasks, but fare substantially worse relative to time-rate technicians for complex tasks involving creative problem-solving.

This third result is consistent with recent research indicating that incentive structures have different impacts on quality depending upon the nature of the job in question. Our results help to clarify the conflicting results from previous studies that have focused on a single type of task. For example, as noted above, studies that look at low-variability tasks have found relatively small decreases in quality from piece-rate compensation. In sharp contrast, recent studies of environments that require exploration and creativity have found that high-powered incentive structures can undermine performance unless appropriately structured (Ederer and Manso 2013).

We also address potential alternative explanations. One obvious alternative is that day-rate and piece-rate technicians are different in ways that affect their performance. We address this partially through our empirical context, since all workers must hold the same set of licenses and certifications to perform the requisite work. But we are best able to address this concern by exploiting "short days" in the sample – days on which there are insufficient jobs to keep employees occupied for the entire day. On short days, employees are intrinsically motivated to work faster because once they finish the jobs required for that day, they are allowed to relax with friends or go home early, even though they are paid to the end of the shift. The analysis demonstrates that on such days, employees in fact work significantly faster, roughly at the level of contractors. It is difficult to reconcile this change in behavior by anything other than incentives.

The paper proceeds as follows. In Section II we describe ServCo, discuss its employment arrangements, and detail how service calls are scheduled and accomplished. Section III presents a description of the data. Section IV provides model specification and the empirical analysis. Section V provides discussion and conclusions.

II. ServCo

ServCo is a large retailer of energy services in North America, with several million customers across many jurisdictions in the United States and/or Canada. As part of its operations, ServCo offers maintenance and repair services. These include installation, maintenance, and service of heating, ventilation, and air conditioning (HVAC) equipment, water heaters, plumbing, and other electrical equipment. ServCo's service unit in BigState is divided into more than 20 geographically based sub-units, mostly conforming to large towns or counties. Each sub-unit has its own dedicated technicians, and is responsible for maintaining staffing levels and for ensuring quality of technical service.

The study focuses on ServCo's maintenance and service activities in a large state or province that we call BigState. In BigState, ServCo has traditionally rented water heaters to customers; of ServCo's one million household customers in 2012, nearly 70% rented their equipment. Under terms of the rental agreement, maintenance and service remain the responsibility of ServCo. Most of the remaining customers were homeowners who owned their heating equipment and purchased annual service contracts from ServCo. It is also possible for a homeowner who owns the equipment and who does not have a service contract to call ServCo for maintenance and service on a fee-per-service basis, although this is relatively rare. As the vast majority of service calls are covered by rental agreements or service contracts, ServCo's chief economic goal is to perform projects at as low a cost as possible. The installation of new parts and the devotion of large amounts of technician time (at least in the case of employee-technicians) impose costs on ServCo with no direct recompense from customers.

ServCo dispatches technicians to a home for one of two types of calls: service or maintenance. Maintenance calls tend to be fairly routine: technicians inspect and adjust the equipment in question, such as a furnace, air conditioner or water heater. In sharp contrast, a service call occurs when the homeowner experiences a problem with the equipment, and consequently calls ServCo for service. Thus, on a service call a technician must diagnose the cause of the problem and develop the appropriate solution. Hence, service calls require far more creativity from technicians than do maintenance calls.

Technician Characteristics

ServCo relies on a mix of company employees and independent contractors to handle maintenance and repair calls. Of particular note for this study, company employees are unionized and, per successive union-ServCo contracts dating back more than 15 years, are paid on a day-rate basis. In contrast, independent contractors are paid per completed job, according to a menu of rates that are based on the expected time necessary to complete a particular job type.

ServCo's technicians are expected to be able to resolve a wide range of problems associated with heating, ventilation and air conditioning (HVAC) equipment. All of ServCo's technicians, employees and contractors, are licensed by BigState. ServCo's technicians all carry personal liability insurance; ServCo pays for this for all of its employees and for virtually all of its independent contractors. In addition, BigState certifies technicians as being qualified for particular types of work, such as servicing of air conditioners (which requires knowledge of both cooling systems and electrical systems), and all of ServCo's technicians carry the requisite certifications.

Aside from the difference in compensation scheme, there are three other work-related differences between ServCo employees and ServCo contractors. First, ServCo employees are fully employed by ServCo. In contrast, some contractors work only part-time for ServCo. Second, ServCo employees are likely to get "better" shifts, such as normal daytime hours rather than evening/nighttime shifts. Third, ServCo employees drive ServCo vans and carry ServCo-mandated inventory on board, while contractors drive their own (or their companies') vans and have discretion over the on-board inventory. Contractors who are fully utilized by ServCo have decals on their vans with the ServCo logo. All but the most casually used contractors have ServCo dashboard computers. For those that do not, data must be captured using pen and paper.

Assigning Technicians to Jobs

When a customer has a problem with her HVAC, or other equipment, she reports the problem by calling the customer service line at ServCo. The customer service representative collects information including the home address and the nature of the problem – for example, "the heat isn't coming on" or "the air conditioner is making excessive noise." The representative enters this information into ServCo's computer system, including the "problem" code that best matches the type of problem described by the customer.

The computer system, which keeps track of all scheduled home visits and of available technician-hours in an area, generates a range of possible four-hour time blocks during which a service technician will be able to visit the customer's house to address the problem. The customer and representative converge on a preferred time block that will fit the customer's schedule, and the representative enters this into the computer system. A typical time block might be between 1pm and 5pm on the day of the customer's phone call.

On the day of the home visit, the homeowner's call is one of several in her geographic region attached to a particular time block. ServCo's dispatching computer system assigns calls to technicians throughout the day. For the first call of each technician's shift, the computer assigns a call that is close to the technician's home. After that, the computer assigns jobs to technicians in real-time as jobs get completed. At any one time, the computer assigns two jobs to a technician – the job he is currently working on and the job that will follow immediately afterward.

Of particular interest for this study is that ServCo's system works much like a taxi dispatching system in that it assigns jobs to technicians based on geographic proximity. Specifically, as the homeowner's job nears the top of the queue, ServCo's dispatching system assigns it to the closest technician who is expected to finish his previous job in time to arrive at the home within the promised time block. Thus, the ServCo dispatching system does not assign technicians based on their status as employee or contractor, but rather simply on their availability and proximity to the particular job site.

From the technician's point of view, the day goes as follows. The technician leaves his home and gets into his van, which he drives home after work each day. He punches the "job" button on his dashboard computer in order to get the details on his first destination of the day. The dashboard computer provides the name of the customer, the address of the call, and a code that indicates the general nature of the problem. The technician then drives to the address. When he arrives, he pushes the "arrived" button on the dashboard computer. The computer then provides additional details about the problem as well as the address for his subsequent call, so that he knows where he will be going after his call is completed. The technician then approaches the home and, if he is able to gain entry, does the job required. As noted above, for maintenance calls this is usually routine and typically requires a fairly straightforward inspection, whereas for service calls the technician must first diagnose and then fix the problem that led to the customer's call.

