Workers responses to piece-rate reductions and increases : Evidence from a Field Experiment

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Abstract

This paper analyzes workers' reactions to changes in wage rates. We use field experimental data from a tree-planting firm in British Columbia where workers are hired to plant trees on given blocks and are paid on a piece rate basis. We conduct two basic experiments to introduce exogenous variations in the workers piece rate. The first one is a reduction of the worker's piece rate coupled with a base wage. The second one is an increase in the worker's piece rate. At the intensive margin, we measure completely piece rate effects on productivity accounting for both piece rate reductions and increases. Our study also provides a direct comparison between the impact of wage cuts and pay raises on productivity within the same framework and highlights significant asymmetries in worker's response. It establishes an empirical foundation for downward wage rigidity.

1 Introduction

Personnel and labor economists have shown keen interest in measuring worker reactions to monetary incentives. A number of papers have concentrated on piece rates (Shearer, 2004; Paarsch and Shearer, 2009; Hossain and List, 2012). These studies generally focused on the impact of a piece rate increase. Comparatively empirical studies that investigate the effect of piece rate reductions on productivity are quite rare. This is mainly due to the fact that wages are generally characterized by downward rigidity (Holden and Wulfsberg, 2009; Fehr and Goette, 2005; Bewley, 1998) and pay reductions treatments are difficult to implement in the field.

Many theories have been advocated to explain this downward rigidity: the choice between layoffs and wage cuts (McLaughlin, 1990, 1991), inequality aversion, implicit income insurance agreements, the bargaining power of insiders and impact on work morale. Bewley (1998) explores majority of these arguments and his findings support none of the existing economic theories of wage rigidity, except those that emphasize the impact of pay cuts on morale.

The morale model of Solow (1979) espoused and elaborated by Akerlof (1982) and Akerlof and Yellen (1988, 1990) assert that pay rates influence productivity through their impact on morale. High pay rates or pay raise would foster high work morale which is essential for sustaining voluntary cooperation and high productivity whereas wage cuts damage work morale and lead to lower productivity (Kube et al., 2013; Bewley, 2021) especially when workers have discretion over their effort level. This holds true even in the presence of explicit performance incentives (Fehr and Falk, 1999). Wage cuts in some cases may even lead to difficulties in the hiring and retention of productive workers (Campbell III and Kamlani, 1997; Bewley, 1998; Sandvik et al., 2021) and to counterproductive behaviors Coviello et al. (2022).

Despite the consensus among economists that pay cuts can be prohibitively costly, real-world evidence on the effects of pay reductions is scarce (Lee and Rupp, 2007; Krueger and Friebel, 2022). This also includes field experiments. Some treatments in particular cutting remuneration paid to workers are difficult to implement within real firms. While laboratory experiments may be good alternatives, they may not reproduce the realism of natural occurring markets especially the labor market which consequently affects and limits their results (Harrison and List, 2004; DellaVigna, 2009; Levitt and List, 2007; Stoop et al., 2012).[1] Shearer (2022) suggests one possible field experiment design to generate piece rate cuts and measure their effects exploiting a non-commitment piece rate strategy. In his experiment, Piece rates were set high above the regular rate with the possibility of a downward revision to analyze ratchet effects. Piece rates were then effectively reduced from the initial rate but remained above the regular rate.

This study proposes an alternative field experiment design to that of Shearer (2022). Instead of initially setting the piece rate higher than its regular rate, we introduce a base wage along with the piece rate. Workers are administered piece rate reductions below their regular rates. This study also implements exogenous pay raises which allows to investigate worker's reaction to wage cuts and pay raises in the same framework. The experiment took place in a tree-planting firm operating in British Columbia, Canada. The workers of this firm are recruited to plant trees on blocks of land and are paid on a piece rate basis. The regular piece rate paid to the worker is fixed by the firm and closely tied to the planting condition of the block. Daily productivity of the workers is accurately measured by the number of trees planted. We conduct two main experiments to introduce

[1]Some authors, however,do argue that many objections against laboratory experiments are misguided and that even more laboratory experiments should be conducted (Falk and Heckman, 2009; Camerer, 2011).

exogenous variations on the workers piece rate. The first one is a reduction of the workers piece rate coupled with a base wage. The second one is an increase in the workers piece rate. Using this experimental data, we analyze workers' reactions in terms of productivity following a piece rate raise versus a piece rate cut. We test empirically if these reactions are asymmetric and to what extent.

The study also estimates worker's elasticity of productivity with respect to the piece rate. Knowledge of this elasticity is of great importance for personnel policies considering performance pay. Stiglitz (1975) showed that the optimal piece rate which a firm should set is an increasing function of worker's elasticity of productivity (effort).[2] Although this value depends on industry or firm-specific characteristics such as the technology used, Paarsch and Shearer (1999) argued that case-study approach such as this one is still useful as long as the characteristics of the firm are taken into account for policy proposals.

Our results show that workers do react to changes in pay rates hence to monetary incentives as depicted by numerous studies (Paarsch and Shearer, 2009; Hossain and List, 2012, etc). We contribute to the literature by providing a "combined estimate" of piece rate incentive effects that accounts for both left marginal effects (piece rate cut) and right marginal effects (piece rate increase). Previous studies have concentrated on measuring right marginal effects because of the difficulties in implementing wage cuts. Using a Semi-Log specification which is our preferred specification, we estimate an elasticity of productivity with respect to the piece rate ranging from 0.35 to 0.40.[3] These values approach that of 0.39 found in Paarsch and Shearer (2009) which focused solely on right marginal effects.

Left and right marginal effects can be viewed as one-sided measures of piece rate incentive effects. Compared to a "combined estimate", left and right marginal estimates are still attractive as they focus to examine one particular aspect - a piece rate increase or a piece-cut reduction. Hence, we also estimate distinctly left and right marginal effects. The estimated right marginal elasticity in our study is around 0.25 below the value of 0.39 in Paarsch and Shearer (2009)[4]. The left marginal elasticity is much larger amounting to 0.73. As we compare left and right marginal effects, our findings provide additional evidence that workers' reactions to a wage rate increase and decrease are asymmetric (Kube et al., 2013). Similar asymmetries are also observed regarding the effects of sanctions and rewards (see for example Sefton et al., 2007; Andreoni et al., 2003). However in our framework, the fact that workers react strongly to wage cut than to corresponding pay raise doesn't necessarily mean they are sanctioning strongly the employer for negative deviation from their regular piece rate. The strict convexity of the marginal cost of effort function is sufficient to generate an asymmetric response in productivity.

By highlighting very strong effects of pay reductions, our study nicely complements theoretical studies such as Dickson and Fongoni (2019) that aims to give more insights on the micro-foundation of downward wage rigidity. It also relates to other empirical studies that have addressed questions on the impact of wage reduction.

Coviello et al. (2022) studied the effects of a pay cut on sales representatives in an American call center. They report increased turnover in reaction to the wage cut as well as an increase in counterproductive behavior (high customer refunds). Krueger and Friebel (2022) analyzed the effects of a pay cut in call centers in Germany over a three-year horizon and find that workers output decreased substantially, and attrition increased. Sandvik et al. (2021) show that staggered commission reductions at a sales firm increases turnover for the most productive

[2] Intuitively, the higher is the elasticity of effort the more beneficial it is for the firm to set a high piece rate.

[3] These estimates are relative to an average productivity of 2000 trees.

[4] The average productivity before the piece rate treatments in Paarsch and Shearer (2009) are much lower than in ours. It is about 773 trees compared to over 2000 in our study, which gives a ratio of at least 2.5. Workers response to Piece rates changes are likely to vary across planters, sites and/or time.

workers and triggers limited effort responses. Shearer (2022) considered the impact of piece rate cuts on worker productivity within a real firm to analyze ratchet effects. He showed that workers withheld output in response to threat to wage cuts. There was, however, no tendency to restrict production when the wage cut was effectively made. This contrast with our results. Indeed in Shearer (2022), despite the wage cut, the piece rate was still above the regular rate. In our study, workers are administered pay reductions below their regular Piece rates

The remainder of this article is organized as follows. Section 2 describes the institutional setting of the study. Section 3 presents the experimental design. Section 4 describes the experimental data. Section 5 presents econometric analysis of the experimental data and Section 6 provides concluding remarks and suggestions for further research.

2 Institutional Setting

Our field experiment took place in a tree-planting firm in British Columbia. Firms in this industry are allocated tracts of land for reforestation to maintain a steady supply of lumber in the region. This allocation is done through a competitive bidding initiated by either the government or another logging firm. The lowest-bidding firm wins the contract and is in charge of reforesting the given site.

The firm recruits workers to plant trees on allotted tract of land. Tree planting is a simple, yet physically exhausting task. It involves digging a hole with a special shovel, placing a seedling in this hole, and then covering its roots with soil, ensuring that the tree is upright and that the roots are fully covered. The amount of effort required to perform the task depends on the terrain on which the planting is done and weather conditions. Workers in this firm represent a very broad group of individuals, including returning seasonal workers and students working on their summer holidays, male, female, youths, adults. They are free to leave the firm at any time if they are not satisfied with the work conditions. There are no unions. The planting season typically runs between March and the end of June.

This firm pays its worker on a piece rate basis. Blocks to be planted typically contain between 20 and 30 planter-days of work, with some lasting over 100 planter-days. For each block, the firm decides on a piece rate that applies to all planting done on the block. The piece rate for a particular block is set to account for the planting conditions on that block. Blocks that are more difficult to plant (due to their steepness for example) require higher Piece rates to attract workers. The piece rate applies to all planting done on a block. Thus all workers on the same block receive the same piece rate. There is no systematic matching of workers to planting conditions of the blocks within the firm. Indeed, workers typically meet at a central location each morning and are transported to the planting sites in trucks. They are then assigned to plots of land as they disembark from the truck. They are placed under the direction of a supervisor who is responsible for monitoring their output.

