The Minimum Wage and Productivity: A Case Study of California Strawberry Pickers

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Abstract

This paper studies how minimum wages and piece rate wages interact to affect worker productivity. In the United States, minimum wage laws set a lower bound on earnings of piece rate workers. In low-wage industries, piece rates and productivity levels often result in minimum wages acting as a binding earnings floor. Here, I develop a simple theoretical framework to demonstrate how an increase in this binding wage floor can cause workers to reduce effort and thus decrease productivity. I then give empirical evidence of this prediction using the payroll records of strawberry harvesters on one large farm in Northern California. Using a fixed effects model, I estimate the productivity change of the average worker in response to increases in an employer-set minimum wage. Results support the theoretical predictions and indicate that a three percent increase in the minimum wage causes the average worker to decrease productivity by seven percent.

For the most recent draft please visit:

`https://alexandraehill.github.io/research/jmp.pdf`

1 Introduction

Compensation policy has been the focus of considerable theoretical and empirical research. Piece rate contracts, where compensation is a direct function of worker output, are common in industries where supervision is costly relative to measuring output. Productivity gains from piece rate contracts relative to hourly pay have been well documented. Less studied is a wage contract where workers are paid a piece rate, but face a binding wage floor, i.e. face a minimum wage. The effects of this payment scheme are not merely of interest to academics. Piece rate contracts with a binding minimum wage are the norm in U.S. agriculture and are common in many other low-wage industries. For example, mechanics, carpenters, and construction workers are commonly paid piece rate and are subject to state minimum wages. Rising state minimum wages will increase the binding wage floor for many of these workers.

This paper studies how increases in a minimum wage impact the productivity of workers who are paid by the piece. I develop a theoretical model to show that an increase in the minimum wage can cause workers to slow down by creating the opportunity for workers to shirk. That is, the minimum wage allows workers to reduce effort a lot in exchange for a little or no decrease in pay. I take the model to data using payroll records of strawberry harvesters on one large farm in Northern California. These data present an ideal setting for this analysis. Unlike workers in many other piece rate pay jobs, the productivity of these workers is easily observed, is not conflated with demand, and is not mediated by technology. Further, these unique panel data span multiple increases in an employer-set minimum wage. I estimate within-worker productivity responses to these increases and find that a three percent increase in the minimum wage causes a seven percent decrease in productivity for the average worker.

The results of this paper are novel, but not surprising in the context of incentive pay. This paper contributes to existing theoretical literature that compares optimal effort under hourly and productivity-based wage schemes. Generally, these papers use principal-agent models and assume that workers experience disutility from exerting effort and that effort cannot be perfectly monitored (see Laffont and Martimort (2002) for a summary). Under these assumptions, the prediction is simple — workers exert more effort when wages are linked to productivity (e.g. Grossman & Hart, 1983; Hart & Holmström, 1987; and Stiglitz, 1975).

A recent empirical literature tests this theoretical prediction. These studies examine the productivity of individual workers after a switch from hourly to piece rate pay. The findings provide clear support that workers are more productive when paid by the piece. Estimates of productivity gains range from 8 to 60 percent (Bandiera et al., 2005; Banker et al., 2000; Fernie & Metcalf, 1999; Frick et al., 2013; Jones et al., 2010; Lazear, 2000; and Paarsch & Shearer, 2000). In most of these empirical studies, the piece rate pay scheme is coupled with a minimum wage. However, these studies do not examine the effects of the wage floor on worker productivities.

Incentive pay is common in U.S. agriculture, but evidence on the productivity effects for U.S. agricultural workers is limited. There is empirical evidence from agricultural workers in other countries (Bandiera et al., 2005; and Paarsch and Shearer, 2000). This literature finds that workers are more productive when paid by the piece than when paid by the hour. Evidence from agricultural field experiments complement these results (Shearer, 2004 and Shi, 2010). Examples in U.S. agriculture include Billikopf and Norton (1992) and Graff Ziven and Neidell (2012). Billikopf and Norton present observational evidence that piece rate paid vineyard pruners work 37 percent faster than those paid by the hour. Graff Ziven and Neidell estimate the effects of pollution on the productivity of workers who are paid piece rate with an hourly floor. They include a simple test for shirking behavior because it threatens identification of pollution effects. They find suggestive evidence that workers do not shirk in their setting and attribute this to the stringent firing constraint set by the employer — i.e. the employer fires workers for receiving the minimum wage.

This paper makes three contributions to existing empirical work. This paper provides the first estimates of the incentive effects of this compensation policy. This policy — piece rate wages with an hourly minimum wage — is common in many industries, and is standard in U.S. agriculture. Previous work has examined effects of the piece rate, but I am the first to identify productivity responses to a change in the wage floor. The data for the empirical application span two mid-season increases in the wage floor and several increases in the piece rate. This allows for causal attribution of the incentive effects of both components of this payment scheme. I find that workers slow down when the minimum wage rises and speed up when the piece rate rises. This is consistent with prior work that shows workers productivity to be lower on hourly payment schemes than piece rate.

Second, I focus on individual-level behavioral responses to a minimum wage change. Most literature on minimum wages focuses on macroeconomic outcomes, e.g. unemployment, wages, and prices. I consider the effects of minimum wages on worker decisions at their current job. I present the first empirical evidence that, under some contracts, minimum wages can cause workers to shirk, accepting a lower income in exchange for exerting less effort. These behavioral changes are overlooked in existing literature, but could affect macroeconomic outcomes in industries where this wage contract is common.

Third, this paper has important policy implications for employers who pay workers by the piece. Rising minimum wages impose obvious direct costs on Employers. But, employers are likely unaware of the indirect costs from changes in productivity. The results from my empirical example are most directly relevant for California fruit and nut farmers. California is the largest agricultural economy in the U.S., and state minimum wages are rising. Almost half of fruit and nut harvesters in the state are paid by the piece and have average hourly earnings just above the legal minimum (NAWS, 2014). My findings suggest that these workers may slow down in response to the minimum wage increases, imposing additional costs on California farmers.

The paper proceeds as follows. In the next section I describe the context and data for the empirical application. This motivates the theoretical framework, which I present in Section 3. The theoretical model describes how minimum wage increases can cause decreases in productivity. The model yields three testable hypotheses. In Section 4 I present graphical evidence from the raw data that are consistent with the theory. In Section 5 I present the empirical methodology to test the theoretical hypotheses. I show results from the empirical specification in Section 6, and present robustness checks in Section 7. Section 8 concludes.