Service/Maintenance Call Outcomes

A service call can end in one of three ways. First, the customer may not answer the door. In this case, the technician returns to his vehicle and enters the "customer didn't answer" code on the dashboard computer. Later, a ServCo representative will call the customer to reschedule the appointment. Second, the technician fixes the problem. In this case, he returns to his vehicle and enters the "successfully completed" code on his computer. Third, the technician diagnoses the problem but finds that he does not have the requisite part(s) to fix it in his van's inventory. In this case, he returns to his vehicle and enters the "need part X" code into his dashboard computer. Later, a ServCo operations person will arrange for part X to be delivered to the customer's home in conjunction with another technician who will fix the problem. ServCo's managers have a strong preference for successful resolution, both because customers prefer this outcome and because it is costly for ServCo to undertake another visit.

Whatever the outcome, the technician enters the appropriate completion code into his dashboard computer upon returning to the vehicle. This enables him to get additional information about the next call he will be making. The ServCo communication system provides information on future jobs to technicians only as they complete existing tasks. This provides the technician with an incentive to enter codes indicating progress upon completion of each task (driving to a home; arriving at the home; completing the job). Thus we are confident that the data regarding time spent on each job is accurate.

Of course, a technician might declare victory over a problem prematurely. Sometimes a technician visits and appears to have resolved a problem, but afterward the customer continues to have trouble. The customer than calls ServCo's customer service line again, and the cycle repeats anew. This feature of the data allows us to generate one measure of work quality, as we can identify whether there is a follow up call to the same address for the same problem or for another problem on the same piece of equipment.

III. Data Description

As described above, ServCo records substantial information about each call that its energy services division handles. We obtained from ServCo the records associated with all calls handled in BigState during the years 2012 and 2009. These comprise over 600,000 service and maintenance calls. Table 1 provides a summary of the data available for each call, including a definition of each variable.

******* Insert Table 1 *******

Sample

In 2012, ServCo undertook 357,981 calls across 22 geographic sub-units in BigState. We eliminated 82,661 observations from the nine geographic sub-units that either relied nearly exclusively on one mode of technician or had sufficiently few calls that most would drop out of regressions after including our numerous fixed effects. We eliminated a further 10,637 observations due to missing data, and 9,540 calls that were canceled before the technician arrived. This left a sample of 255,143 calls, of which 141,066 were for service and 114,077 for maintenance. An analogous procedure yielded a sample of 254,716 calls in 2009, of which 166,994 were for service and 87,722 for maintenance.[2]

[2] Results for the 2009 and 2012 samples are qualitatively identical for all estimations. We therefore present descriptive statistics and empirical results only for 2012 in the paper, and provide the analogous material for 2009 in the appendix. [NB: Appendix not submitted to DRUID due to space constraints.]

ServCo had 286 company employees and 188 independent contractors in BigState in 2012. Employees handled 74% of the service jobs and 56% of the maintenance jobs. 89% of employees worked more than 100 days in a given year, and 95% worked more than 30 days. In contrast, 48% of contractors worked more than 100 days, and 65% worked more than 30 days. This reflects ServCo's reliance on contractors to manage peak demand at certain times of the year. For the bulk of our results, we focus on the "core" set of technicians who work for ServCo more than 30 days per year. The results are the qualitatively the same when we restrict the sample to technicians with more than 100 days of work, or when we include all technicians regardless of how many days/year they work for ServCo. Our results are also qualitatively unchanged when we restrict the sample to include only those technicians that appear in both the 2009 and 2012 data sets.

On average, independent contractors were more likely to work overnight shifts and weekends, and some contractors work during the peak seasons of October-November (when customers typically request maintenance calls for their heating systems, or discover heating problems) and May-June (for air conditioner maintenance/service).

Figure 1 highlights several important aspects of the data. First, there is a brief period in the spring when all employees are on holiday, resulting in 100% of the jobs being done by contractors. The results we present below are robust to the exclusion or inclusion of this two-week period. Second, there is significant variation in the number of jobs as well as the proportion of the jobs done by contractors over the year.

******* Insert Figure 1 *******

Given this, we further investigate the mix of contractors and employees throughout the sample period. Figure 2 presents the prevalence of employees and contractors, by hourly window and by day of week. The figure has four categories highlighted: those periods in which the proportion of contractors is less than 20%, more than 80%, somewhere in between. There are also three cells during which no jobs were initiated. The vast majority of calls occur during windows that have a "healthy" mix of contractors and employees, i.e. during which the percentage of contractor-conducted calls is between 20% and 80%. A similar picture emerges if we use cutoffs of 10%, 15%, or 25%. The results of the analysis presented below are robust to restricting the data to windows that fit any of these cutoffs.

******* Insert Figure 2 *******

Descriptive statistics are provided in Table 2. The average time it takes all technicians to complete jobs (Jobtime) for the entire sample was just under 50 minutes. The average drive time between jobs (Drivetime) is 14½ minutes. For 3.1% of all visits, technicians do not find anyone in the home, and hence are unable to gain entry. Technicians report that 6.7% of the time that they needed a part, and 90.1% of all jobs are fixed successfully.

As noted above, we are able to identify when a technician services a site that had been previously served by the company within 15, 30, 45 and 60 days. Here we focus on the 30-day window, as the results are not qualitatively impacted by the window chosen. The defect rate, i.e. a visit back to the same address within the 30 days, for the exact same problem is 3.4%. The defect rate for equipment – i.e., a callback for a problem on the same piece of equipment but a different problem is 4.5%.

ServCo technician calls span 54 different job types. Each job type identifies a specific piece of equipment and a specific problem or task. Examples include "air conditioner making excessive noise," "furnace not working," and "water from water heater not hot enough." The ten most frequent job types are also listed in Table 2, and collectively account for over 80% of all calls. Of all calls in 2012, 44.7% were maintenance jobs; contractors undertook nearly 35% of all jobs.

Table 2 also provides a correlation matrix for all the variables used in our analysis. All but four of the correlation coefficients are below 0.4 (in absolute value). The three larger correlations are between variables that never appear in the same regression; hence we are not concerned about multicollinearity in our analysis.

******* Insert Table 2 *******

IV. Empirical Analysis

In this section, we measure whether there are systematic differences in the behavior and outcomes of contractors and employees. As noted above, we anticipate that contractors, who are paid by the number of jobs completed, will work and drive faster than employees. After demonstrating this, we explore systematic quality differences between these two groups of technicians.