Worker's productivity is precisely measured by the number of trees planted per day and his daily earnings is determined by the product of the piece rate and the number of trees planted. The firm maintains payroll data which contains information on the piece rate received by each planter, as well as the planter's daily productivity and earnings.

By introducing exogenous piece rate cuts and raise in this setting, we analyze workers' reactions in terms of productivity following a piece rate raise versus a piece rate cut and test empirically if these reactions are asymmetric.

3 Experimental Design

We conducted two separate experiments within the same tree-planting firm : a piece rate reduction experiment and a piece rate increase experiment. Our experiments took place during the 2019 planting season.

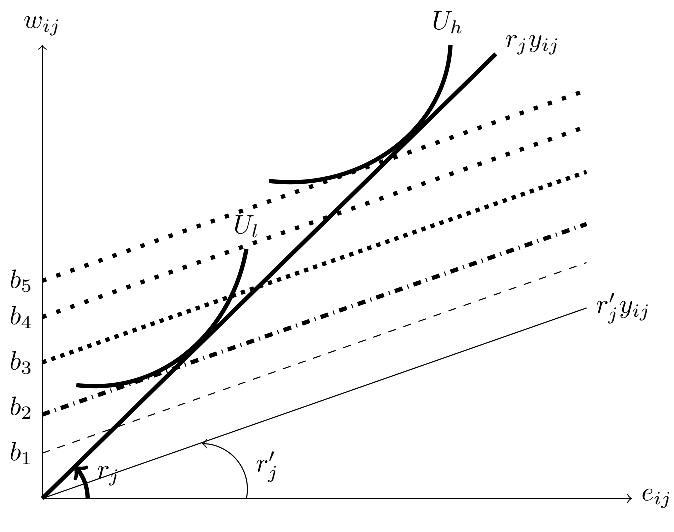
3.1 The Piece rate reduction Experiment

This experiment was conducted to introduce exogenous piece rate reductions. We accompanied these reductions with a base wage to ensure that workers would accept the reduction of the incentive pay.

The experiment lasted 8 days and took the form of a contract choice game. During the experiment, workers were offered a menu of choices between their regular piece rate without base wage and a reduced piece rate coupled with a base wage in a decision sheet. An example of the decision sheet is given in the Appendix A.To complete the decision sheet, workers were asked to indicate their willingness to accept a given piece rate reduction for different levels of the base wage on the decision sheet. For example, suppose a worker's regular piece rate is 20 cents per tree and the piece rate reduction is 4 cents per tree. The worker would make 14 decisions. Each decision is between the regular piece rate of 20 cents and the reduced piece rate of 16 cents plus a base wage. The base wage for the first decision is C\$20. It increases by C\$20 dollars at each decision. As the base wage increases, once would expect the willingness of the worker to accept the incentive pay reduction increases also. Note that the worker complete each decision.

Before making his choices, the worker was told that one of his decisions would be drawn at random and he would be paid according to his choice for that decision. By indicating his preference for the complete sequence, the worker reveals the minimum base wage he/she requires to accept the piece rate reduction. Below this value, the worker has no willingness to accept the piece rate cut. The economic intuition and mechanic behind the piece rate cut experiment is depicted in Figure 1.

Figure 1: Piece rate cut Experiment



The regular piece rate is represented by the solid thick line while the thin line represents the slope of the reduced piece rate. For each level of base wage b, the worker indicates his/her willingness to accept the piece rate cut. For strictly convex preferences, there is a unique value of base wage below which the worker has no willingness to accept the piece rate cut. This threshold (minimum base wage) is worker-specific and is given by b_2 and b_5 for the worker with utility U_l and U_h respectively.

The piece rate cut experiment involved two basic treatments, applying reduction of 4 cents and 6 cents per tree respectively. This corresponds to reductions ranging from 15% to 33% depending on the regular piece rate in place on the blocks. The offered base wages varied from C$20 to C$280 for the reduction of 4 cents per tree and from C$20 to C$320 for the reduction of 6 cents per tree. These ranges were sufficiently broad to identify the threshold at which each worker is willing to accept the piece rate cuts.

These treatments are split into 2 sub-treatments. First, worker is administered either the regular piece rate or the piece rate cut based on a random selection of his decisions over the entire range of proposed base wages in the contract choice game. This sub-treatment will be labeled unrestricted base wage draw. A second sub-treatment used the same decision sheet as in the first sub-treatment, but here the worker is administered either the regular piece rate or the piece rate cut based on a random selection of his decisions around his identified minimum base.[5] This will be labeled restricted base wage draw. The goal of this sub-treatment is to increase our chances of observing each worker under the cut-down piece rate treatment and to reduce selection bias in the experiment.

- **Treatment 1** : piece rate cut of 4 cents per output and unrestricted base wage draw **(T1)**.
- **Treatment 2** : piece rate cut of 6 cents per output and unrestricted base wage draw **(T2)**.
- **Treatment 3** : piece rate cut of 4 cents per output and restricted base wage draw **(T3)**.
- **Treatment 4** : piece rate cut of 6 cents per output and restricted base wage draw **(T4)**.

On each experimental day, one half of the workers were randomly offered the contract choice treatments (exposed group) while the other half of the workers planted under their regular piece rate. We call this group the non-exposed group. The following day, the exposed group and the non-exposed group are switched. This process of switching between exposed and non-exposed group is repeated throughout the experiment. The treated group is composed of workers who are observed under the reduced piece rate. This includes workers who drew a base wage that was greater than their reservation base wage identified on their decision sheet. The control group is composed of workers who are observed under the regular piece rate contract. Based on the experimental design, we distinguish two control sub-groups: first, those who were randomly allocated to the non-exposed group and second, those who were in the exposed group and drew a base wage below their reservation base wage.

Workers were given paper instructions, a decision sheet, a clipboard, and an ink pen on each experimental day in the morning before planting. The decision sheet presents to each participant a series of decisions between two options : Option A indicating the worker's regular piece rate contract and Option B indicating a base wage contract (reduced piece rate). For each decision, workers must choose either Option A or Option B but not both. They are informed that only one of their decisions between Option A and Option B will be randomly chosen to determine their contract and thus their earnings. Each decision is represented by a poker chip numbered accordingly. We have an equal number of decisions and poker chips. The experiment proceeds as follows. The chips are placed in a bag. After the workers made all the decisions, they are asked to draw one chip out of the

[5] Some workers had changed planting blocks (and hence regular Piece rates) from the day on which they had filled in the decision sheet, necessitating that we allow them to revise their willingness to accept the piece rate cut.

bag. The selected chip indicates which decision will be used to determine the worker's contract. For example, if the worker draws the chip with the number 3, then his choice between Option A and option B for decision 3 will determine his contract. If he draws the chip with the number 8, then his choice for decision 8 between Option A and option B will determine his contract. Each decision has an equal chance of being selected based on the chip drew out of the bag. The decision sheet and detailed instructions of the experiment are presented in Appendix A.

3.2 The piece rate increase Experiment

Compared to the piece rate cut experiment, the piece rate increase experiment is relatively straightforward to implement. It was conducted 2 days after the piece-cut experiment and lasted 4 days. Its goal was to introduce exogenous piece rate increase. It involved the same workers that participated in the piece-cut experiment. This experiment was conducted under a randomized-block design. During the experiment, each block was divided into two parts : one of these parts was randomly assigned the regular piece rate (control) and the other part was randomly assigned a piece rate increase of 4 cents (treatment). All workers are both observed under the regular piece rate and the increased piece rate.

4 Experimental Data

The summary statistics for the experiments is presented in Tables 1, 2 and 3. The two experiments involved the same workers - a total of 37.

In Table 1, the average regular piece rate before the 4 cents reduction treatment was 0.22 cents per tree. After the piece-cut, it was reduced to 0.19 cents per tree. The 6 cents reduction treatment reduced the average regular piece rate from 0.21 to 0.15. In the absence of the 4 cents reduction, average daily productivity was 2369 trees compared to 2215 trees when workers incurred the piece rate cut. The differential in productivity is about 6.5%. This productivity loss increases to 7.7% when workers incur a piece rate cut of 6 cents.

The piece rate increase Experiment consists in only one treatment : a piece rate increase of 4 cents. Average regular piece rate during the experiment rose from 19 cents to 23 cents. Consequent to the piece rate increase of 4 cents, average daily productivity increased from 2903 to 3035 trees. The observed productivity gain is about 4.5% much lower than the productivity loss of 6.5% following a piece-cut of the same amount - suggesting asymmetric worker's response to the piece rate cut and increase.

Table 3 gives a sense of workers' willingness to incur a piece rate cut. The average minimum base wage required by workers to accept piece rate cut of 4 cents per tree is C$132.24. This rises to C$182.25 when the piece rate cut is 6 cents per tree. During the piece rate cut experiment, average workers daily piece rate earnings was reduced about 21.3% and 33.6% following the piece-cut of 4 cents and 6 cents respectively. This corresponds in absolute terms to income loss of C$106.48 and C$181.23. The piece rate cut experiment compensated for these income losses by providing base wages to workers who incurred the piece rate cut. Average base wages paid to workers who suffered the piece rate cut of 4 cents and 6 cents are C$195.92 and C$234.67 respectively. It is important to note that this compensation can generate income effects that contribute to the observed productivity decreases. This income effects need to be purged out in order to isolate the piece-cut effect.

In the next section we will use regression analysis to control for the effects of base wages and other confounding factors in order to isolate the effect of piece rate changes on worker productivity.