2 Context and Data

California accounts for roughly 90% of total strawberry production in the U.S. (NASS, 2018). With an annual value over $1.8 billion, strawberries are the state's fourth most important crop by value (CDFA, 2017). Strawberries, and more broadly fruits and nuts, are labor-intensive. In California, fruit and tree nut farming employs over 20% of all hired farmworkers (Martin et al., 2017). For strawberry production, a majority of these workers are hired for harvesting tasks. The labor costs of harvesting for California strawberry producers are estimated to account for 30 to 50% of total variable production costs (Martin, 2011; Bolda et al., 2016). More than half of these harvesters are paid by the piece, and all are required to earn at least the state minimum wage (Martin, 2009).

In this paper, I study one large strawberry farm in Northern California. The farmer offers the same wage contract to all strawberry harvesters. As is common in the industry, this contract is a piece rate wage with an hourly minimum. All strawberry pickers on the farm are paid the same (per-flat) piece rate and are subject to the same minimum wage. A worker's daily productivity (in flats per hour) determines whether they receive the piece rate or minimum wage. Workers receive the minimum wage if their daily piece rate earnings averaged over picking hours are below the minimum, otherwise they receive the piece rate. Thus, the payment scheme (hourly or piece rate) is determined by daily worker productivity.

The piece rate is set at the start of each harvesting season and is increased periodically as the season progresses. The initial minimum wage on this farm was the California minimum. When statewide shortages of agricultural workers made completing the harvest a challenge, the farmer raised the minimum wage above the state mandated level in an effort to attract more workers. These increases in the employer-set minimum wage are the focus of the empirical analysis. Two of these increases occur midway through the harvest season, which allow for identification of the behavioral responses of individual workers within a season.

In many industries with easily observable output, employers set a minimum productivity standard. Employers fire workers who produce below this standard, which is often set at or just below the minimum wage. While is is the norm in some industries, it is increasingly rare in agriculture. Because of ongoing labor shortages, most farmers are reluctant to fire workers. On the farm I study, workers are rarely fired for working too slowly. In other words, the farm has no formal firing constraint.

While there is no stated minimum productivity that workers must meet, it is unlikely that workers can produce nothing and keep their job. In general, supervision prevents this behavior. Presumably workers experience a disutility from supervisor attention and with enough of it workers will quit. Thus, supervisors impose an implicit firing constraint that sets a lower bound on the productivity required to continue working.

Each day a picker shows up for work they are assigned to the same crew and report to the field they will be picking that day. There is no strategic assignment of crews to fields; ranch management determines the number of crews needed for each field and assigns them in order. Pickers are restricted to certain rows within the field at a time, but move up the rows as the day progresses. Crew leaders decide the area workers will be restricted to based on crew size.

Pickers generally work 8 to 10 hour days, 6 days a week (Monday through Saturday). Fruit ripeness and abundance determine the fields that will be picked on a given day and play a large role in worker productivity. Many harvest conditions could feasibly impact worker productivity, but, importantly, workers within each crew should be affected similarly. This farm does not use any picking assist technology. This lack of a productivity enhancing technology means that a worker's output is almost entirely determined by effort, ability, and harvest conditions.

2.1 Data

I use daily payroll records of strawberry pickers on the farm described above. The data are an unbalanced panel of worker-day observations spanning the 2013-2015 growing seasons. I observe the field the worker is picking in, the crew they are assigned to, the number of hours they work, the number of strawberry flats they pick, and the piece rate and minimum hourly wage they face. From 2010 to 2012, the minimum wage on the farm was set at the California minimum of $8.00 per hour. Beginning in 2013, the producer began raising the minimum hourly rate on the farm above the state mandated minimum.[1] In 2013, the farmer increases the minimum wage mid-season without making any other changes on the farm. In 2015, the farmer again increases the minimum wage mid-harvest season and simultaneously increases the piece rate.

I combine these payroll data with daily weather data from a nearby weather station. These data come from the University of California Statewide Integrated Pest Management Program.[2] I include daily high and low temperatures because they are likely to affect productivity. In particular, both very high and very low temperatures might cause workers to pick more slowly.

Table 1 presents descriptive statistics.[3] From 2013 to 2015, the number of unique pickers increased from 950 to 1,600. The number of picking days decreased from 125 to 115. The number of observations are highest in 2014 and lowest in 2013, ranging from almost 33,000 to 38,500. The number of crews and fields increase across the years. The number of crews increase from 16 to 27 and the number of fields increase from 28 to 51. In 2013, the average picker worked 60 days, while in 2015 the average picker worked 43 days. This shows that the farmer employs more short term workers in the 2015 season than in 2013 and 2014. This explains the large increase in the number of unique pickers without with no corresponding

[1] I do not give the dollar value of the wage floor or the piece rate to preserve anonymity of the farm and farmer.

[2] Available at: `http://ipm.ucanr.edu/WEATHER/wxactstnames.html`

[3] The first two and last four weeks of each picking season and the top and bottom 1% of productivity observations are removed from the sample.

Table 1: Summary Statistics

	2013	2014	2015
# Pickers	952	895	1,601
# Picking days	125	127	115
# Picker-day observations	32,900	38,518	36,567
# Crews	16	19	27
# Fields	28	33	51
Average worker tenure	60.49	72.70	43.18
	(24.55)	(28.64)	(24.90)
Average productivity	6.23	7.18	7.33
	(2.59)	(3.24)	(3.65)
Average picking hours	7.45	7.35	7.16
	(1.47)	(1.83)	(1.80)
Piece rate*	(0.110)	(0.200)	(0.103)
% Worker-day observations receiving minimum wage	34.05	25.52	35.65
	(0.474)	(0.436)	(0.479)
% Workers receiving minimum wage at least once	71.95	76.42	74.77
	(0.449)	(0.425)	(0.434)
Daily high temperature	70.63	71.15	72.80
	(6.20)	(6.75)	(6.73)
Daily low temperature	50.21	53.01	54.32
	(4.26)	(4.21)	(4.49)

Standard deviations in parentheses
*Only standard deviations reported

increase in the number of picker-day observations. Average productivity, measured in flats per hour, is not significantly different across the years of the data. The annual averages range from 7.16 to 7.45.

A unique feature of these data compared with prior empirical work is the large share of workers earning the minimum wage. One barrier to identifying productivity effects from the minimum wage in prior work comes from the formal or informal firing constraint set at the wage floor. In our sample, however, workers frequently receive the minimum and are not fired for doing so.