To test our predictions, we estimate the following model:

$$Outcome_i = \alpha + \beta(Contractor_i) + \Sigma_m \gamma_i^m(month_i) + \Sigma_d \gamma_i^d(day_i) + \Sigma_h \gamma_i^h(hour_i) + \Sigma_c \gamma_i^c(city_i) + \Sigma_j \gamma_i^j(Jobtype_i) + \varepsilon_i \quad (1)$$

where *Contractor$_i$* is a dummy variable equal to 1 if the technician on the particular call is a contractor and 0 if an employee, γ_i^mcaptures month fixed effects, γ_i^dday fixed effects, γ_i^h hour fixed effects, γ_i^ccity fixed effects, and γ_i^j jobtype fixed effects. The coefficient of interest is β which captures the difference in the outcome measure for contractors and employees, after controlling for the fixed effects noted above.

We first focus on outcome variables that speak to the speed, or quantity output, of technicians: Drivetime, Customer Not Home (which is inversely related to quantity output because the technician must then drive to another job), and JobTime. Consider these in turn.

Table 3 presents results of regressions with DriveTime as the dependent variable. Model 1 presents results for all jobs and without fixed effects, while model 2 presents results with fixed effects. Models 3 and 4 then distinguish between service calls and maintenance calls. (We will follow this practice of regressing with and without fixed effects, and for the entire sample and then for service and maintenance separately, throughout the paper.) The results are consistent with the predictions of theory: Regardless of the model, the coefficient on Contractor is negative and statistically significant. Contractors reach their next destination roughly 3 minutes faster than employees, or nearly 20% of the average 15-minute journey time.[3]

******* Insert Table 3 *******

Before a technician can complete a job, he must gain entry into the customer's home. It is possible that a customer will be out, or will not hear the technician knocking, despite being aware of the ServCo appointment. In the event that a technician cannot gain entry into a home, he returns to the vehicle and enters the "customer not home" code into the dashboard computer. Given the

[3] The Contractor Drivetime advantage for maintenance jobs is smaller than that for service jobs. This is because ServCo is often able to schedule maintenance jobs with an eye toward geographic proximity. This is not possible for service jobs, which arise due to urgent needs.

random assignment of technicians to jobs, one would expect there to be little difference in the true incidence of people not being at home for contractors or for employees. However, if contractors are more motivated financially than employees to complete a job, then one might expect contractors to find customers at home more readily than employees.

Table 4 presents results of regressions with Customer Not Home as the dependent variable. Given that Customer Not Home is a binary variable, Models 1-4 present results based on linear estimation and Models 5-8 present results based on logit regression. Across all eight models, the coefficient on Contractor is negative, statistically significant, and economically substantial. Thus, contractors are substantially less likely than employees to report that a customer is not at home; put differently, contractors find the customer at home, and therefore are able to gain entry and attempt to complete the job, far more readily than employees.

******* Insert Table 4 *******

Theory suggests that, once inside the home, a contractor has a significantly stronger incentive to complete the job more quickly than an employee. Table 5 presents results of regressions with JobTime as the dependent variable. Once again, as Models 1-4 demonstrate, the coefficient on Contractor is negative and statistically significant. Contractors successfully complete jobs between 10 and 17 minutes faster than employees, again a substantive speed advantage given the average employee job time of 57 minutes. Just to be clear, in the fixed-effect model (2) one may interpret the result as: when contractor X and employee Y are both sent out on the *same* day, at the *same* hour, in the *same* month, in the *same* town, to do the *same* type of job, X will finish 12 minutes faster than Y. As robustness checks, Models 3a, 4a, 3b, and 4b replicate Models 3 and 4 for potentially relevant subsets of the data, and find qualitatively identical results.

******* Insert Table 5 *******

Overall, then, we find evidence consistent with prior research: technicians who earn piece-rate compensation (which offers extrinsic incentives for speed) drive faster, work faster, and find the customer at home more frequently than technicians who earn time-based compensation.

Incentive compensation and creativity

There is one intriguing regularity in Table 5: Although contractors work faster than employees for both service and maintenance jobs, this speed differential is substantially larger contractors for maintenance jobs than for service jobs.

One possible source of this disparity relates to differences in complexity and the need for creatively – that is, maintenance jobs tend to be routine and non-complex, whereas service jobs tend to require creativity in resolution. These results accord well with previous evidence which demonstrates that incentive compensation works well in routine environments, but in contrast, tends to not work well for tasks that require exploration (Amabile 1996; Ederer and Manso 2013). As such, it is possible that the nature of the tasks involved drive the relatively fast and more effective contractor performance in maintenance jobs.

As the creativity literature focuses primarily on the quality of output rather than on quantity, we turn to quality-related measures to explore this further, notably the rate of "defective" jobs completed by technicians. Conventional incentive-systems theory suggests that piece-rate compensation will increase a technician's incentive to work quickly, but at the cost of lower-quality work (to the extent that work quality is less easily monitored than work quantity). Recent work on creativity would propose that this lower quality would be particularly pronounced in tasks that require creativity (Amabile 1996; Gneezy et al. 2011; Ederer & Manso 2013).

Our direct measure of quality is manifested as another call from the same customer within 30 days for the identical problem – Defect–SameProblem – and our broader measure is a callback for a different problem with the same equipment – Defect–SameEquipment. Table 6 presents results of regressions with Defect–SameProblem and Defect–SameEquipment as dependent variables. For Defect–SameProblem, the coefficient on Contractor is positive and statistically significant for Service jobs, but not for Maintenance jobs. For Defect–SameEquipment, the coefficient on Contractor is positive and significant for Maintenance jobs, but not for Service jobs.

******* Insert Table 6 *******

At first blush, these results are challenging to interpret. For example, one interpretation of the Defect–SameProblem results would be that piece-rate technicians – contractors – indeed perform significantly lower-quality work when it is complex (i.e. service jobs) than when it is routine. However, an alternative interpretation is that customers are unlikely to call for a second maintenance visit if the first one is poorly done; rather, the customer will not recognize that the maintenance was poorly done until something goes wrong with the equipment, at which point her call will be recorded as a different problem with the same equipment (which could explain the significant positive coefficient on Contractor for maintenance jobs when Defect–SameEquipment is the dependent variable).