Table 1: Piece rate reduction and productiveness

		Piece rate reduction of 4 cents		Piece rate reduction of 6 cents		All	
		Control	Treatment	Control	Treatment	Control	Treatment
Number of trees	Average	2369.54	2215.51	2608.78	2407.22	2496.96	2307.29
	sd	794.90	786.96	874.49	900.88	844.49	844.32
	Minimum	750.00	650.00	510.00	840.00	510.00	650.00
	Maximum	4100.00	3855.00	4470.00	4200.00	4470.00	4200.00
	Observations	86	49	98	45	184	94
piece rate paid	Average	0.22	0.19	0.21	0.15	0.22	0.17
	sd	0.03	0.04	0.04	0.04	0.03	0.04
	Minimum	0.18	0.14	0.18	0.12	0.18	0.12
	Maximum	0.32	0.28	0.33	0.25	0.33	0.28
	Observations	86	49	98	45	184	94
piece rate earnings	Average	501.01	394.53	539.66	358.43	521.59	377.25
	sd	138.09	112.41	155.98	124.05	148.75	118.87
	Minimum	150.00	91.00	102.00	117.60	102.00	91.00
	Maximum	820.00	764.80	883.00	747.00	883.00	764.80
	Observations	86	49	98	45	184	94
Base wage paid	Average	0.00	195.92	0.00	234.67	0.00	214.47
	sd	0.00	50.82	0.00	43.36	0.00	51.00
	Minimum	0.00	100.00	0.00	160.00	0.00	100.00
	Maximum	0.00	280.00	0.00	340.00	0.00	340.00
	Observations	86	49	98	45	184	94

Table 2: Piece rate increase and productiveness

		Piece rate increase of 4 cents	
		Control	Treatment
Number of trees	Average	2903.96	3035.00
	sd	688.19	765.88
	Minimum	1115.00	930.00
	Maximum	4620.00	4805.00
	Observations	67	72
piece rate paid	Average	0.19	0.23
	sd	0.01	0.01
	Minimum	0.18	0.22
	Maximum	0.22	0.26
	Observations	67	72
piece rate earnings	Average	541.39	688.19
	sd	119.50	164.42
	Minimum	211.85	241.80
	Maximum	831.60	1057.10
	Observations	67	72

Table 3: Minimum base wage reported for the piece rate reduction experiment

	Average	sd	Minimum	Maximum	Observations
piece rate reduction of 4 cents	132.24	40.30	80.00	240.00	67
piece rate reduction of 6 cents	182.25	44.02	60.00	280.00	71
All	157.97	49.01	60.00	280.00	138

5 Econometric analysis

In subsequent analysis, we consider reduced-form regressions that exploit exogenous variations introduced by our experiments to effectively measure productivity differentials resulting from changes in Piece rates.

5.1 Workers response to piece rate incentives

We estimate worker's elasticity of productivity with respect to the piece rate by considering the following regression model.

$$\log y_{ijt} = \gamma_0 + \gamma_1 \log \tilde{r_j} + Control\ variables + u_i + \epsilon_{ijt} \tag{1}$$

where

- y_{ijt} is the number of trees planted by worker i on a block j and on day t ;
- $\tilde{r_j}$ is the piece rate paid on block j such as :

$$\tilde{r_j} = \begin{cases} r_j & \text{for control group observations} \\ R_j & \text{for treatment-group observations} \end{cases}$$

- $Controlvariables$ include base wage paid to the worker, block-specific variables and weather or day-specific variables. Accounting for these factors help to effectively isolate the piece rate effect ;
- u_i is a worker-specific time-invariant productivity parameter ;
- ϵ_{ijt} denotes random unobservable factors which vary across days, blocks and workers.

This model uses the exogenous experimental changes in the piece rate to estimate worker's elasticity of productivity which is given directly by the coefficient γ_1 on the logarithm of the piece rate. We consider three different versions of the regression model specified in equation (1) to estimate worker's elasticity of productivity with respect to piece rate. Model 1 is the basic model that does not account for weather variables or day-specific effects. It accounts only for block-specific and worker-specific effects. Model 2 accounts for a set of weather variables : Maximum temperature, Minimum temperature, Maximum 2-meter air temperature above 19^oC, Precipitation, average relative humidity, average dew point and minimum wind speed.[6] Model 3 further introduces day-specific dummy variables to capture daily specific effects beyond the weather variables that can influence worker productivity. All three models account for the base wage effects (income effects) related to the piece rate cut Experiment. They also all incorporate a No rotation dummy variable that equals 0 if the worker is observed on different planting conditions (different blocks) on the same day and 1 if he is observed on the same block throughout the day.

The results of our estimations are given in Table 4. We produced Fixed effects that accounts for worker's unobservable heterogeneity such as ability that influences productivity. Random effects estimations are provided in Appendix B. We run a test of overidentification restrictions (orthogonality conditions) for panel data estimation to choose between Fixed effects and Random effects estimation. Fixed effects estimation exploits the orthogonality conditions that the regressors are uncorrelated with the error term ϵ_{ijt}. Besides these conditions, Random effects estimation assumes and exploits the additional orthogonality conditions that the regressors are uncorrelated with the worker-specific time invariant parameter u_i. Arellano (1993) and Wooldridge (2002) proposed an overidentification test of these additional orthogonality conditions. This test extends the usual Hausman Fixed vs Random effects test to account for heteroskedastic and cluster-robust standard errors. The null hypothesis is preference for the Random Effects estimation whereas the alternative hypothesis is preference for the Fixed effects estimation. The results are presented in bottom panel of Table 4. The p-values are all zero, suggesting that fixed-effect estimation is preferred.

[6] Weather conditions generally include a set of factors such as temperature (degrees Celsius), humidity, wind speed (km/h) and precipitation (millimeters). Temperature and precipitation are the most common factors. Maximum 2-meter air temperature above 19^oC is a dummy variable that equates 1 if maximum temperature recorded during day is above 19^oC and 0 otherwise. Temperature is mainly measured from a dry bulb thermometer which don't account for the moisture or humidity in the air. Dew point is a measure of the humidity of the air. It is the temperature to which the air would have to be cooled to reach saturation with respect to liquid water. Saturation occurs when the air is holding the maximum water vapor possible at a given temperature and atmospheric pressure. Relative humidity in percentage is the ratio of the quantity of water vapor the air contains compared to the maximum amount it can hold at a given temperature.

Table 4: Fixed Effects Estimation of piece rate incentives and elasticity of output

	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	0.14319	0.26231***	0.21420**
	(0.09270)	(0.08871)	(0.08899)
Base wage	-0.00004	0.00008	0.00003
	(0.00015)	(0.00014)	(0.00014)
No Rotation	0.01491	0.03288	0.02966
	(0.02340)	(0.02192)	(0.02113)
Maximum temperature		-0.02508***	
		(0.00765)	
Minimum temperature		-0.00911	
		(0.00768)	
Maximum 2-meter		-0.09469***	
air temperature$> 19^oC$		(0.02149)	
Precipitation		0.00425	
		(0.00460)	
Average relative humidity		-0.01534***	
		(0.00362)	
Average dew point		0.07922***	
		(0.01445)	
Minimum wind speed		-0.06234***	
		(0.01841)	
Constant	8.21644***	9.69177***	8.11563***
	(0.15499)	(0.33490)	(0.15404)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Fixed vs Random effects Test		
Statistic	186.2410	243.2838	286.5747
P-Value	0.0000	0.0000	0.0000

The estimated elasticity varies from 0.14 for Model 1 to 0.26 for Model 2. Weather variables or day-specific effects are statistically significant and their inclusion has an impact in the production of the elasticity estimate. Their inclusion increases the value of the elasticity of at least 1.5. Moreover, accounting for weather variables improves statistical significance. The elasticity estimates from Model 2 and 3 are more precise whereas that from Model 1 is not statistically significant. We, however, lose some precision with Model 3 because of the degrees of freedom that are reduced with the inclusion of day-specific dummy variables.

Our estimated elasticities are smaller than those found in previous studies.Paarsch and Shearer (2009) estimated a value of about 0.39 for the same firm using experimental data that introduced piece rate increases. A potential explanation for this difference is that workers react to increases differently from decreases. Indeed Paarsch and Shearer (2009) focused solely on right marginal effects (impact of positive changes in Piece rates) to estimate worker's elasticity of productivity with respect to Piece rates whereas in our study, we consider both the impact of positive and negative changes in Piece rates (right and left marginal effects) to characterize worker's elasticity of productivity. In section 5.3, we provide a more detailed analysis of left and right marginal effects.

5.2 Constant elasticity Specification versus a Semi-Log Specification

The model defined in equation (1) is a standard regression model allowing to directly estimate worker's elasticity of output with respect to the piece rate without further computations.Though very convenient, this specification imposes a constant elasticity. An alternative more flexible specification that relaxes the assumption of a constant elasticity is the Semi-Log specification where the dependent variable is the number of trees in levels instead of its logarithm transformation. The Semi-Log specification is thus given as :

$$y_{ijt} = \alpha_0 + \alpha_1 \log \tilde{r_j} + Control\ variables + u_i + \epsilon_{ijt} \tag{2}$$

We consider a Box-Cox regression test between the constant elasticity specification defined in equation (1) and the Semi-Log specification defined in equation (2) fits better our data (Details of the Box-Cox transformations is in the Appendix C). The Box-Cox transformations enable us to compare power specifications in general. In our case, they provide a basis for comparison between log and linear specifications corresponding respectively to the constant elasticity and Semi-Log specifications.

The results are given in Table 5. Using a convenient Box-Cox transformation, it emerges that the Semi-Log specification fits better our data because displaying the highest log likelihood (or the lowest Residual Sums of Squares (RSS)). A likelihood-ratio test shows that the two specifications are statistically different. Indeed, we have a P-Value of 0.000 under the null hypothesis that the two specifications are the same. These conclusions are robust across all models (Model 1, Model 2 and Model 3).