Table 1 shows that the percentage of observations that receive the minimum wage are highest in 2013 (34 percent) and 2015 (36 percent), the years with mid-season increases in the minimum. In 2014, the percentage is lower (26 percent), but still substantial. Most of the workforce receives the minimum wage at least once during the growing season. From 2013 to 2015, roughly 72 to 76 percent of workers receive the minimum wage at least once. Finally, the bottom rows of Table 1 show that daily high and low temperatures increase across years in the data, but are similar.

3 Theoretical Framework

The theoretical framework uses a principal-agent model that is tailored to the empirical context. Consider workers who are endowed with an ability, A, face variable harvest conditions, θ, and a piece rate wage, p. Each day, workers observe θ and p and choose their effort level, E, which yields output q. For simplicity, define θ so that higher values represent better harvest conditions. Harvest conditions encompass both shocks (e.g. weather) and seasonal trends (e.g. fruit abundance). I assume that workers derive utility from income, Y, and experience a disutility from exerting effort.

A worker's utility function can be written:

$$\text{Utility} = U(Y, E). \tag{1}$$

Utility is strictly increasing in income at a decreasing rate and strictly decreasing in effort at a decreasing rate, i.e. $U_y > 0$, $U_{yy} < 0$, $U_e < 0$, and $U_{ee} < 0$. A worker's output can be written:

$$q = f(A, E, \theta) \geq 0. \tag{2}$$

Output is increasing at a decreasing rate in ability, effort, and harvest conditions, i.e. f_a, f_e, $f_\theta > 0$ and f_{aa}, f_{ee}, $f_{\theta\theta} < 0$. The link between output and income depends on the wage scheme. I begin with considering worker behavior under a pure piece rate payment scheme, and later introduce a minimum wage. Define p as the piece rate wage set by the firm. Under a pure piece rate payment scheme, income is jointly determined by p and q and can be written:

$$Y = p \cdot q = p \cdot f(A, E, \theta). \tag{3}$$

Substituting this definition of income into the worker's utility function, the maximization problem can be written:

$$\max_{E} \quad U(p \cdot f(A, E, \theta),\ E), \tag{4}$$

with the first order condition:

$$p \, \frac{\partial U}{\partial Y} \, \frac{\partial f}{\partial E} + \frac{\partial U}{\partial E} = 0. \tag{5}$$

Under the pure piece rate payment scheme, the worker chooses effort that equates the marginal value of effort to the marginal cost. The first order condition shows that optimal effort will depend on the piece rate wage, ability, and harvest conditions. Let $E^*_{pr}(p, A, \theta)$ denote the effort that solves this maximization problem. Denote the optimized utility for any realization of the exogenous piece rate wage, ability level, and harvest conditions as:

$$U^*_{pr}(p, A, \theta) = U(p \cdot f(A, E^*_{pr}(p, A, \theta),\ E^*_{pr}(p, A, \theta)). \tag{6}$$

Now, consider what happens with the introduction of a minimum wage. Define $\underline{w}$ as daily income at the hourly minimum wage. Daily income under a piece rate scheme with a minimum wage can be written:

$$Y = \max[\underline{w},\ p \cdot q] = \max[\underline{w},\ p \cdot f(A, E, \theta)]. \tag{7}$$

The wage floor introduces a new problem for employers. Workers earning the minimum wage are paid more per unit of output than those earning the piece rate. To demonstrate that this is the case, consider any worker who earns the minimum wage. The worker's output must be such that $\underline{w} > p \cdot q$. Rewriting that equation implies that for any worker earning the minimum wage $\frac{\underline{w}}{q} > p$, i.e. per-unit earnings are higher than the piece rate.

This means that workers impose a higher marginal cost on employers. To prevent marginal costs that are too high, the employer must impose a minimum productivity standard, i.e. a minimum output required to keep the job. Because harvest conditions affect worker productivity, I assume that the employer will have a higher productivity standard when harvest conditions are good, and a lower standard when conditions are bad. This flexible firing constraint can be represented as a lower bound on productivity that varies with harvest conditions, $\underline{q}(\theta) \geq 0$. Under the new wage scheme, the worker's optimization problem becomes:

$$\begin{aligned} \max_{E} \quad & U(\max[\underline{w},\ p \cdot f(A, E, \theta)],\ E) \\ \text{subject to} \quad & f(A, E, \theta) \geq \underline{q}(\theta). \end{aligned} \tag{8}$$

Because the worker faces a nonlinear constraint on income, the worker will maximize utility in two steps. The worker will first choose optimal effort under the minimum wage and piece rate separately. Then the worker will compare utility in the two regimes. Optimal effort in the piece rate regime remains at $E^*_{pr}(p, A, \theta)$, the optimal effort without the minimum wage, with corresponding utility $U^*_{pr}(p, A, \theta)$.

Under the minimum wage regime workers gain no marginal benefit from exerting effort, but face a nonzero marginal cost. Because workers derive no positive utility from exerting effort, optimal effort is a corner solution. The worker will choose to exert as little effort as possible to keep the job, i.e. choose effort that yields output $\underline{q}(\theta)$. Denote this level of effort as $E^0(\underline{w}, A, \theta)$, then the worker's effort and output at this level can be written:

$$\underline{q}(\theta) = f(A, E^0(\underline{w}, A, \theta), \theta). \tag{9}$$

Let the value of utility associated with this level of effort be represented by $U^0(\underline{w}, A, \theta) = U(\underline{w},\ E^0(\underline{w}, A, \theta))$. The value function of the worker's final optimized utility can be written:

$$U^*(\underline{w}, p, A, \theta) = \max[U^*_{pr}, U^0]. \tag{10}$$

And optimal effort, i.e. effort that solves 8, can be written:

$$E^*(\underline{w}, p, A, \theta). \tag{11}$$

The effort that maximizes utility is a function of the minimum wage, the piece rate wage, ability, and harvest conditions. Workers who choose an effort level below E^0 under the pure piece rate scheme (i.e. $E^*_{pr} < E^0$) may choose to increase productivity to E^0 to keep the job, or they will exit the workforce. Workers who choose an effort level above E^0 under the pure piece rate scheme (i.e. $E^*_{pr} > E^0$) will either reduce productivity to $\underline{q}$ or continue to produce at q^*_{pr}. The reduction of effort to $\underline{q}$ under the minimum wage regime is called *shirking behavior*. For this behavior to occur, the distribution of abilities and harvest conditions must be such that some workers can increase utility by decreasing effort and accepting the minimum wage. Further, this requires that $\underline{q}$ is set at a level below the output required to earn the piece rate, i.e. $p \cdot \underline{q}(\theta) < \underline{w}$. Importantly, these are also the necessary conditions for workers to earn the minimum wage. This implies that on days when workers maximize utility by earning the minimum wage, it is always optimal for workers to choose effort E^0 and produce output $\underline{q}$. This leads to the first hypothesis:

Hypothesis 1(a): *All workers earning the minimum wage on the same day choose effort $E^0(A_i)$ and produce the same output, $\underline{q}$.*

Further, from the strict convexity of the worker utility function:

Hypothesis 1(b): *There exists a range of income just above $\underline{w}$ that is never optimal. Workers will not choose efforts that yield incomes within this range.*

This range can be formally defined such that:

$$\begin{aligned} &\forall\theta\ \exists\ \varepsilon_\theta > 0 \text{ such that if} \\ &\qquad \underline{w} < p \cdot f(A,\ E^*_{pr}(p, A, \theta),\ \theta) \leq \underline{w} + \varepsilon_\theta, \\ &\text{then} \\ &\qquad U^0(\underline{w}, A, \theta) > U^*_{pr}(p, A, \theta). \end{aligned} \tag{12}$$

In words, given the opportunity, workers are likely to accept a small reduction in income for a large reduction in effort. However, workers are unlikely to accept a large reduction in income to reduce effort a little. $\underline{w} + \varepsilon_\theta$ is defined as the point of indifference between utility at the minimum wage and utility under the piece rate, i.e. where $U^*_{pr} = U^0$. Combined, Hypotheses 1(a) and 1(b) have two major implications: (1) workers will not choose outputs just above the minimum wage and (2) the productivities of workers receiving the minimum will be clustered around the minimum required output.

I now extend this model by considering an increase in the minimum wage. Define $\underline{w}'$ as a new minimum wage that is larger than the prior, i.e. $\underline{w}' > \underline{w}$. Fixing harvest conditions and assuming that the minimum required output does not rise with the minimum wage yield the final two hypotheses:

Hypothesis 2(a): *After a minimum wage increase, no workers increase effort and workers on the cusp of the prior minimum wage decrease effort.*

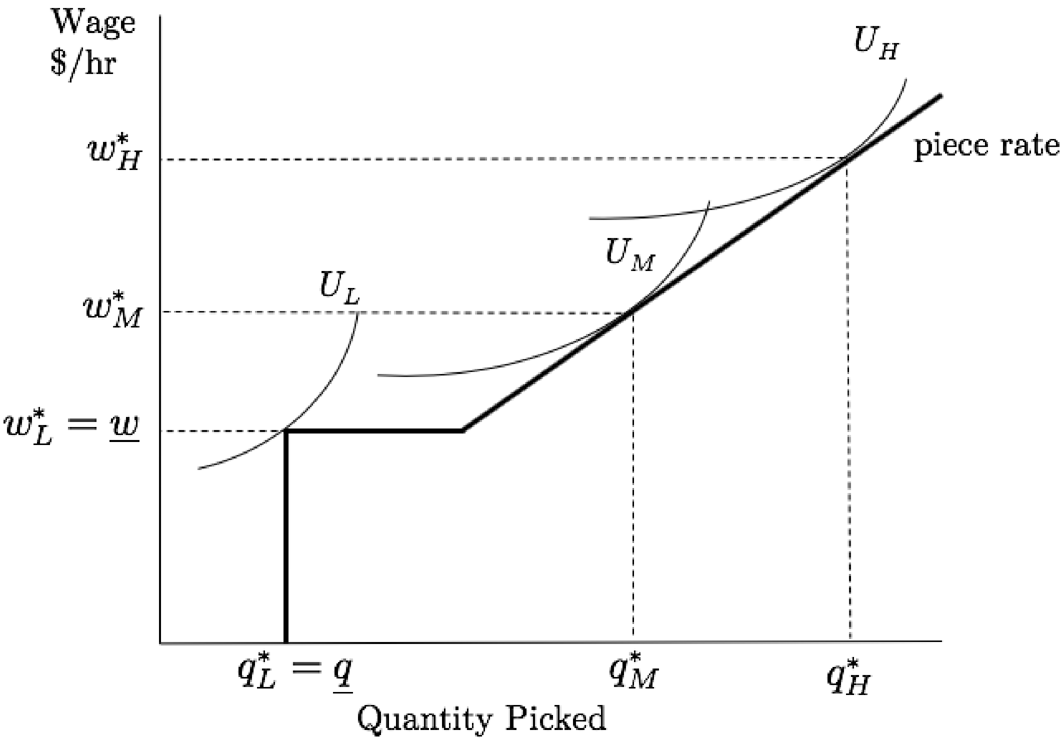
After an increase in the minimum wage, workers who were on the *cusp* of the prior minimum wage, i.e. those with incomes just above $\underline{w} + \varepsilon_\theta$ can now increase utility by decreasing effort from E^*_{pr} to E^0, producing output $\underline{q}$, and earning the minimum wage. For these workers, productivity is strictly decreasing. Workers who were previously earning the minimum wage will continue to exert effort E_0, and workers who are earning well above the new minimum wage will continue to exert E^*_{pr}. For these workers, effort is unaffected by the change in the minimum wage. This leads to the final hypothesis:

Hypothesis 2(b): *After a minimum wage increase, average workforce productivity is weakly decreasing.*

This follows directly from Hypothesis 2(a). An increase in the minimum wage causes no change in effort for some workers and a decrease in effort for others, and output is strictly increasing in effort. Holding constant the piece rate wage, ability, and external conditions, this implies that an increase in the minimum wage causes average workforce productivity to remain constant or fall.

Figures 1 and 2 present a graphical depiction of hypotheses 2(a) and 2(b). Figure 1 shows optimal productivity at an initial minimum wage, $\underline{w}$, for three example workers. These three workers can be thought of as having low (L), medium (M), and high (H) ability levels. The relative steepness of the worker indifference curves reflect differences in the costs of exerting effort. Low ability workers have the steepest indifference curves because they face the largest costs to exerting effort. For these workers to be indifferent between bundles of effort and income, a small increase in effort must be compensated with a relatively large increase in