To disentangle this, we conduct two further sets of estimations. First, we identify jobs that take an above-average amount of time to complete, denoted LongJob. One interpretation of unusually long jobs is that the technician has encountered an unusual challenge in resolving the problem and thus must engage in more creative problem-solving. We include Longjob and an interaction term Contractor*Longjob as independent variables in the defect estimations, to see whether such jobs differentially affect the quality of contractor vs. employee outcomes. Table 7 presents these results. Of particular note, whereas contractors continue to generate a higher rate of defective Service jobs for Defect–SameProblem, the main action for defects on Maintenance jobs is centered in long jobs – the coefficient on Contractor*Longjob is positive and significant for Maintenance jobs for both dependent variables, indicating that contractors generate more defective jobs than employees only when the jobs take an unusually long time to complete. To the extent that Longjob captures the need for creative problem-solving, this is consistent with the Ederer & Manso (2013) argument that incentive compensation for creative work can be counter-productive.

******* Insert Table 7 *******

One might be concerned that Longjob doesn’t capture the need for creativity as much as it reflects piece-rate workers’ anxiety about not earning as much in a given day as anticipated. Therefore, in a second approach to this question we solicited expert opinions from ServCo managers regarding the level of complexity associated with each of the ten most common jobtypes, with complexity specifically defined as requiring creative problem-solving for resolution. ServCo managers ranked these jobs across four levels of complexity, as displayed in Table 8. We include job-specific complexity measures and contractor-complexity interaction terms in additional estimations, presented in Table 9.[4] In Models 1-4, we rely on the 0-3 scale for jobs running from low complexity to maximal complexity. In Models 5-8, we create separate categorical variables for each level of complexity. As that Table indicates, for the Defect–SameProblem estimations, the greater rate of defective work associated with contractors is entirely located in the more complex jobs; the main effect of Contractor has a statistically insignificant coefficient in every model.

***** Insert Tables 8 and 9 *****

Addressing alternative explanations: Employees resemble contractors on "short days"

We have found that piece-rate-compensated contractors drive faster and complete jobs faster than time-rate-compensated employees, as well as finding customers home more readily. We have also found that contractors have a greater rate of defective jobs, but that this is largely driven by contractors' substantially higher rate of defects among jobs that appear to require more creativity in their resolution. Our preferred interpretation is that employees and contractors are comparable technicians and that these differences are caused by the different compensation schemes afforded to them.

However, an alternative explanation could be that employees and contractors differ on unobserved dimensions that drive these results. For example, if employees are on average older, then they may drive more prudently and work at a more steady, measured rate than their immature contractor counterparts. More generally, there might be an employee "trait" that generates these differences between employees and contractors, with incentive compensation merely spuriously correlated with the differences.

An ideal experiment would assign the same technician to jobs under different compensation systems, sometimes as a piece-rate technician and sometimes as a day-rate technician. ServCo does not do this. However, we are able to exploit one source of variation in employee incentives that allows us to approximate this experiment. Specifically, we can identify particular days in which there are increased incentives for employees to work quickly.

[4] We cannot run a separate model for maintenance jobs when using these complexity measures, because both of the maintenance jobs among the most common job types are of the lowest complexity level.

A few times during the year, ServCo experiences “short days,” on which there are too few jobs to keep an employee occupied for the entirety of his shift. On such days, the employee remains on call throughout his shift but is allowed to go wherever he wants during the downtime. As reported in Table 2, 8.8% of all jobs were done on short days in 2012. Most employees choose to either spend their downtime at home or at coffee shops (usually with other employees). Put differently, on a short day an employee who finishes his work will be able to relax at home or with friends. This results in an incentive for employees to work faster, relative to days when there are sufficient jobs to keep them busy through the end of their shift. This of course would not apply to contractors as they are paid only by the number of jobs. If there are not sufficient jobs to keep the contractor busy, he is dismissed for the rest of the day and hence does not get any further compensation.

This allows us to estimate a type of differences-in-differences regression:

$$Outcome_i = \alpha + \beta^{c}(Contractor_i) + \beta^{SD}(Shortday_i) + \beta^{c,SD}(Contractor_i * Shortday_i) + \Sigma_m \gamma_i^m (month_i) + \Sigma_d \gamma_i^d (day_i) + \Sigma_h \gamma_i^h (hour_i) + \Sigma_c \gamma_i^c (city_i) + \Sigma_j \gamma_i^j (Jobtype_i) + \varepsilon_i \quad (2)$$

In this model, β^{SD} reflects the degree to which employees change their pace of work on short days, and $\beta^{SD} + \beta^{c,SD}$ reflects the degree to which contractors change their pace on shortdays.

Regression results are provided in Table 10 for both DriveTime and JobTime. As the DriveTime results indicate, on short days employees reduce their drive time by 2-4 minutes, essentially getting from one job to the next roughly as quickly as do contractors on normal days. The contractor*shortday coefficient is positive and, on average, more than half the size of the shortday coefficient, indicating that this shortday-related thirst for driving speed is substantially more pronounced among employees than among contractors. The JobTime results are even more compelling: The coefficient on Shortday is very similar to the coefficient on Contractor in every model, indicating that employees on short days work as quickly as contractors on normal days, and the coefficient on Contractor*Shortday is positive and roughly ¾ the magnitude of the coefficient on Shortday, indicating that contractors speed up very little on short days. Overall, then, employees dramatically reduce their driving and job-completion time averages relative to contractors on short days. It is difficult to accommodate this in any explanation that rests on an employee "trait" rather than on the influence of incentive compensation.

***** Insert Table 10 *****

V. Conclusion

Using a unique data set, we have been able to contribute to the literature on creativity and incentive compensation. Unlike previous studies, workers in the current context undertake a mix of routine and non-routine jobs. As such, we are able to measure how piece-work compensation impacts worker effort and quality in both dimensions.

In the context of a large North American energy-related home services company, we find that piece-rate technicians complete jobs faster, drive between jobs faster, and are more likely to find customers at home relative to regular daily-rate technicians, consistent with incentive theory. Since compensation for piece rate contractors is tied directly to the number of jobs completed, they work faster. We also find that these behaviors are particularly stark for maintenance jobs, which tend to be routine, as compared to service jobs, which are characterized by higher variability and creativity. That is, we confirm earlier results that incentive compensation has a much stronger impact in routine tasks relative to more complex tasks requiring more creativity and discovery.

We have also been able to exploit a unique feature of these data to better measure the role OF incentives. There are several days in the sample where there are insufficient jobs to keep employees occupied for the entire day. On such "short days", employees are motivated to work faster because once they finish the jobs required for that day, they are allowed have coffee or go home early, even though they are paid to the end of the shift. Unlike on normal days, employees on such short days have an incentive to work faster. The analysis demonstrates that on such short days, employees in fact work significantly faster, making them look more like contractors on these days. It is difficult to reconcile the change in such behavior to anything other than incentives.