Table 5: Box-Cox regression test

	Model 1	Model 2	Model 3
Constant elasticity Specification (Dependent variable : $\log y_{ijt}$)			
Log likelihood	-3079.283	-3058.129	-3054.985
RSS	65466791	59136175	58248805
Observations	416	416	416
Semi-Log Specification (Dependent variable : y_{ijt})			
Log likelihood	-3023.424	-3001.274	-2998.849
RSS	50048301	44992732	44471072
Observations	416	416	416
Constant elasticity Specification vs Semi-Log Specification			
LR Statistics	111.719	113.71	112.272
P-Value	0.000	0.000	0.000
Observations	416	416	416

Estimations from the Semi-Log specification is given in Table 6. The coefficient on the logarithm of the piece rate shows here that the expected change in worker's productivity associated to a $p\%$ increase in the piece rate is give by $\hat{\alpha_1}.\log(1+\frac{p}{100})$ (where $\hat{\alpha_1}$ is an estimate of α_1). Thus, a 1% increase of the piece rate will induce approximately a daily productivity of 8 trees based on Model 2 and Model 3. The productivity gain will be of 5 trees for Model 1. Indeed, the inclusion of weather variables or day-specific effects amplifies the estimated coefficient α_1 (value of 465.75 in Model 1) by at least 1.5.

Under the Semi-Log specification, the elasticity of worker's productivity with respect to the piece rate (ξ), evaluated at a given level of productivity ($\bar{y}$) is given by

$$\xi = \frac{\alpha_1}{\bar{y}}$$

Interestingly with an average productivity of 2000 trees, the estimated elasticities under the Semi-Log specification for Model 2 and Model 3 are 0.40 and 0.37 respectively. They approach the value of 0.39 found in Paarsch and Shearer (2009). Note that in the Semi-Log specification, the elasticity depends on the level of productivity. Thus different levels of worker ability which translates into different levels of productivity influence the value of the elasticity. Using worker's average productivity as a proxy of his level of ability, worker-specific elasticities can be computed.

Estimates from Model 3 where we account for day-specific effects include day-specific effects to control for all day-specific observables and unobservables that affect productivity. However, they render the model less parsimonious and are difficult as they require forecasting the day-specific effects. Moreover, including day-specific dummy variables reduces our degrees of freedom and consequently may affect the precision of our estimates. It is noteworthy to point out that accounting for weather variables in Model 2 yield quite similar results to when we account for day-specific effects in Model 3. This shows that daily factors affecting worker's productivity are essentially weather variables and the set we consider as controls is sufficiently exhaustive. We can then have a more parsimonious model to make plausible predictions based on weather forecast - which are quite frequent and reliable.

Table 6: Semi-Log estimates of piece rate incentives on worker's productivity : Fixed Effects Estimation

	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	465.7517*	800.5619***	754.1824***
	(235.1590)	(215.0058)	(213.5987)
Base wage	0.1361	0.468	0.4106
	(0.3682)	(0.3343)	(0.3247)
No Rotation	21.3895	64.16	60.7715
	(56.6396)	(53.2349)	(53.3738)
Maximum temperature		-44.5082**	
		(18.3090)	
Minimum temperature		-20.652	
		(14.4873)	
Maximum 2-meter		-218.2523***	
air temperature$> 19^oC$		(51.3799)	
Precipitation		9.3868	
		(11.1088)	
Average relative humidity		-29.4259***	
		(9.2260)	
Average dew point		161.8821***	
		(36.4583)	
Minimum wind speed		-120.2509***	
		(38.5553)	
Constant	3819.1019***	6757.1352***	3849.3022***
	(394.1336)	(889.6448)	(367.2267)
Elasticity (at $y = 2000$)	0.2329**	0.4003***	0.3771***
	(0.1176)	(0.1075)	(0.1068)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Fixed vs Random effects Test		
Statistic	101.6713	159.6218	778.1257
P-Value	0.0000	0.0000	0.0000

5.3 Left and right marginal effects of piece rate

The piece rate effects estimates obtained in equations 1 and 2 are assessed using exogenous variation from both the piece rate cut and increase experiments. They can be viewed as a kind of a “combined estimate” that draws from a two-sided exogenous variation. A combined estimate has the advantage of being more exhaustive and exploits a wider range of variation to characterize piece rate effects. Indeed piece rate changes of different magnitudes are useful to further help to pin down the curvature of the piece rateoutput function.

Figure 2 presents combined, left and right marginal estimates of worker’s response to changes in Piece rates based on the estimation of the Semi-Log specification.

The combined estimate is obtained from the estimation of equation (2) using exogenous variation from both the piece rate reduction and increase experiments. The left marginal and right restrict estimation of equation (2) to the piece rate reduction and increase experimental data respectively. The complete regression results are in Table 7.[7] Though the three estimates overlap at some points when considering a 95 percent confidence, left marginal estimates are stronger in general, representing at least the double of right marginal estimates for all the three models : Model 1, Model 2 and Model 3. These discrepancies are not negligible highlighting that workers react differently to piece rate cuts and increases - workers appear more responsive to piece rate cut than to piece rate increase.

These discrepancies are also reflected in computed elasticities. For an average productivity of 2000 trees, the right margin elasticity is around 0.25 (for Model 2 and Model 3) below the value of 0.39 in Paarsch and Shearer (2009)[8]. The left margin elasticity is much larger. It amounts to 0.73 for both Model 2 and Model 3 reinforcing the idea that workers are more responsive to piece rate cut than to piece rate increase.

[7] In Model 2, some variables are dropped due to collinearity when we consider the Right margin estimation.

[8] The average productivity before the piece rate treatments in Paarsch and Shearer (2009) are much lower than in ours. It is about 773 trees compared to over 2000 in our study, which gives a ratio of at least 2.5. Workers response to Piece rates changes are likely to vary across planters, sites and/or time.

Figure 2: Left Margin Effect, Right Margin Effect and combined Effect at a 95 percent confidence interval: Fixed Effects Estimation of the Semi-Log Model

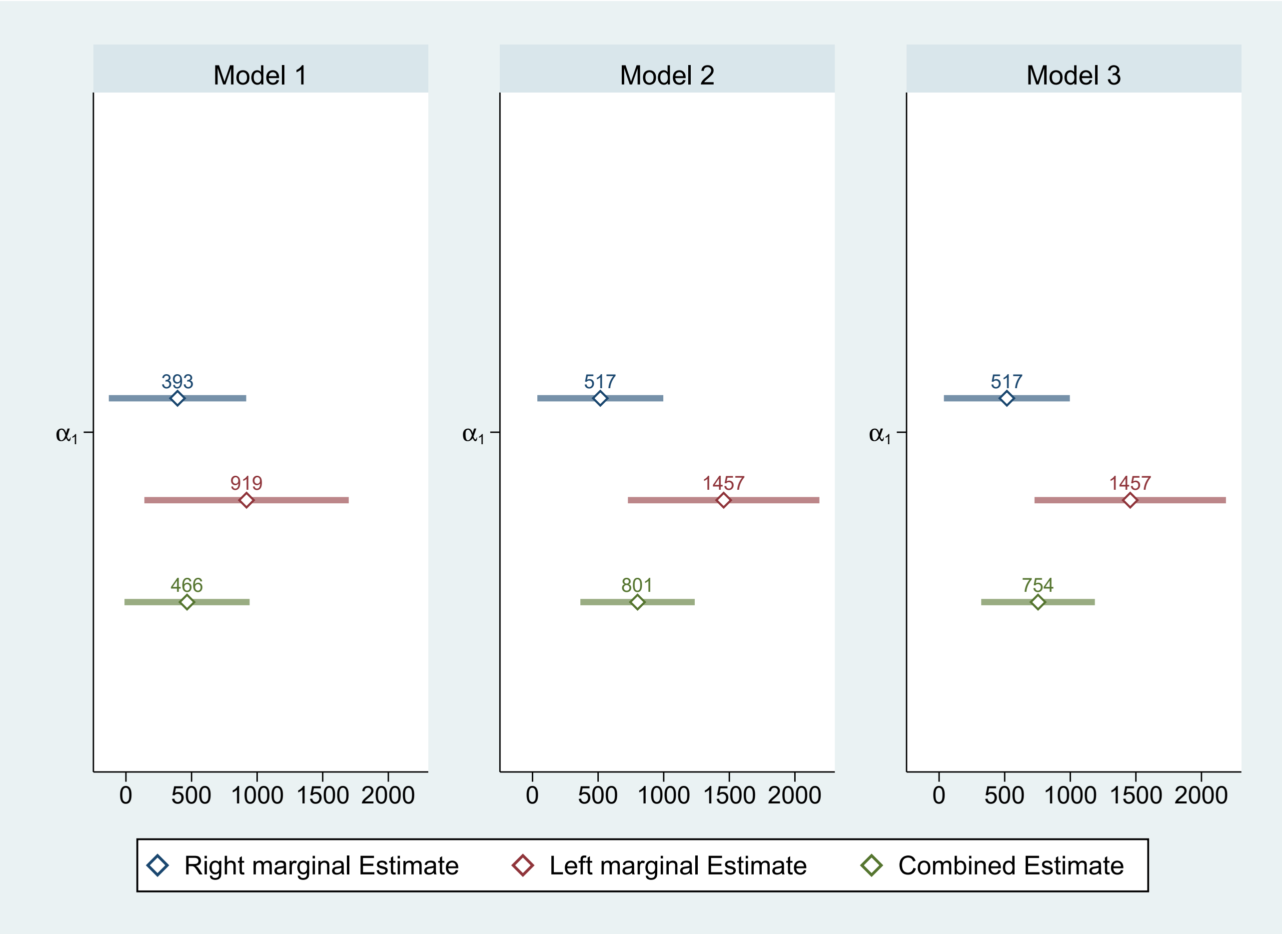


Table 7: Left and right margin Estimates of the Semi-Log Specification : Fixed Effects Estimation