Figure 1: Output and Wages for Three Ability Types

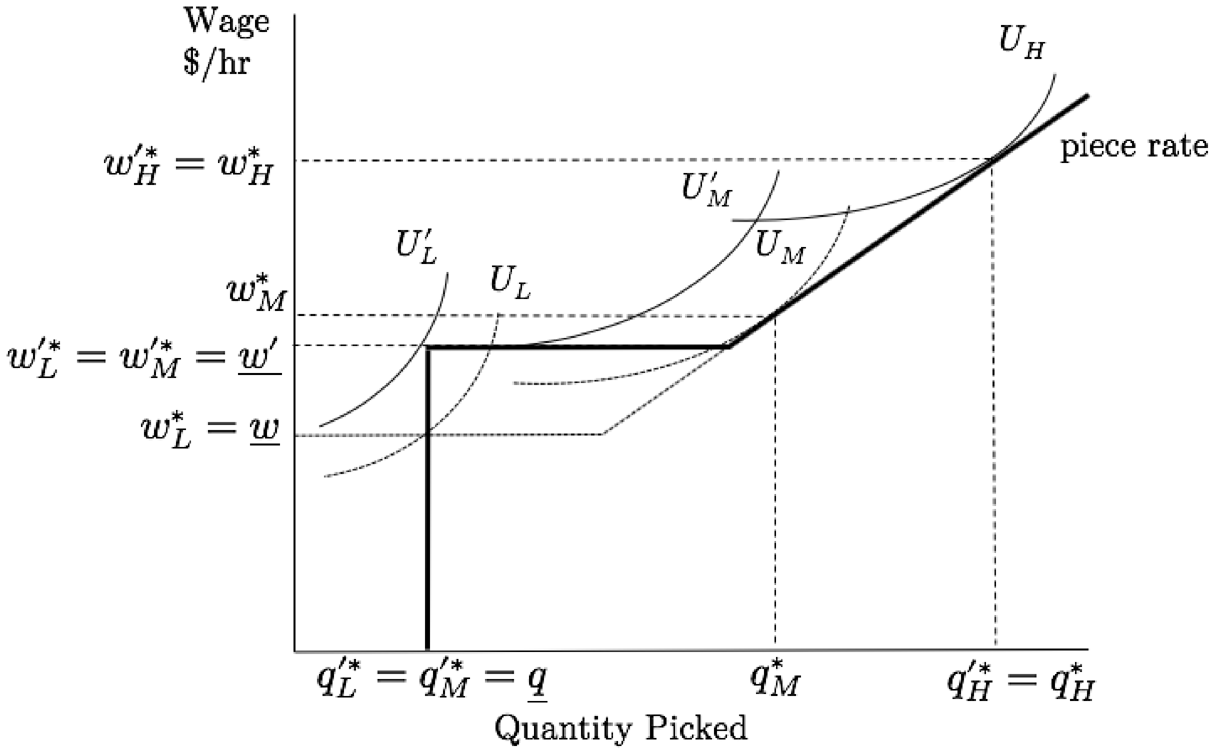


wages. At the initial minimum wage, Figure 1 shows that the example low ability worker is producing at $\underline{q}$ and is earning the minimum wage. The medium and high ability workers are producing at levels above this and are earning the piece rate wage associated with their outputs.[4]

Figure 2 shows how a minimum wage increase can cause medium ability workers to pick slower, while having no impact for low and high ability workers. The medium ability worker can increase utility by decreasing output to $\underline{q}$ and accepting the new minimum wage $\underline{w}'$. The low ability worker increases utility because wages increase, but continues to produce at the same level, $\underline{q}$. The high ability worker maintains the same level of utility and continues to produce at q^*_H. Combined, these example workers demonstrate the net negative productivity effect that is driven by workers on the cusp of the prior minimum wage.

[4]Note that this implies the low ability worker has chosen to exert effort E^0_i and the medium and high ability workers have chosen efforts $E^*_{pr,i} > E^0_i$.

Figure 2: Output, Wages, and a Minimum Wage Increase



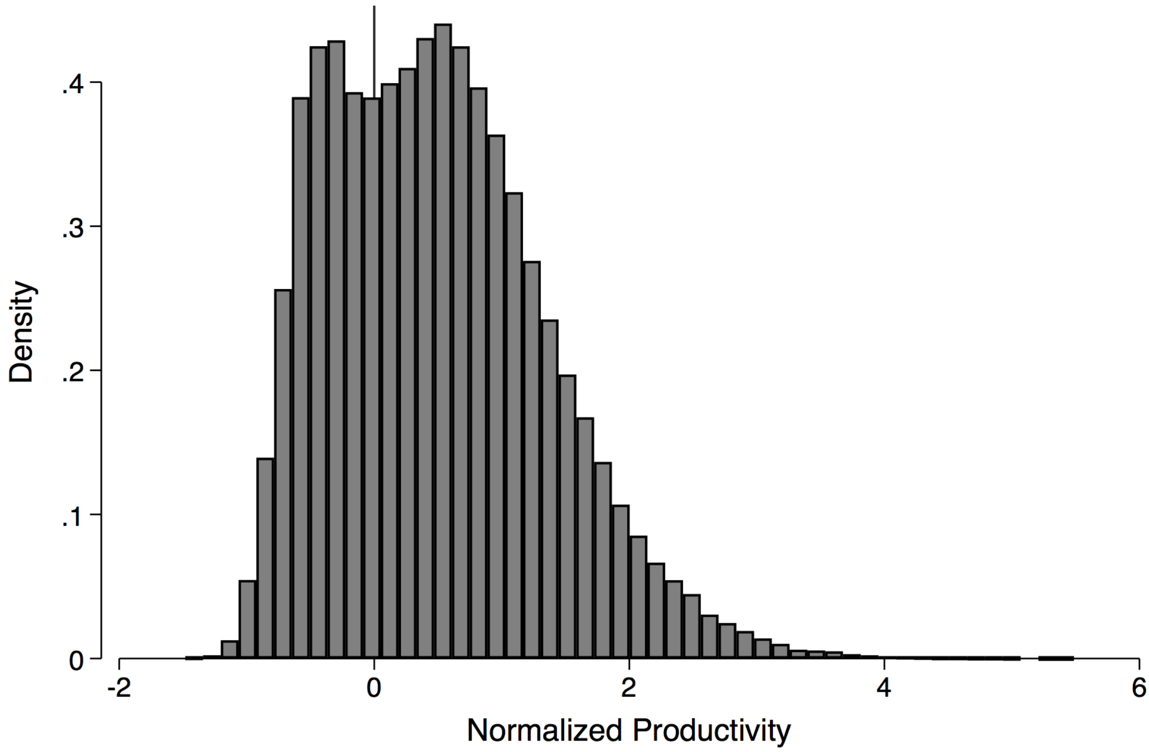
4 Graphical Evidence

Hypotheses 1(a) and 1(b) suggest that we should observe productivity bunching below the minimum wage, more specifically, at the firing constraint. Here I support theses hypothesis with graphical evidence from the raw data. Figure 3 shows the distribution of daily worker productivities normalized around the minimum wage. Each observation in Figure 3 gives the worker productivity (in flats per hour) minus the flats needed to earn the minimum wage divided by the sample standard deviation. Aggregating data across all years, Figure 3 shows two modes in the productivity distribution. One falls below the minimum wage, and one above. This bimodal productivity distribution supports the shirking hypothesis. Workers earning the minimum wage have productivities centered below the minimum, and workers earning the piece rate have productivities centered above the minimum. The decreased density of worker productivities immediately above the minimum wage support Hypothesis

1(b), which states that is is suboptimal for workers to choose productivities just above the minimum wage when the firing constraint is below the minimum.