We also find that piece-rate technicians generate comparable levels of quality in their work for routine maintenance jobs, but offer lower levels of quality for non-routine service jobs. This result links prior empirical studies that have focused on either routine or non-routine tasks, and suggests situations in which piece-rate compensation may be particularly suitable or particularly unsuitable. By considering the length of time it takes to complete any particular job, we are able to link the higher contractor defect rates to those jobs which are taking an above average amount of time to complete. Since these contractors are paid by the job, they tend to hurry when they realize these jobs are taking longer than average to finish, thus causing them to rush, which of course leads to higher defects.

To the best of our knowledge, this is the first study to consider an environment where both piece-rate workers and time-rate workers are engaged simultaneously in an environment that includes both routine and non-routine jobs. Given that jobs are allocated to technicians independent of their incentive-compensation status, we are not only able to measure the impact of incentives on quality and quantity, but also how these effects vary by job complexity.

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Table 1. Variable Definition	
Panel A. Variables in the raw ServCo data	
Field	Description
District ID_j	Unique identifier for specific geographic district in which call j occurs
Site ID_j	Unique identifier for home where call j occurs
Technician ID_j	A unique code identifying the technician who makes call j; the last digit indicates whether he is an employee or a contractor
Job $Type_j$	Code denoting the type of equipment that is the subject of call j and the type of problem that is reported
$Activity_j$	Categorical variable denoting either maintenance call or service call
Creation $Time_j$	Date/time that the work order was created for call j
$Window_j$	Date/time that is arranged for call j (4-hour window)
Enroute $time_j$	Date/time that technician begins to drive to the site for call j
Arrival $time_j$	Date/time that technician arrives at the site of call j
Completion $time_j$	Date/time that technician completes call j
Completion $code_j$	Code denoting one of three possible results for call j: 1) Customer not home; 2) Need additional part to fix the problem; 3) Call successfully completed
Needed-part $code_j$	Code denoting the type of part needed to fix the problem for call j (if applicable)
Panel B. Variables constructed from the ServCo data	
Drive $Time_j$	Arrival Time - Enroute time for call j, measured in minutes
Job $Time_j$	Completion time - Arrival time for call j, measured in minutes
$Completed_j$	1 if the technician enters completion code "successfully resolved" for call j, else 0
Customer Not $Home_j$	1 if the technician enters completion code "customer not home" for call j, else 0
Need $Part_j$	1 if the technician enters completion code "need additional part" for call j, else 0
$Contractor_j$	1 if technician is a contractor; 0 if technician is an employee
Defect – Same $Problem_j$	1 if technician reports the problem fixed and then customer calls back with same problem within 30-day window. 0 if technician reports the problem fixed and customer does not call back within 30 days. Undefined if technician does not report the problem fixed. (Qualitatively identical results are obtained using 15-, 60-, and 90-day windows.)
Defect – Same $Equipment_j$	1 if technician reports the problem fixed and then customer calls back with different problem on the same piece of equipment within 30-day window. 0 if technician reports the problem fixed and customer does not call back within 30 days. Undefined if technician does not report the problem fixed. (Qualitatively identical results are obtained using 15-, 60-, and 90-day windows.)
$Longjob_j$	1 if Job Time for call j > average Job Time for all calls of the same Job Type, else 0. If call j is undertaken by a contractor, then compare to the average Job Time for contractors; else compare to the average Job Time for employees.
$Shortday_j$	1 if call j occurs on day during which technician worked a shift < 6 hours, else 0
$Complexity_j$	Based on expert opinion of ServCo managers: 0 if $jobtype_j$ is of "Low" Complexity; 1 if $jobtype_j$ is of "Moderate" Complexity; 2 if $jobtype_j$ is of "High" Complexity; 3 if $jobtype_j$ is of "Maximal" Complexity

Table 2: Summary statistics, 2012 data [n=255,143]

	Mean	StdDev	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Jobtime	49.77	33.92	1.000									
2. Drivetime	14.57	14.62	0.090	1.000								
3. Customer not home	0.031	0.174	-0.191	0.011	1.000							
4. Need part	0.067	0.251	0.057	0.005	-0.048	1.000						
5. Fixed successfully	0.901	0.298	0.063	-0.011	-0.544	-0.811	1.000					
6. Defect – Same Problem	0.034	0.181	0.022	0.007	-0.034	-0.050	0.062	1.000				
7. Defect – Same Equipment	0.045	0.208	0.051	-0.003	-0.039	-0.058	0.072	-0.041	1.000			
8. Contractor	0.348	0.476	-0.219	-0.115	-0.105	-0.025	0.083	-0.013	-0.001	1.000		
9. ShortDay	0.088	0.283	-0.102	-0.054	-0.015	-0.033	0.036	-0.018	-0.001	0.126	1.000	
10. LongJob	0.568	0.495	0.579	0.051	-0.191	-0.039	0.188	-0.011	0.014	0.005	-0.032	1.000
11. Maintenance job	0.447	0.497	-0.172	-0.061	0.044	-0.236	0.172	-0.136	-0.053	0.196	0.136	0.126
12. Ctrl Htg Sys – Clean	0.337	0.472	-0.151	-0.049	0.037	-0.183	0.142	-0.106	-0.049	0.166	0.086	0.080
13. Ctrl Htg Sys – No Heat	0.089	0.284	0.074	0.000	-0.028	0.170	-0.105	0.072	0.013	-0.031	-0.052	-0.054
14. Ctrl Htg Sys – Install Part	0.035	0.184	0.078	0.012	-0.009	0.041	-0.027	0.001	0.046	-0.033	-0.025	-0.040
15. Ctrl Htg Sys – Adjust	0.024	0.154	0.008	-0.012	-0.002	0.054	-0.042	0.002	0.019	-0.045	-0.008	0.029
16. Wtr Htr – No Hot Water	0.140	0.347	-0.062	0.034	-0.014	0.046	-0.015	0.111	-0.054	-0.023	-0.044	-0.054
17. Wtr Htr – Water Leak	0.043	0.204	-0.063	0.014	-0.013	-0.044	0.047	-0.008	-0.027	-0.014	-0.021	-0.031
18. Wtr Htr – Adjust	0.032	0.177	-0.047	0.003	0.003	-0.024	0.013	-0.012	-0.016	-0.046	-0.019	-0.000
19. Wtr Htr – Install Part	0.018	0.133	0.013	0.015	0.001	0.008	-0.007	-0.003	0.022	-0.008	-0.016	-0.021
20. Wtr Htr – Insufficient Water	0.016	0.126	-0.015	0.008	0.001	-0.010	0.010	-0.010	-0.003	-0.037	-0.013	-0.012
21. Air Conditioner – Clean	0.072	0.259	-0.047	-0.021	0.010	-0.073	0.052	-0.040	-0.005	0.044	0.076	0.073