	Right margin Estimates			Left margin Estimates		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	393.1021	516.7919**	516.7919**	919.2683**	1456.9530***	1456.9530***
	(258.2098)	(236.6510)	(236.6510)	(384.1320)	(359.8332)	(359.8332)
Base wage				0.6611	1.2555**	1.2555**
				(0.5515)	(0.4840)	(0.4840)
No Rotation	-4.7996	9.6227	9.6227	28.3311	100.7843	100.7843
	(85.9086)	(91.4931)	(91.4931)	(72.2240)	(67.8181)	(67.8181)
Maximum temperature		-29.5474***			-98.9956*	
		(7.5118)			(51.8300)	
Minimum temperature		14.8391			-98.9032**	
		(14.2360)			(44.4891)	
Maximum 2-meter air temperature$> 19^oC$					-306.5254***	
					(91.4176)	
Precipitation		-63.9137			93.1192*	
		(86.9694)			(47.2356)	
Average relative humidity					-81.0630**	
					(32.0698)	
Average dew point					308.3368***	
					(97.5725)	
Minimum wind speed					-117.7201**	
					(50.2056)	
Constant	3679.3719***	4215.5137***	3934.7602***	4628.2707***	11598.6082***	5023.3947***
	(407.8851)	(403.8050)	(373.8830)	(648.2675)	(2735.5739)	(593.0152)
Elasticity (at $y = 2000$)	0.1966	0.2584**	0.2584**	0.4596**	0.7285***	0.7285***
	(0.1291)	(0.1183)	(0.1183)	(0.1921)	(0.1799)	(0.1799)
Block-specific effect	yes	yes	yes	yes	yes	yes
Day-specific effect	no	no	yes	no	no	yes
Observations	139	139	139	274	274	274

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Fixed vs Random effects Test					
Statistic	29.95598	28.007	28.00702	131.3267	1045.734	1045.703
P-Value	0.00004	0.00095	0.00095	0	0	0

5.4 Symmetry test of piece rate incentive effects

This section develops a formal statistical test to assess if the worker's reaction to piece rate cut and increase are asymmetric. For this purpose, we specify the following regression model to compare beforehand piece rate cut effects and piece rate increase effects.

$$y_{ijt} = \beta_0 + \beta_1 Treatment1_{it} + \beta_2 Treatment2_{it} + \beta_3 Treatment3_{it} + Control\ variables + u_i + \epsilon_{ijt} \quad (3)$$

where

- $Treatment1_{it}$ is a dummy variable equal to 1 if the worker received a piece rate reduction of 6 cents on day t and 0 otherwise;
- $Treatment2_{it}$ is a dummy variable equal to 1 if the worker received a piece rate reduction of 4 cents on day t and 0 otherwise;
- $Treatment3_{it}$ is a dummy variable equal to 1 if the worker received a piece rate increase of 4 cents on day t and 0 otherwise;

The results of estimations from equation (3) are given in Table 8. We proceed with Fixed effects estimations as in previous sections (Random effects estimations provided in Appendix B). Figure 3 shows the estimated piece rate cut and increase effects. It appears that workers react more strongly to piece rate cut than to piece rate increase for all models (Model 1, Model 2 and Model 3). For example, Model 3 predicts a productivity gain of 111 trees following a piece rate increase of 4 cents compared to a productivity loss of 450 trees following a piece rate decrease of the same amount (4 cents). Model 1 and Model 2 yield similar results - productivity gain of 79 trees vs productivity loss of 460 trees and productivity gain of 133 trees vs productivity loss of 487 trees respectively. Figure 3 also shows that for all models, the productivity loss confidence intervals are larger than those of the productivity gains.

Table 8: Average effect of a piece rate change: Fixed Effects Estimation

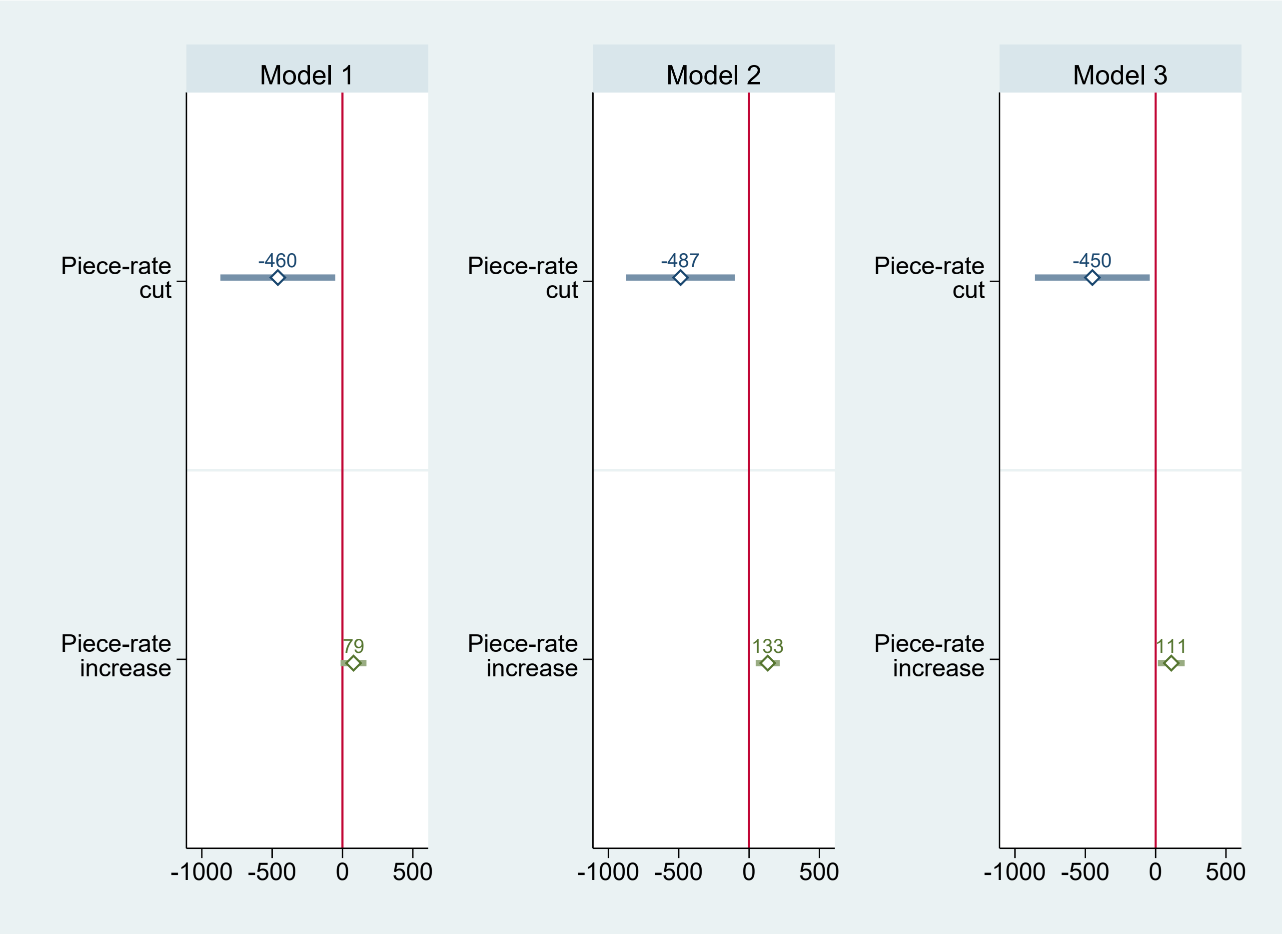
	Model 1	Model 2	Model 3
piece rate reduction	-458.9965**	-588.1279***	-598.9550***
of 6 cents	(202.3721)	(172.5322)	(167.7384)
piece rate reduction	-459.5370**	-486.9629**	-449.7383**
of 4 cents	(201.2024)	(190.9549)	(201.1220)
piece rate increase	78.5375*	132.5191***	111.2582**
of 4 cents	(45.3559)	(42.1979)	(47.0005)
Base wage	1.5550*	1.8381**	1.7856**
	(0.8956)	(0.8095)	(0.8143)
No Rotation	28.9075	69.5406	66.0382
	(55.6143)	(52.3975)	(53.2273)
Maximum temperature		-51.6335***	
		(17.6346)	
Minimum temperature		-16.8667	
		(14.2189)	
Maximum 2-meter		-198.6326***	
air temperature$> 19^oC$		(54.8316)	
Precipitation		7.461	
		(11.0599)	
Average relative humidity		-31.6215***	
		(8.6560)	
Average dew point		168.3596***	
		(34.4406)	
Minimum wind speed		-128.9449***	
		(40.0039)	
Constant	3040.5096***	5650.1381***	2583.9047***
	(60.1938)	(761.5499)	(94.2622)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Fixed vs Random effects Test		
Statistic	249.1629	543.62	630.2763
P-Value	0	0	0

Figure 3: Fixed Effects Estimation of piece rate cut and increase effects of 4 cents at 95 percent confidence interval



In Table 9, we provide a formal test to assess if worker's response to piece-cut ($Treatment2$) is asymmetric to reactions to a piece rate increase of the same amount ($Treatment3$). For this purpose we evaluate if the coefficient β_2 on $Treatment2_{it}$ is statistically the opposite of the coefficient β_3 on $Treatment3_{it}$. This is equivalent to testing if the value $\beta_2 + \beta_3$ is statistically significant. Table 9 shows that $\beta_2 + \beta_3$ is statistically significant at 5% for Model 1 and 10% for Model 2 and Model 3. These results suggest that that workers reactions to piece rate cut and increase are effectively asymmetric.