Causal evidence on Hypotheses 1(a) and 1(b) might come from comparing the distribution of productivities for workers on days they are subject to a minimum wage and days they are not, but this is not observed in the data. In the absence of the counterfactual, causal evidence for Hypotheses 1(a) and 1(b) is challenging, but the productivity bunching in Figure 3 is consistent with the hypotheses.

Figure 3: Productivity Distribution: 2013 - 2015



While Hypotheses 1(a) and 1(b) are not directly testable with these data, Hypotheses 2(a) and 2(b) are. These hypotheses make predictions based on exogenous changes in the minimum wage. In the next section I outline the empirical approach for identifying these effects. Here, I present evidence that the effects are visible in the raw data. I do this by comparing trends before and after the mid-season increases in the minimum wage. Table 2 presents these summary statistics for 2013 and 2015. The sample is restricted to workers present both before and after the increase. This removes productivity effects from workers attracted by the minimum wage increase, i.e. sorting effects. The farm employs more unique pickers and has more picker-day observations in the 2015 season than in 2013. The number of picking days reveals an important difference in the timing of the minimum wage increases. The 2013 increase is implemented early in the season and the 2015 increase is implemented late in the season. As a result, in 2013 the average number of days picking (worker tenure) is highest post-change, and in 2015 is highest pre-change. The average picking hours is higher post-change in both years.

Table 2: Summary Statistics

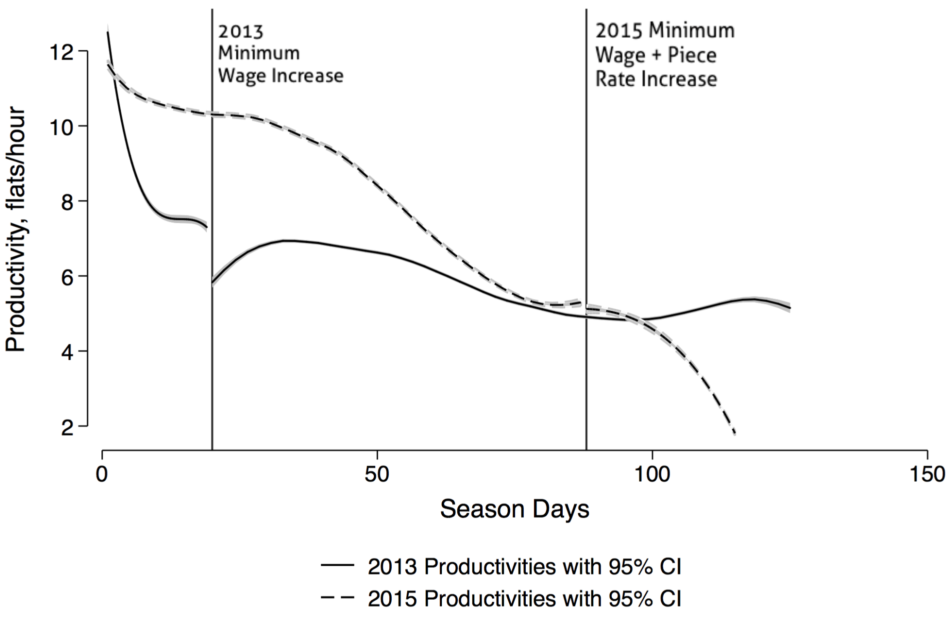
	2013		2015	
	Pre-change	Post-change	Pre-change	Post-change
# Pickers	510	510	671	671
# Picking days	18	105	86	28
# Picker-day observations	4,500	21,176	20,727	5,853
# Crews	16	16	25	26
# Fields	18	28	44	44
Average worker tenure	10.95	59.19	45.02	10.81
	(4.03)	(18.73)	(19.82)	(4.35)
Average picking hours	5.80	7.76	7.17	8.00
	(0.99)	(1.32)	(1.74)	(1.50)
Average productivity	8.65	5.93	7.81	4.13
	(2.53)	(2.34)	(3.40)	(2.58)
% Receiving minimum wage	5.24	37.32	29.96	72.25
	(0.22)	(0.48)	(0.46)	(0.45)
Daily high temperature	67.01	71.16	71.73	80.05
	(4.56)	(6.14)	(5.17)	(6.54)
Daily low temperature	47.45	50.83	54.42	56.19
	(4.07)	(4.05)	(4.06)	(4.76)
Minimum Wage Increase (%)	2.84		2.56	

Standard deviations in parentheses

In both years, productivity is significantly highest in the pre-change period. This is primarily driven by harvest abundance and reflects seasonal variation more than effects from the minimum wage increase. Seasonal variation similarly drives the differences between the pre- and post-change percentage of observations receiving the minimum wage. Finally, there is a small but insignificant difference in the daily high and low temperatures before and after both increases. Temperatures are higher in the post change period in both years.

Figure 4 depicts productivity over the 2013 and 2015 harvest seasons. Unrelated to the minimum wage increases, the productivity of strawberry pickers decreases due to declining harvest abundance over the season. Productivities drop significantly immediately following the 2013 minimum wage increase, but there is no significant change immediately after the 2015 increase. The contrast between the 2013 and 2015 productivity changes is explained by the structure of the minimum wage increases. In 2013, the minimum wage was increased without any other changes to the payment scheme. In 2015, the producer simultaneously increased the piece rate with the minimum wage. This provides suggestive evidence that increasing piece rates simultaneously with the minimum wage may mitigate negative productivity effects.

Figure 4: Local Polynomial of Average Daily Productivities



5 Empirical Analysis

While the graphical evidence is consistent with the theoretical model, it does not control for variation in harvest conditions, worker-specific characteristics, or changes in the piece rate wage. Causal identification of the productivity effects of a minimum wage increase require a formal analysis. I now turn to the empirical methodology to address these issues.

Hypothesis 2(b) states that an increase in the minimum wage causes average productivity to decrease, holding ability, harvest conditions, and the piece rate constant. In this setting, the piece rate is observed, but worker ability and harvest conditions are not. To identify productivity effects, ability and harvest conditions must be proxied with observables.