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
11. Maintenance job	1.000										
12. Ctrl Htg Sys – Clean	0.801	1.000									
13. Ctrl Htg Sys – No Heat	-0.278	-0.223	1.000								
14. Ctrl Htg Sys – Install Part	-0.170	-0.136	-0.059	1.000							
15. Ctrl Htg Sys – Adjust	-0.140	-0.112	-0.049	-0.030	1.000						
16. Wtr Htr – No Hot Water	-0.360	-0.288	-0.126	-0.077	-0.064	1.000					
17. Wtr Htr – Water Leak	-0.190	-0.152	-0.067	-0.041	-0.033	-0.086	1.000				
18. Wtr Htr – Adjust	-0.163	-0.131	-0.057	-0.035	-0.029	-0.074	-0.039	1.000			
19. Wtr Htr – Install Part	-0.121	-0.097	-0.042	-0.026	-0.021	-0.055	-0.029	-0.025	1.000		
20. Wtr Htr – Insufficient Water	-0.114	-0.091	-0.040	-0.024	-0.020	-0.051	-0.027	-0.023	-0.017	1.000	
21. Air Conditioner – Clean	0.313	-0.199	-0.087	-0.053	-0.044	-0.112	-0.059	-0.051	-0.038	-0.035	1.000

Table 3: Linear estimation: Drive Time as a function of compensation type, 2012 data

	(1)	(2)	(3)	(4)
	All Calls	All Calls	Service	Maintenance
Contractor	-3.544***	-2.223***	-3.734***	-1.004***
	(0.060)	(0.064)	(0.095)	(0.090)
Month FE	No	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes
Hour FE	No	Yes	Yes	Yes
Metro area FE	No	Yes	Yes	Yes
Job type FE	No	Yes	Yes	Yes
Constant	15.808***	30.124***	34.417***	12.507
	(0.035)	(3.368)	(4.027)	(7.540)
Observations	255,143	255,143	141,066	114,077
Adjusted R^2	0.013	0.076	0.082	0.078
F	3449.8***	215.4***	136.1***	140.4***

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 4: Linear and logit estimation: Customer Not Home as function of compensation type, 2012 data

	Linear				Logit			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Service	Service	Maint.	Maint.	Service	Service	Maint.	Maint.
Contractor	-0.026*** (0.000)	-0.024*** (0.001)	-0.060*** (0.001)	-0.063*** (0.001)	-1.815*** (0.074)	-1.802*** (0.078)	-2.318*** (0.054)	-2.404*** (0.057)
Month, Day, Hour, Metro Area, and Job Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.031*** (0.000)	0.009 (0.043)	0.067*** (0.000)	0.036 (0.105)	-3.476*** (0.017)	-14.250 (382.683)	-2.625*** (0.015)	-26.523 (1549.803)
No. Obs	141,066	141,066	114,077	114,077	141,066	141,014	114,077	113,953
Adjusted R^2	0.006	0.009	0.023	0.027				
F	801.9***	15.16***	2739.8***	46.45***				
Pseudo-R^2					0.031	0.050	0.084	0.096
χ^2					1022.30***	1613.68***	3217.23***	3686.97***
Log lklhd					-15916.0	-15460.7	-17619.5	-17379.5

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 5: Linear estimation of Job Time for successfully completed jobs, 2012 data

	All jobs				"Well-mixed" times only: 10am-9pm		Excluding the two-week employee vacation period	
	(1)	(2)	(3)	(4)	(3a)	(4a)	(3b)	(4b)
	All jobs	All jobs	Service.	Maintenance.	Service	Maintenance	Service	Maintenance
Contractor	-17.401*** (0.140)	-12.563*** (0.136)	-10.240*** (0.234)	-14.097*** (0.159)	-10.846*** (0.239)	-13.798*** (0.091)	-9.838*** (0.245)	-13.983*** (0.160)
Month, Day, Hour, Metro Area, and Job Type FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	56.778*** (0.084)	46.050*** (7.262)	56.856*** (10.060)	53.867*** (12.959)	59.786*** (8.201)	68.384*** (13.679)	45.366*** (10.198)	45.270** (13.01)
No. Obs	229,835	229,835	120,533	109,302	91,958	72,802	116,749	108,805
Adjusted R^2	0.063	0.266	0.297	0.146	0.263	0.127	0.299	0.078
F	15424.5***	849.7***	549.6***	271.3***	415.42***	190.06***	543.25***	271.44***

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 6: Estimation of defective jobs, 2012 data

	Linear estimation						Logit estimation					
	Defect – Same Problem			**Defect – Same Equipment**			**Defect – Same Problem**			**Defect – Same Equipment**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All jobs	Service	Maintenance	All jobs	Service	Maintenance	All jobs	Service	Maintenance	All jobs	Service	Maintenance
Contractor	0.002*** (0.000)	0.008*** (0.001)	-0.000 (0.000)	0.006*** (0.001)	0.001 (0.001)	0.010*** (0.001)	0.098*** (0.027)	0.133*** (0.029)	-0.099 (0.081)	0.158*** (0.022)	0.019 (0.030)	0.313*** (0.037)
Month, Day, Hour, Metro Area, and Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.007 (0.047)	-0.012 (0.077)	-0.007 (0.045)	-0.032 (0.054)	-0.058 (0.075)	-0.030 (0.099)	-16.735 (586.703	-17.253 (857.474)	-27.688 (1646.748)	-22.712*** (1.272)	-16.978 (691.202)	-15.555 (958.645)
No. Obs	229,835	120,533	109,302	229,835	120,533	109,302	229,785	120,500	108,438	229,517	120,241	109,225
Adjusted R^2	0.041	0.020	0.001	0.034	0.043	0.005						
F	101.60***	27.51***	3.26***	85.12***	59.25***	8.92***						
Pseudo-R^2							0.124	0.046	0.023	0.071	0.086	0.018
χ^2							9218.79***	2719.13***	213.15***	6602.97***	5033.97***	604.35***
Log lklhd							-32551.4	-27995.0	-4480.1	-42793.027	26554.7	-16139.6