Table 9: Symmetry test of piece rate incentive effects: Fixed Effects Estimation

	Model 1	Model 2	Model 3
$\beta_2 + \beta_3$	-380.9995**	-354.4438*	-338.4801*
	(182.1785)	(182.6151)	(185.6494)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

5.5 Test for selection bias in the piece rate reduction experiment

Our estimation strategies relied mainly on exogenous experimental variations to produce unbiased estimates.[9] In the piece rate increase experiment, workers are randomly assigned to treatments. In the piece rate reduction experiment, however, workers may exert some indirect control regarding assignment to the different treatments through their reservation base wage (see discussion of the experimental design in section 3.1). This may give rise to selection bias as the treated group may not be completely random - being composed of a specific sub-group of workers (tired workers for instance). Fixed effects estimations served as a strategy to account for individual time-invariant characteristics that may affect both productivity and assignment to treatment through worker's reservation base wage.[10]

Selection and endogeneity issues may, however, persist if they are some time-varying unobservables that affect both productivity and assignment to treatment through worker's reservation base wage - fatigue from a poor night sleep is one example. To address these issues, we need to test formally for the presence or not of section bias to validate our results.

Our experimental design offers the framework to perform such test. Recall in the piece rate reduction experiment, our control group is formed of two subgroups: a non-exposed group which was randomly determined and a exposed group which was offered the piece rate reduction experiment but ended up not receiving the piece rate reduction because they drew a base wage below their reservation value. For the non-exposed control subgroup, random assignment eliminates selection bias. Moreover, each worker has been randomly assigned to this subgroup at least once during the whole experiment. If there is a selection bias, then it must be in the exposed control group. We therefore test for the presence of selection bias by comparing productivity of workers between the exposed and non-exposed control group. We specify for this purpose the following regression model restricted to the control group sample :

$$y_{ijt} = \lambda_0 + \lambda_1 CD_{it} + Control\ variables + u_i + \epsilon_{ijt} \tag{4}$$

where CD_{it} denotes a dummy variable equal to 1 if the worker belongs to the exposed control subgroup on day t and 0 if he belongs to the non-exposed control subgroup. If the coefficient of the dummy control non-exposed group variable, λ_1 is significant, this will suggest selection bias (and endogeneity), otherwise there is no statistical evidence for selection bias (and endogeneity).

The results of our estimations are presented in Table 10. The coefficient on the dummy control non-exposed group variable is not statistically significant for all the different models. There is no statistical evidence of selection bias in our piece rate reduction experiment.

[9] Regular Piece rates are endogenous. They are determined by the firm in function of planting conditions. Using experimental data avoids endogeneity problem by providing exogenous variation in the piece rate for a given set of planting conditions.

[10] Note that almost all workers (36 out of 37) are observed both under the regular piece rate and the reduced piece rate thanks to Treatment 3 and Treatment 4, described in section 3.1.

Table 10: Test for selection bias in the piece rate reduction experiment : Fixed Effects Estimation

	Model 1	Model 2	Model 3
Dummy control	-36.7136	-25.125	-25.125
non-exposed group	(69.5537)	(68.3781)	(68.3781)
No Rotation	-34.5216	19.159	19.159
	(67.3317)	(90.7280)	(90.7280)
Maximum temperature		-17.1507	
		(68.2317)	
Minimum temperature		-45.9137	
		(63.5837)	
Maximum 2-meter		-102.064	
air temperature $> 19^oC$		(109.8353)	
Precipitation		52.7825	
		(60.6875)	
Average relative humidity		-22.5636	
		(41.7761)	
Average dew point		87.2654	
		(125.0003)	
Minimum wind speed		-85.9758	
		(60.1032)	
Constant	3182.7007***	4796.633	2899.2918***
	(116.0643)	(3443.5031)	(192.4777)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	178	178	178

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Fixed vs Random effects Test		
Statistic	9.93904	44.56717	44.56717
P-Value	0.44586	0.00028	0.00028

6 Discussion and conclusions

This study has implemented two basic experiments to introduce exogenous variation on the worker's piece rate in a tree-planting firm in British Columbia. The first one is a reduction of the piece rate coupled with a base wage. The second one is an increase in the workers piece rate. This setting enables us to characterize completely piece rate effects on productivity accounting for both left and right marginal effects. Previous studies focused predominantly on the right marginal effects. Besides measuring separately piece rate cut and increase effects on productivity, the study contributes to the literature by providing a formal test which shows that workers reactions to piece rate cuts and increases are asymmetric. piece rate cuts generate stronger worker responses than equivalent piece rate increases.

Work morale (Kube et al., 2013), fairness (Fehr et al., 2009; Chen and Horton, 2016), social comparison (Larkin et al., 2012; Cohn et al., 2014; Obloj and Zenger, 2017) and/or the convexity of the marginal cost of effort function (Bellemare et al., 2016) may explain why pay cuts generate stronger worker responses than equivalent piece rate increases. Identifying the relative importance of these different explanations is an important area for future research. A structural model where complete workers preferences are specified will clarify these mechanisms. Analyzing these mechanisms is important for scientific understanding and personnel policies. We leave this for future research.

Our experiment is a one-shot experiment in a short-term setting. It thus abstracts from repeated games effects and focus on the direct effect of monetary incentives. A longer-term field study such as that of Mas (2006) where repeated games and piece rate changes can be analyzed simultaneously represent another interesting direction for future research. A longer setting would allow to introduce more diverse treatments over an extended period. In a longer term setting, we can also address questions on how persistent is the impact of piece rate changes as in Stafford (2015), Lee and Rupp (2007), Krueger and Friebel (2022) and Coviello et al. (2022). Addressing these questions will increase our understanding to tailor adequately personnel policies.

Appendices

A Contract Choice Experimental design

Piece-rate reduction Experiment instructions

You have before you a decision sheet. Your decision sheet shows 15 decisions listed on the left. For each decision, we would like you to choose between "Option A" and "Option B.", marking your choice with an X in the appropriate column. For each of the 15 decisions, you must choose Option A or Option B, but not both. While you will make 15 choices, only one of these choices will be used to determine your contract and earnings. Before you start making your 15 choices, please let me explain how these choices will affect your contract and earnings.

Here are 15 chips that will be used to determine earnings. These poker chips are numbered from 1 to 15. After you have made all of your choices, you will pick one of the 15 chips out of a bag. The chip you draw will select which of the 15 Decisions will be used to calculate your contract. For example, if you draw the chip with the number 3, then your choice for Decision 3 will determine your contract. If you draw the chip with the number 8, then your choice for Decision 8 will determine your contract. Again, even though you will make 15 Decisions, only one of these will end up determining your contract. However, each Decision has an equal chance of being selected.

Now, please look at Decision 1 at the top of the decision sheet. Option A pays your regular piece-rate contract of 16 cents per tree. Option B denotes a base wage contract paying 20 dollars per day plus 12 cent per tree contract. This means that if the chip that you draw is numbered 1 and you chose option A for decision 1, then you will be paid 16 cents for each tree that you plant over the next 2 days. However, if the chip that you draw is numbered 1 and you chose option B for that decision, then you will be paid 20 dollars plus 12 cents for each tree that you plant over the next 2 days. The other Decisions are similar, the piece-rate contract is always the same but as you move down the table, the Option B contract pays a higher base wage with the same piece-rate of 12 cents per tree. For example, if the first chip you draw selects Decision 5 and you selected Option A for that Decision, then you will be paid 16 cents for each tree planted. However, if the first chip you draw selects Decision 5 and you selected Option B for that Decision, then you will be paid 100 dollars plus 12 cents for each tree. For Decision 14, in the bottom row, your choice is between a piece-rate contract paying 16 cents per tree and a base wage of 280 dollars per day plus 12 cents per tree.

To summarize, you will make 14 choices: for each row in the table you will have to choose between Option A and Option B. You may choose Option A for some decision rows and Option B for other rows. When you are finished, you will come one by one to our table and draw a chip out of a hat to select which of your 14 Decisions will be used. So, for example, if the chip you draw selects Decision 2, then you will be paid 16 cents for each tree that you plant if you chose Option A for Decision 2, or $40 per day plus 12 cents per tree planted if you chose Option B. However, if the chip you draw selects Decision 8, then you will be paid 16 cents per tree planted if you chose Option A for Decision 8, or $160 per day plus 12 cents per tree planted if you chose Option B for Decision 8.

DATE : ____________________

NAME: ______________________________ Regular rate: __________

	Option A		My Choice is A	Option B		My Choice is B
	Base Wage	Piece Rate		Base Wage	Piece Rate	
Decision 1	0	Regular rate		$20	Regular rate - $.04	
Decision 2	0	Regular rate		$40	Regular rate - $.04	
Decision 3	0	Regular rate		$60	Regular rate - $.04	
Decision 4	0	Regular rate		$80	Regular rate - $.04	
Decision 5	0	Regular rate		$100	Regular rate - $.04	
Decision 6	0	Regular rate		$120	Regular rate - $.04	
Decision 7	0	Regular rate		$140	Regular rate - $.04	
Decision 8	0	Regular rate		$160	Regular rate - $.04	
Decision 9	0	Regular rate		$180	Regular rate - $.04	
Decision 10	0	Regular rate		$200	Regular rate - $.04	
Decision 11	0	Regular rate		$220	Regular rate - $.04	
Decision 12	0	Regular rate		$240	Regular rate - $.04	
Decision 13	0	Regular rate		$260	Regular rate - $.04	
Decision 14	0	Regular rate		$280	Regular rate - $.04	

The minimum base wage that I am willing to accept in order to take a 4 cents reduction in my piece rate is ___________.