Panel data allow for the comparison of the productivity of an individual worker before and after minimum wage increases. This eliminates the need to control for worker ability and can be estimated with a person-specific fixed effects model. Picker fixed effects control for time invariant characteristics over the harvest season. However, there are reasons to worry about time varying unobservables, e.g. picker ability might increase as workers learn on the job. To account for this, I control for each worker's cumulative number of working days over the season. This term proxies for the average learning effect. Another potential bias arises because workers are occasionally assigned to a new harvesting team, i.e. join a new crew. Each crew has a unique supervisor and differences in management styles are likely to affect worker productivity. Crew fixed effects absorb these supervision effects because crew supervisors are constant within the season.

In a worker-specific fixed effects model, with daily worker productivity as the outcome variable, I use time trends, field fixed effects, and daily high and low temperatures to control for harvest conditions. For strawberry pickers, the time in the season is the most significant predictor of harvest conditions. Productivity generally declines over the course of the harvest season, but not at a constant rate. To capture nonlinearities in seasonal productivity trends, I include piecewise linear time splines over the season. Specifically, I divide the season into thirds over the number of picking days, and include a separate time trend for each portion of the season. Each day crews are assigned to different fields, which likely have different harvest conditions. Field fixed effects control for these field-specific conditions. Finally, weather is likely to have significant effects on worker productivity. Very high temperatures may fatigue workers, causing them to pick more slowly. Very low temperatures may reduce finger dexterity, also causing workers to slow down. To control for temperature effects on productivity, I include the daily high and low temperatures from the closest weather station.

I test Hypothesis 2(b) using:

$$\begin{aligned} y_{it} = \alpha_i + \mu \text{Post}_t + \eta p_t + \beta_1 t_t + \sum_{k=1}^{2} b_k (t_t - k_k)_+ \\ + \beta_2 w_t^h + \beta_3 w_t^l + \beta_4 x_{it} + \lambda_f + \lambda_c + \epsilon_{it}. \end{aligned} \tag{13}$$

Where, y_{it} is the productivity (in logged flats per hour) of worker i at time (day) t, α_i are individual fixed effects, Post_t is an indicator variable that takes the value 1 if the date is in the post-minimum wage change period and zero otherwise, p_t is the logged piece rate wage, t_t is a time trend, w are weather controls, where w^h is the daily high temperature and w^l is the daily low, x_{it} are the cumulative days working that season for worker i at time t, λ_f are field fixed effects, and λ_c are crew fixed effects. The linear splines are represented by $(t_t - k_k)_+$, where the knots are denoted by k_k and are equally spaced over thirds of the picking days in the season. $(t_t - k_k)_+$ is equal to zero when $t_t - k_k < 0$, i.e. for days below the relevant knot, and equal to $t_t - k_k$ otherwise.

The main coefficient of interest is μ. This gives the average productivity effect of the minimum wage increase. A negative value of μ would support Hypothesis 2(b). A secondary coefficient of interest is η, which gives the productivity-piece rate elasticity. Because increases in the piece rate raise the marginal value of effort and directly incentivize productivity, theory predicts that this coefficient will be positive. The relative values of μ and η can be used to determine whether, and to what extent, changes in the piece rate can offset productivity effects of the minimum wage.

Hypothesis 2(a) suggests that the negative average effect is driven by productivity decreases among medium ability workers. To test this prediction, I estimate the average productivity of each worker prior to the minimum wage increase, purged of effects from harvest conditions, crew, weather, and the piece rate. Specifically, I estimate the predicted fixed effect, $\hat{\alpha_i}$, from Equation 13 for the subset of worker-day observations prior to the minimum wage increase.[5] I omit the indicator variable for the post minimum wage period and adjust the number of linear time splines included.[6] Estimates $\hat{\alpha_i}$ are average worker productivity prior to the minimum wage increase that are purged of effects from harvest conditions, the piece rate wage, assigned crew, and picking experience. Using these estimates, I group workers into quantiles of the ability distribution, i.e. $\hat{\alpha}_i^q = \mathbb{1}[\hat{\alpha}_i \in \alpha_q]$.

These quantiles serve as proxies for a worker's ability relative to their peers. Workers in the lower quantiles have relatively low productivities, and can be thought of as the low ability workers from the theoretical model. Those in the top quantiles have relatively high productivities, and can be thought of as the high ability workers. However, this is an imperfect map to the abilities defined in the theoretical model. Mapping workers into latent ability groups is challenged by productivity shocks. There are some days in which a majority of the workforce earns the minimum wage, and some days where no workers earn the minimum. Because of these shocks, almost all workers are affected by the minimum wage increase at some point during the season. However, workers in the middle of the $\hat{\alpha_i}$ distribution should be the most responsive to the change in the minimum wage. Results supporting the theoretical model would be smaller productivity effects for workers in the top and bottom quantiles, and the largest effects for workers in the middle.

Using these proxies of worker ability, I extend Equation 13 to estimate the ability-specific

[5] The estimating equation can be written: $y_{it} = \alpha_i + \eta p_t + \beta_1 t_t + \sum_{k=0}^{j} b_k (t_t - k_k)_+ + \beta_2 w_t^h + \beta_3 w_t^l + \beta_4 x_{it} + \lambda_f + \lambda_c + \epsilon_{it}$.

[6] In 2013, because the pre-minimum wage increase period is only 20 picking days, I only include a single linear time trend (t_t). In 2015, because the minimum wage increase occurs later in the season, I include the splines from Equation 13 which fall before the increase. In 2015, these splines split the pre-change season into two segments.

productivity effect. The new equation can be written:

$$\begin{aligned} y_{it} = \quad & \alpha_i + \sum_{q=1}^{6} \mu_q \text{Post}_t \cdot \hat{\alpha}_i^q + \eta p_t + \beta_1 t_t + \sum_{k=1}^{2} b_k (t_t - k_k)_+ \\ & + \beta_2 w_t^h + \beta_3 w_t^l + \beta_4 x_{it} + \lambda_f + \lambda_c + \epsilon_{it}. \end{aligned} \tag{14}$$

where each μ_q gives the average change in productivity following a minimum wage increase for workers with an estimated ability in quantile q.

In Equations 13 and 14, a causal interpretation of μ (or μ_q) requires that time varying unobserved factors that affect productivity are uncorrelated with the minimum wage increase. Anecdotal support for this claim comes from conversations with the farmer. According to the farmer, the minimum wage increases were part of the effort to attract more workers in the face of ongoing labor shortages. The timing of the increases reflect the timing of worker shortages from worker exit and limited mid-season entry. Restricting the sample to workers present both before and after the changes eliminates effects from pre-change worker exit and post-change worker entry. This removes the group of workers who were targeted by the minimum wage increase.