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

Table 7: Estimation of defective jobs as a function of LongJob, 2012 data

	Linear estimation						Logit estimation					
	Defect – Same Problem			**Defect – Same Equipment**			**Defect – Same Problem**			**Defect – Same Equipment**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All jobs	Service	Maintenance	All jobs	Service	Maintenance	All jobs	Service	Maintenance	All jobs	Service	Maintenance
Contractor	0.003** (0.001)	0.007*** (0.002)	-0.002*** (0.000)	-0.000 (0.001)	-0.001 (0.002)	0.001 (0.001)	0.082** (0.036)	0.122*** (0.038)	-0.305** (0.124)	-0.015 (0.034)	-0.017 (0.041)	0.042 (0.064)
Longjob	-0.000 (0.001)	0.000 (0.001)	-0.003 *** (0.000)	-0.000 (0.001)	-0.002 (0.001)	0.002 (0.001)	-0.018 (0.027)	0.007 (0.028)	-0.401*** (0.103)	-0.023 (0.024)	-0.033 (0.028)	0.093* (0.055)
Contractor* Longjob	-0.000 (0.002)	0.001 (0.003)	0.002** (0.001)	0.012*** (0.001)	0.004 (0.003)	0.015*** (0.002)	0.030 (0.048)	0.021 (0.051)	0.324** (0.152)	0.294*** (0.041)	0.072 (0.055)	0.396*** (0.075)
Month, Day, Hour, Metro Area, and Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.007 (0.047)	-0.012 (0.077)	-0.005 (0.045)	-0.028 (0.054)	-0.057 (0.075)	-0.022 (0.099)	-16.728 (587.363)	-17.253 (857.313)	-27.263 (1540.39)	-22.621*** (1.031)	-16.956 (691.166)	-14.301 (579.658)
No. Obs	229,835	120,533	109,302	229,835	120,533	109,302	229,785	120, 500	108,438	229,517	120, 241	109,225
Adjusted R^2	0.041	0.020	0.002	0.035	0.043	0.006						
F	99.57***	26.93***	3.42***	84.03***	58.03***	10.29***						
Pseudo-R^2							0.124	0.046	0.025	0.072	0.087	0.021
χ^2							9219.36***	2719.67***	228.06***	6667.68***	5036.05***	703.00***
Log lklhd							-32551.2	-27994.7	-4472.7	-42760.6	-26553.6	-16090.3

Standard errors in parentheses
* $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table 8: Index of complexity for ten most common job types

(based on expert opinion from ServCo managers) [a]

Maximal Complexity
Ctrl Htg Sys – No Heat
Ctrl Htg Sys – Adjust
High Complexity
Wtr Htr – No Hot Water
Wtr Htr – Adjust
Wtr Htr – Insufficient Water
Moderate Complexity
Wtr Htr – Install Part
Ctrl Htg Sys – Install Part
Wtr Htr – Water Leak
Low Complexity
Ctrl Htg Sys – Clean
Air Conditioner – Clean

[a] The surveyed ServCo managers were not aware of our intended use of this measure, hence presumably did not answer in a way that would be "tainted" by our expectations.

Table 9: Estimation of defective jobs as a function of job-type complexity, 2012 data

(Linear estimation; logit estimation in Appendix [NB for DRUID: Not included due to space constraints])

	Defect – Same Problem			Defect – Same Equipment			Defect – Same Problem			Defect – Same Equipment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All jobs	All jobs	Service	All jobs	All jobs	Service	All jobs	All jobs	Service	All jobs	All jobs	Service
Contractor	0.002* (0.002)	-0.002 (0.001)	0.000 (0.005)	0.005*** (0.001)	0.009*** (0.001)	0.007 (0.004)	0.002*** (0.000)	-0.002 (0.000)	0.000 (0.003)	0.005*** (0.001)	0.010*** (0.001)	0.000 (0.003)
Complexity	0.028*** (0.001)	0.026*** (0.000)	0.025*** (0.001)	0.005*** (0.000)	0.006*** (0.000)	0.003*** (0.001)						
Contractor* Complexity		0.005*** (0.000)	0.004 (0.002)		-0.004*** (0.000)	-0.003 (0.002)						
MedComplex							0.023*** (0.001)	0.022*** (0.001)		0.030*** (0.001)	0.033*** (0.001)	
HighComplex							0.067*** (0.001)	0.061*** (0.001)	0.039*** (0.002)	-0.010*** (0.001)	-0.007*** (0.001)	-0.040*** (0.002)
MaxComplex							0.076*** (0.001)	0.073*** (0.001)	0.050*** (0.002)	0.037*** (0.001)	0.042*** (0.001)	0.008*** (0.002)
Contractor* MedComplex								0.003 (0.002)			-0.009*** (0.003)	
Contractor* HighComplex								0.016*** (0.002)	0.013*** (0.004)		-0.009*** (0.002)	0.000 (0.003)
Contractor* MaxComplex								0.011*** (0.002)	0.007(0.005)		-0.014*** (0.003)	-0.005 (0.004)
Month, Day, Hour, Metro Area, and Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.023 (0.031)	-0.023 (0.031)	-0.033 (0.067)	-0.002 (0.036)	-0.002 (0.033)	-0.032 (0.056)	-0.025 (0.031)	-0.025 (0.031)	-0.017 (0.067)	-0.002 (0.033)	-0.002 (0.033)	0.001 (0.056)
No. Obs	189,287	189,287	88,839	189,287	189,287	88,839	189.287	189.287	88.839	189.287	189.287	88,839
Adjusted R^2	0.034	0.035	0.019	0.005	0.005	0.005	0.035	0.036	0.010	0.010	0.010	0.015
F	127.67***	126.19***	30.21***	17.23***	17.48***	8.89***	126.61***	121.10***	17.23***	37.28***	35.92***	25.12***