DATE : ____________________

NAME: ______________________________ Regular rate: ___________

	Option A		My Choice is A	Option B		My Choice is B
	Base Wage	Piece Rate		Base Wage	Piece Rate	
Decision 1	0	Regular rate		$20	Regular rate - $.06	
Decision 2	0	Regular rate		$40	Regular rate - $.06	
Decision 3	0	Regular rate		$60	Regular rate - $.06	
Decision 4	0	Regular rate		$80	Regular rate - $.06	
Decision 5	0	Regular rate		$100	Regular rate - $.06	
Decision 6	0	Regular rate		$120	Regular rate - $.06	
Decision 7	0	Regular rate		$140	Regular rate - $.06	
Decision 8	0	Regular rate		$160	Regular rate - $.06	
Decision 9	0	Regular rate		$180	Regular rate - $.06	
Decision 10	0	Regular rate		$200	Regular rate - $.06	
Decision 11	0	Regular rate		$220	Regular rate - $.06	
Decision 12	0	Regular rate		$240	Regular rate - $.06	
Decision 13	0	Regular rate		$260	Regular rate - $.06	
Decision 14	0	Regular rate		$280	Regular rate - $.06	
Decision 15	0	Regular rate		$300	Regular rate - $.06	
Decision 16	0	Regular rate		$320	Regular rate - $.06	
Decision 17	0	Regular rate		$340	Regular rate - $.06	

The minimum base wage that I am willing to accept in order to take a 6 cents reduction in my piece rate is ___________.

B More Regressions results

Table 11: Random Effects Estimation of Piece-rate incentives and elasticity of output

	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	0.14985	0.26858***	0.21957**
	(0.09353)	(0.08920)	(0.08932)
Base wage	-0.00003	0.00009	0.00003
	(0.00015)	(0.00014)	(0.00014)
No Rotation	0.01322	0.03161	0.02821
	(0.02318)	(0.02161)	(0.02075)
Maximum temperature		-0.02579***	
		(0.00764)	
Minimum temperature		-0.00889	
		(0.00768)	
Maximum 2-meter air temperature ¿19C		-0.09521***	
		(0.02152)	
Precipitation		0.00434	
		(0.00457)	
Average relative humidity		-0.01566***	
		(0.00361)	
Average dew point		0.08019***	
		(0.01446)	
Minimum wind speed		-0.06293***	
		(0.01841)	
Constant	8.22198***	9.72427***	8.11850***
	(0.15538)	(0.34576)	(0.16573)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Semi-Log estimates of piece-rate incentives on worker's productivity : Random Effects Estimation

	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	479.3111**	814.1740***	766.0617***
	(236.0511)	(215.7483)	(214.2762)
Base wage	0.153	0.4841	0.4248
	(0.3665)	(0.3344)	(0.3241)
No Rotation	19.5165	62.7685	58.8605
	(55.4753)	(52.1087)	(52.2736)
Maximum temperature		-46.0031**	
		(18.2790)	
Minimum temperature		-20.1948	
		(14.4950)	
Maximum 2-meter air temperature ¿19C		-219.7303***	
		(51.5702)	
Precipitation		9.5331	
		(11.0426)	
Average relative humidity		-30.0930***	
		(9.2138)	
Average dew point		164.0701***	
		(36.5536)	
Minimum wind speed		-121.5984***	
		(38.3357)	
Constant	3825.4576***	6823.0194***	3852.2282***
	(409.9295)	(926.6346)	(393.5640)
Elasticity (at $y = 2000$)	0.2397**	0.4071***	0.3830***
	(0.1180)	(0.1079)	(0.1071)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4: Left Margin Effect, Right Margin Effect and combined Effect : Random Effects Estimation of the Semi-Log Model

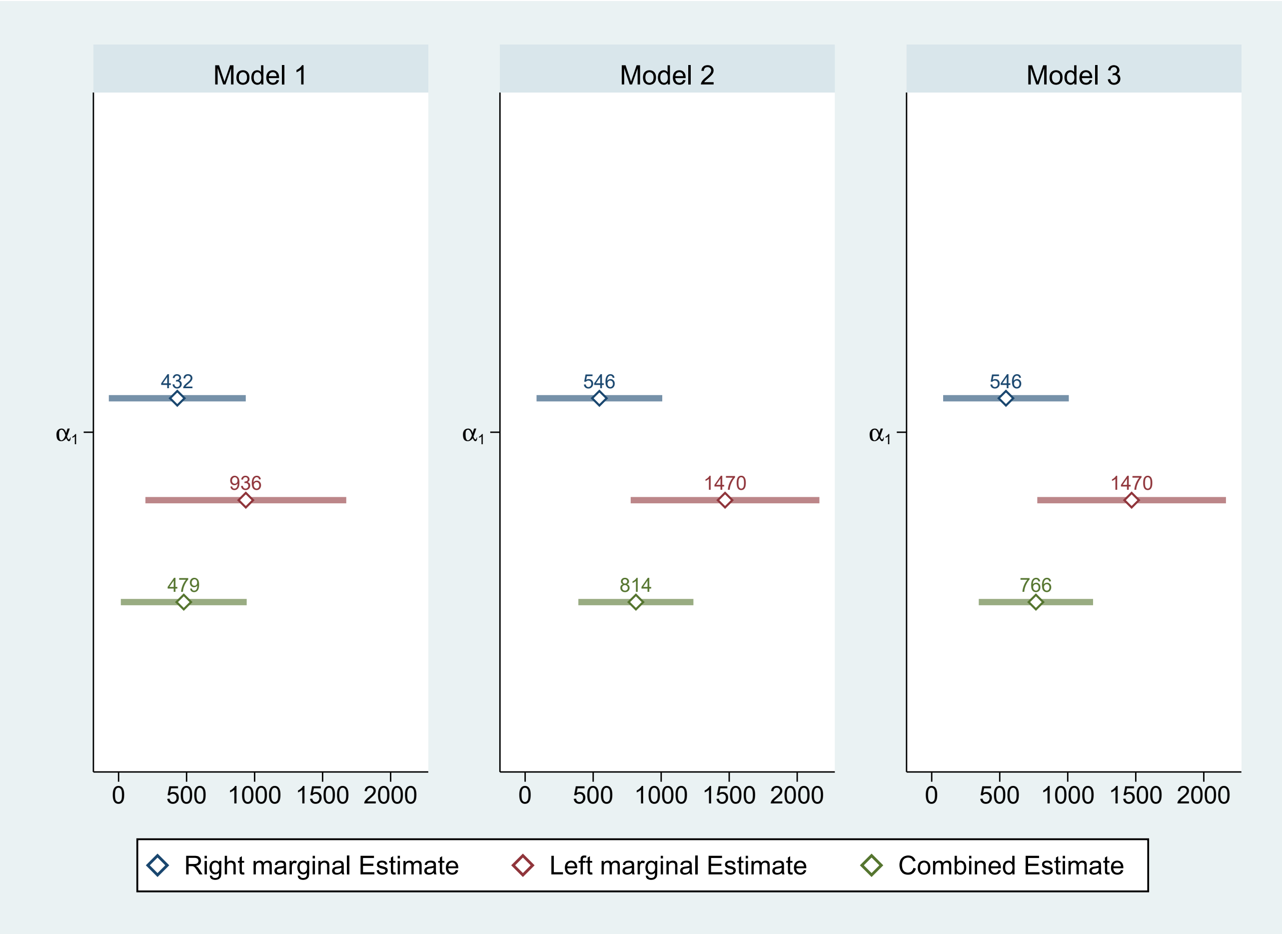


Table 13: Left and right margin Estimates of the Semi-Log Specification : Random Effects Estimation

	Right margin Estimates			Left margin Estimates		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$\log \tilde{r_j}$	431.7001*	545.9101**	545.9101**	935.5450**	1469.5544***	1469.5544***
	(256.7972)	(235.7050)	(235.7050)	(376.6168)	(353.8597)	(353.8597)
Base wage				0.6816	1.2708***	1.2708***
				(0.5416)	(0.4768)	(0.4768)
No Rotation	-5.5406	6.5842	6.5842	26.6235	98.757	98.757
	(83.6690)	(87.3314)	(87.3314)	(70.4449)	(65.3366)	(65.3366)
Maximum temperature		-29.1949***			-106.4023**	
		(7.6987)			(52.2109)	
Minimum temperature		15.194			-100.6473**	
		(14.2651)			(44.8349)	
Maximum 2-meter					-312.2870***	
air temperature ¿19C					(90.5211)	
Precipitation		-63.4718			96.7032**	
		(86.4304)			(46.8225)	
Average relative humidity					-85.4076***	
					(32.0895)	
Average dew point					322.0989***	
					(97.9158)	
Minimum wind speed					-124.7743**	
					(49.4211)	
Constant	3723.1437***	4239.6794***	3964.6674***	4623.5756***	11946.3945***	5000.6119***
	(446.7210)	(443.4446)	(410.7718)	(643.5826)	(2761.7110)	(591.2516)
Elasticity (at $y = 2000$)	0.2159*	0.2730**	0.2730**	0.4678**	0.7348***	0.7348***
	(0.1284)	(0.1179)	(0.1179)	(0.1883)	(0.1769)	(0.1769)
Block-specific effect	yes	yes	yes	yes	yes	yes
Day-specific effect	no	no	yes	no	no	yes
Observations	139	139	139	274	274	274

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Average effect of a piece-rate change : Random Effects Estimation