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

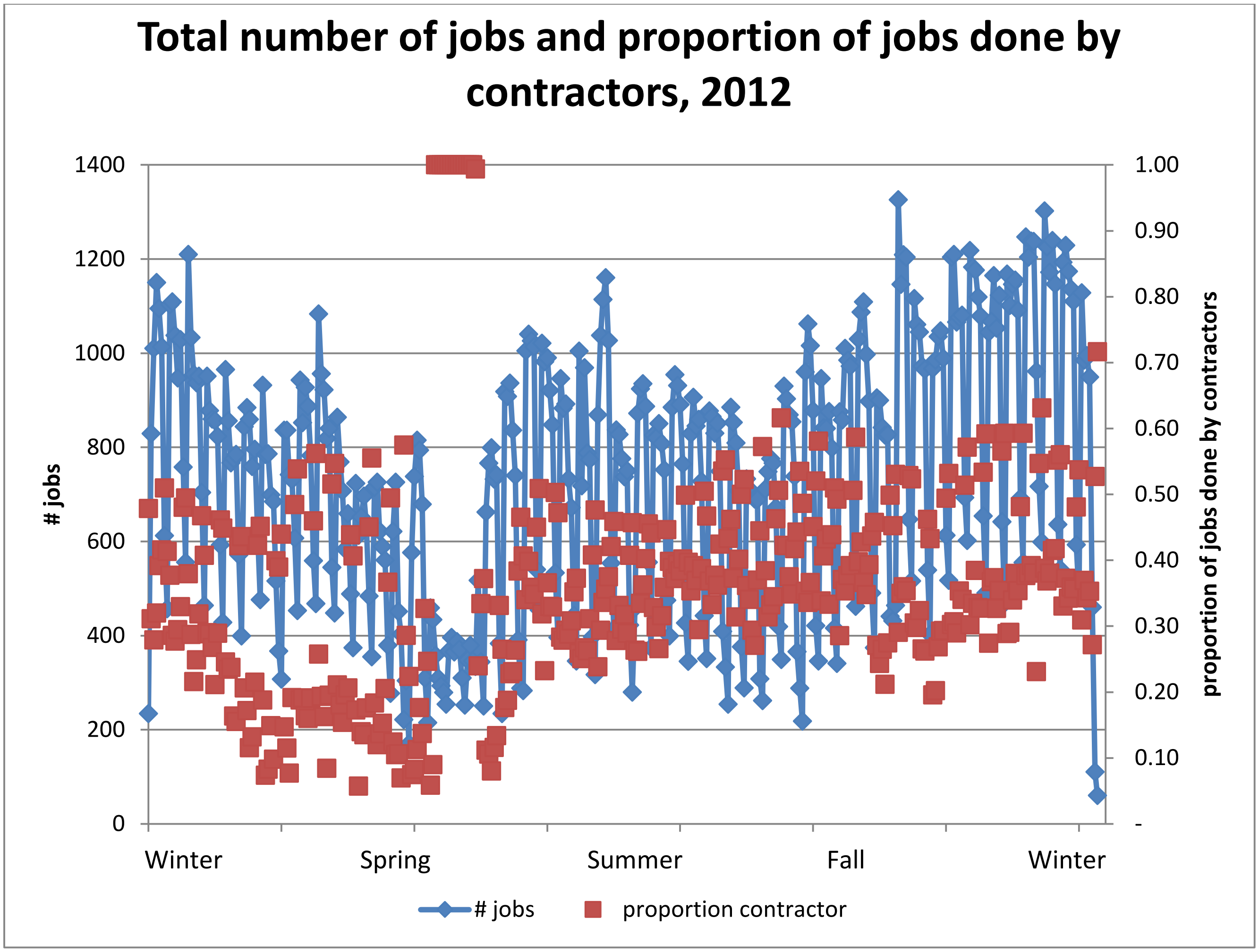
Table 10: Linear estimation of DriveTime and JobTime for short days, 2012 data[a]

	2012 DRIVETIME				2012 JOBTIME			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	All jobs	All jobs	Service	Maintenance	All jobs	All jobs	Service	Maintenance
Contractor	-3.542*** (0.063)	-2.192*** (0.067)	-3.634*** (0.098)	-0.867*** (0.096)	-17.872*** (0.148)	-12.993*** (0.143)	-10.505*** (0.240)	-14.696*** (0.168)
ShortDay	-2.915*** (0.147)	-3.232*** (0.145)	-1.750*** (0.209)	-4.139*** (0.200)	-15.467*** (0.344)	-14.976*** (0.310)	-11.278*** (0.512)	-16.974*** (0.353)
Contractor* ShortDay	1.584*** (0.204)	1.575*** (0.199)	-0.635 (0.355)	1.747*** (0.255)	11.908*** (0.470)	11.414*** (0.420)	8.324*** (0.867)	13.206*** (0.444)
Month, Day, Hour, Metro Area, and Job Type FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Constant	15.988*** (0.036)	30.643*** (3.364)	35.011*** (4.026)	12.927 (7.519)	57.754*** (0.086)	47.867*** (7.223)	58.640*** (10.040	46.073*** (12.802)
No. Obs	255,143	255,143	141,066	114,077	229,835	229,835	120,533	109,302
Adjusted R^2	0.015	0.078	0.083	0.083	0.072	0.274	0.300	0.165
F	1311.62***	217.98***	134.81***	146.38***	5901.38***	866.52***	545.58***	304.87***

Standard errors in parentheses
* p<0.05; ** p<0.01; *** p<0.001

[a] Job Time regressions are restricted to successfully completed jobs

Figure 1



Total number of jobs and proportion of jobs done by contractors, 2012
1400
1200
1000
800
600
400
200
0
jobs
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
-
proportion of jobs done by contractors
Winter
Spring
Summer
Fall
Winter
jobs
proportion contractor

Figure 2 Number of jobs and mix between contractor/employee, 2012 - 20% cutoffs

	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total (#)	Total (%)
00:00-01:00	3	7	10	14	7	9	3	53	0.02%
01:00-02:00	2	2	9	7	5	2	3	30	0.01%
02:00-03:00	2	3	1	4	9	6	1	26	0.01%
03:00-04:00	1	3	3	3	6	2	0	18	0.01%
04:00-05:00	2	2	1	3	2	1	1	12	0.00%
05:00-06:00	0	0	0	2	1	2	1	6	0.00%
06:00-07:00	6	10	11	12	8	6	1	54	0.02%
07:00-08:00	578	708	737	661	610	227	126	3,647	1.38%
08:00-09:00	3,659	4,487	4,436	4,205	3,743	1,724	1,143	23,397	8.84%
09:00-10:00	3,399	3,729	3,859	3,640	3,313	2,068	1,486	21,494	8.12%
10:00-11:00	3,828	4,242	4,412	4,151	3,881	2,539	1,732	24,785	9.36%
11:00-12:00	3,779	4,116	4,165	4,017	3,852	2,655	1,939	24,523	9.26%
12:00-13:00	3,725	3,878	3,995	3,795	3,653	2,627	1,935	23,608	8.92%
13:00-14:00	4,032	4,296	4,247	4,207	3,943	2,612	1,961	25,298	9.55%
14:00-15:00	4,658	4,794	4,748	4,571	4,573	2,576	1,976	27,896	10.54%
15:00-16:00	4,259	4,112	3,956	4,028	3,873	2,168	1,812	24,208	9.14%
16:00-17:00	3,090	3,195	3,105	3,014	2,802	1,721	1,544	18,471	6.98%
17:00-18:00	2,165	2,362	2,257	2,181	2,010	1,352	1,303	13,630	5.15%
18:00-19:00	1,889	2,005	1,924	1,784	1,704	1,141	1,098	11,545	4.36%
19:00-20:00	1,695	1,786	1,768	1,644	1,500	847	816	10,056	3.80%
20:00-21:00	1,422	1,516	1,417	1,314	1,196	630	608	8,103	3.06%
21:00-22:00	549	592	515	510	391	229	244	3030	1.14%
22:00-23:00	133	116	137	113	102	70	58	723	0.28%
23:00-24:00	33	21	23	21	21	15	16	150	0.06%
							Total	255,143	100.00%

Legend	(white)	0.20 <= contractor proportion <= 0.80
	(light grey)	contractor proportion < 0.20
	(dark grey)	contractor proportion > 0.80
	0	No jobs in these windows