	Model 1	Model 2	Model 3
Piece-rate reduction	-474.1980**	-600.1009***	-610.4023***
of 6 cents	(201.8888)	(172.3407)	(167.0823)
Piece-rate reduction	-471.2638**	-497.3792***	-460.3442**
of 4 cents	(202.5312)	(192.2448)	(202.3782)
Piece-rate increase	80.2629*	134.5655***	113.0464**
of 4 cents	(45.4153)	(42.1245)	(46.9940)
Base wage	1.6133*	1.8861**	1.8331**
	(0.8969)	(0.8122)	(0.8156)
No Rotation	27.1666	68.226	64.0107
	(54.4739)	(51.2960)	(52.0899)
Maximum temperature		-53.3343***	
		(17.6911)	
Minimum temperature		-16.3259	
		(14.2066)	
Maximum 2-meter		-199.6436***	
air temperature ¿19C		(55.0728)	
Precipitation		7.5631	
		(11.0256)	
Average relative humidity		-32.3556***	
		(8.6742)	
Average dew point		170.7518***	
		(34.7034)	
Minimum wind speed		-130.4753***	
		(39.8105)	
Constant	3024.6308***	5700.1366***	2566.9310***
	(135.7291)	(809.1079)	(146.7770)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5: Random Effects Estimation of Piece-rate cut and increase effects of 4 cents

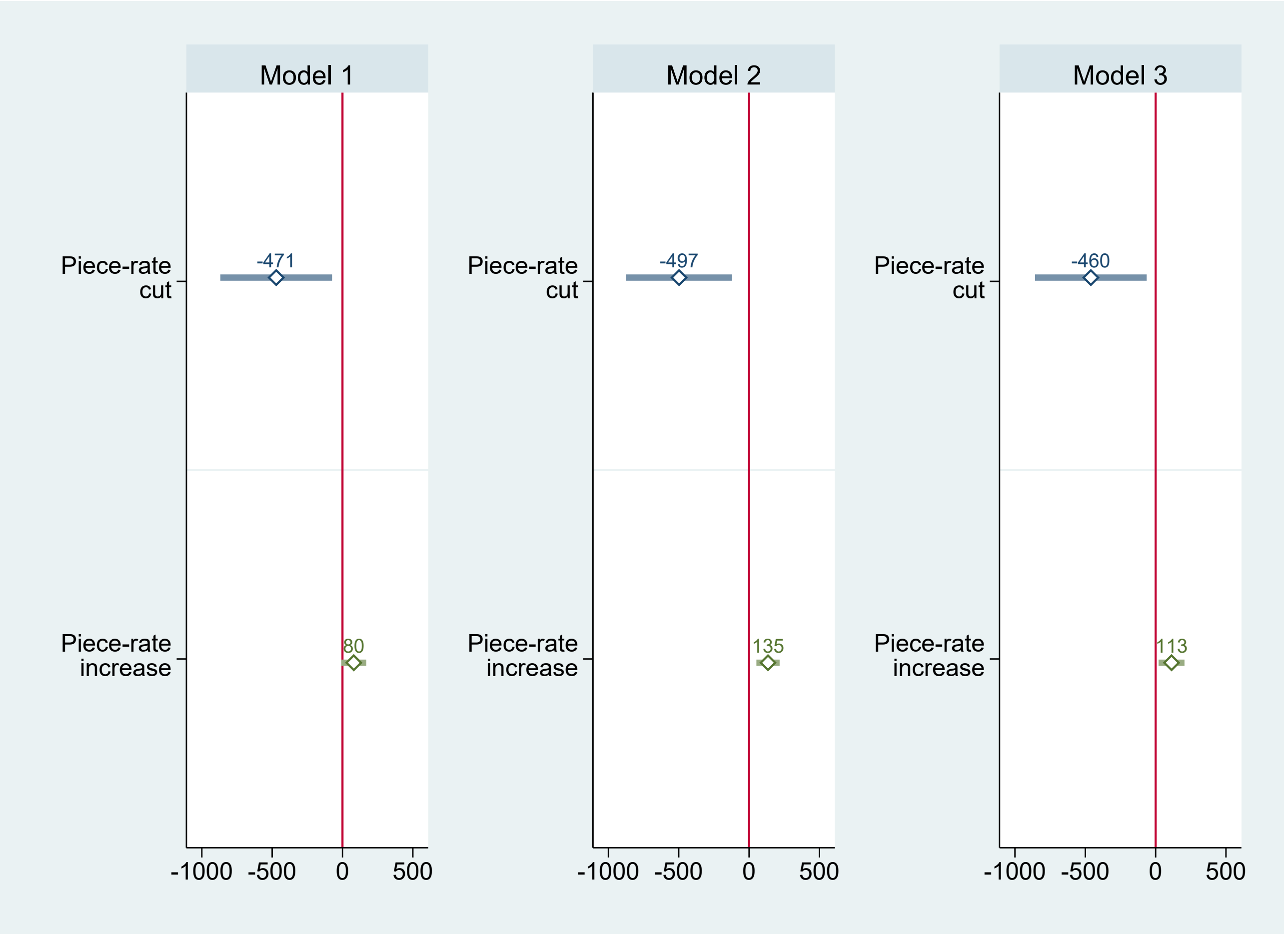


Table 15: Test of symmetry of effects between $Treatment2$ and $Treatment3$: Random Effects Estimation

	Model 1	Model 3	Model 4
$\beta_2 + \beta_3$	-391.0009**	-362.8137**	-347.2977*
	(183.2838)	(183.6133)	(186.6094)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	416	416	416

Table 16: Test for selection bias in the piece-rate reduction experiment : Random Effects Estimation

	Model 1	Model 2	Model 3
Dummy control	-41.1629	-28.1992	-28.1992
non-exposed group	(70.1141)	(70.6725)	(70.6725)
No Rotation	-37.8859	19.1715	19.1715
	(61.7344)	(82.1431)	(82.1431)
Maximum temperature		-24.8611	
		(68.0915)	
Minimum temperature		-44.3998	
		(64.0839)	
Maximum 2-meter		-75.7127	
air temperature ¿19C		(117.3169)	
Precipitation		56.3184	
		(60.8676)	
Average relative humidity		-24.6134	
		(41.7599)	
Average dew point		91.3371	
		(123.6849)	
Minimum wind speed		-102.8472*	
		(58.0775)	
Constant	3158.4484***	5030.607	2851.3411***
	(172.7331)	(3432.8791)	(233.5384)
Block-specific effect	yes	yes	yes
Day-specific effect	no	no	yes
Observations	178	178	178

Panel-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Box-Cox Regressions

Box and Cox (1964) proposed normalizing transformations for univariate y and univariate response regression using a likelihood approach. The Box-Cox transformation is given by

$$y^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda} & \lambda \neq 0 \\ \log y & \lambda = 0 \end{cases} \tag{5}$$

This transformation embeds several popular functions (level when $\lambda = 1$, logarithm when $\lambda = 0$ and power functions in general) and serve as a basis for testing functional forms.

Consider a statistical model on the transformed variable $y^{(\lambda)}$ in function of independent variables $x_1, x_2, ..., x_k$ and coefficients $\theta_1, \theta_2, ..., \theta_k$ given by

$$y_i^{(\lambda)} = \theta_0 + \theta_1 x_{1i} + \theta_2 x_{2i} + ... + \theta_k x_{ki} + \epsilon_i$$

Where $\epsilon \sim N(0, \sigma^2)$ and index i is for the observation. The unconcentrated log likelihood for the above model is given by

$$\log L(\theta, \sigma^2, \lambda) = -\frac{N}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}RSS(y_i^{(\lambda)}) + (\lambda - 1)\sum_{i=1}^{N}\log y_i$$

Where θ is the vector of $(\theta_1, \theta_2, ..., \theta_k)$ and $RSS(y_i^{(\lambda)})$ is the residual sum of squares of the Box-Cox transformed variable $y_i^{(\lambda)}$. Substituting maximum likelihood estimates of θ and σ^2, we obtain the concentrated log-likelihood given by

$$\log L_c(\lambda) = -\frac{N}{2}\left[\log(\frac{2\pi}{N}) + 1 + \log RSS(y_i^{(\lambda)})\right] + (\lambda - 1)\sum_{i=1}^{N}\log y_i$$

Using the concentrated log-likelihood, models with different values of λ can now be compared. Moreover a test statistic can also be calculated for these values. Let λ_0 and λ_1 represent the values of λ for the models we want to compare. Assume λ_1 yields the highest concentrated log-likelihood and λ_1 the lowest concentrated log-likelihood, we can test the hypothesis $H_0 : \lambda_1 = \lambda_0$ by calculating the likelihood ration criterion :

$$\chi^2 = 2(L_c(\lambda_1) - L_c(\lambda_0)) \tag{6}$$

This statistic has approximatively in large samples a chi-squared distribution with one degree of freedom.

Box and Cox (1964) also proposes an alternative transformation of equation 5 which allows to compare models with different values of λ directly in terms of RSS. This alternative transformation is given by

$$z^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda \bar{y}^{\lambda-1}} & \lambda \neq 0 \\ \bar{y}\log y & \lambda = 0 \end{cases}$$

Where $\bar{y}$ is the geometric average of the original variable y. The concentrated log likelihood then simplified to

$$\log L_c(\lambda) = -\frac{N}{2}\left[\log(\frac{2\pi}{N}) + 1 + \log RSS(z_i^{(\lambda)})\right]$$

Where $RSS(z_i^{(\lambda)})$ is the residual sum of squares of the transformed variable $z_i^{(\lambda)}$. Models with different values of λ can then be compared directly in terms of RSS. The one exhibiting the highest log likelihood (or the lowest RSS) fits the data better. Using log likelihood values, we can also perform likelihood ratio test on different values of λ as specified in equation 6.

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