6 Results

Tables 3 and 4 present the main results from estimating Equation 13. I run these regressions separately for the two years with mid-season increases in the minimum wage, 2013 and 2015. I present the main coefficients of interest, those on the post minimum wage indicator and on the logged piece rate, in Tables 3 and 4 and include the full regression results in the Appendix. These capture the average productivity effect and the productivity-piece rate elasticity, respectively.

To demonstrate robustness to model specification, I show results from four model specifications. The first column of Tables 3 and 4 show results from a model that only controls for time trends. The second column shows results from a model that includes time trends and the piece rate wage. The third column shows results after adding crew and field fixed effects, daily high and low temperatures, and a worker's cumulative picking experience. The fourth column shows results from the preferred regression specification which includes all control variables and worker-specific fixed effects.

Tables 3 and 4 both show that an increase in the minimum wage causes the average worker to decrease productivity by roughly seven percent. In Table 3, the productivity effect of the 2013 minimum wage increase is negative and significant for all models. The estimate is largest in magnitude in the model with fewest controls, -0.10, and smallest in the preferred specification, -0.07. The control variables increase the explanatory power of the model and reduce the estimated effect of the minimum wage increase. Shown in the last column of Table 3, the results from the preferred specification indicate that in the 2013 harvest season, the average worker decreases productivity by seven percent in response to the minimum wage increase. This model also estimates a large and statistically significant productivity-piece rate elasticity of 1.2. This suggests that in response to a ten percent increase in the piece rate, the average worker in the 2013 season increases productivity by roughly twelve percent.

Table 3: 2013 Fixed Effects Results: Average Productivity Effects

Outcome variable: log (flats/hour)	Time splines	Splines + piece rate	Splines + all controls	FE
Post	-0.102***	-0.106***	-0.0806***	-0.0703***
	(0.00948)	(0.00953)	(0.00994)	(0.00839)
log(piece rate)		0.718***	1.043***	1.191***
		(0.189)	(0.134)	(0.132)
R^2	0.234	0.236	0.468	0.466
N	25,676	25,676	25,676	25,676
Time splines	yes	yes	yes	yes
Field and crew FE	no	no	yes	yes
Weather & experience	no	no	yes	yes
Individual FE	no	no	no	yes

Standard errors in parentheses, clustered at worker

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

Table 4: 2015 Fixed Effects Results: Average Productivity Effects

Outcome variable: log (flats/hour)	Time splines	Splines + piece rate	Splines + all controls	FE
Post	0.0857***	-0.0816***	-0.0663***	-0.0645***
	(0.0116)	(0.0113)	(0.0106)	(0.0100)
log(piece rate)		1.583***	1.793***	1.644***
		(0.128)	(0.113)	(0.105)
R^2	0.519	0.522	0.611	0.651
N	26,580	26,580	26,580	26,580
Time splines	yes	yes	yes	yes
Field and crew FE	no	no	yes	yes
Weather & experience	no	no	yes	yes
Individual FE	no	no	no	yes

Standard errors in parentheses, clustered at worker

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

Table 4 shows that the estimate of the 2015 minimum wage effect is more sensitive to model specification. The coefficient is positive and significant in the model that only controls for time trends and negative and significant in all other models. The positive coefficient shown in the first column arises because the 2015 minimum wage increase was implemented simultaneously with a piece rate increase. This positive coefficient suggests that the net effect from increasing the piece rate and minimum wage simultaneous is positive. Meaning that this piece rate increase was large enough to offset the negative productivity effects from the minimum wage increase.

After controlling for the piece rate, as shown in the second column, the coefficient on the post term becomes negative and significant. The fourth column of Table 4 shows results from the preferred specification. These indicate that the average worker decreases productivity by seven percent in response to the minimum wage increase. The estimate of the productivity-piece rate elasticity from the preferred specification is 1.6, which is larger than in the 2013 season.

In 2013 and 2015 the productivity-piece rate elasticities are 1.2 and 1.6, respectively.

This is similar to prior estimates in similar settings. Paarsch and Shearer (1999) estimate a productivity-piece rate elasticity of 2.14 for tree planters in British Columbia. Haley (2003) follows the same methodology and finds an elasticity of 1.51 for workers at a Midwest logging company. Coefficients suggest that a ten percent increase in the piece rate causes productivity to increase by 13 to 16 percent. Combined with the estimates of the minimum wage effect, this suggests that piece rate increases of four to six percent would offset the productivity losses from the three percent increases in the minimum wage.

Table 5: Fixed Effects Results by Worker Ability

Outcome variable: log (flats/hour)	2013	2015
Post $\cdot \mathbb{1}[\hat{\alpha}_i \in \alpha_{q1}]$	-0.0051	-0.0044
	(0.0197)	(0.0164)
Post $\cdot \mathbb{1}[\hat{\alpha}_i \in \alpha_{q2}]$	-0.0787*	-0.0830***
	(0.0310)	(0.0176)
Post $\cdot \mathbb{1}[\hat{\alpha}_i \in \alpha_{q3}]$	-0.0761**	–0.1090***
	(0.0288)	(0.0218)
Post $\cdot \mathbb{1}[\hat{\alpha}_i \in \alpha_{q4}]$	-0.101***	-0.0967***
	(0.0304)	(0.0237)
Post $\cdot \mathbb{1}[\hat{\alpha}_i \in \alpha_{q5}]$	-0.0812**	-0.0149
	((0.0304)	(0.0317)
log(piece rate)	1.192***	1.675***
	(0.0285)	(0.111)
R^2	0.467	0.653
N	25,676	26,580
Time Splines	yes	yes
Field and crew FE	yes	yes
Weather & experience	yes	yes
Individual FE	yes	yes

Standard errors in parentheses, clustered at worker

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

The results in Tables 3 and 4 are consistent with Hypothesis 2(b)— average productivity declines by roughly seven percent in response to the minimum wage increases. I now turn to Hypothesis 2(a) which claims that workers in the middle of the ability distribution drive the negative average effect. Table 5 presents the ability-specific productivity effects from estimating Equation 14 with workers divided into quintiles of the productivity distribution.

The regression coefficients shown in Table 5 imply that in both 2013 and 2015, workers in the bottom quintile do not change productivity significantly in response to the minimum wage increase. This aligns with the theoretical prediction that low ability workers do not adjust productivity in response to the new minimum wage. In both years, the coefficients are negative and significant for workers in quintiles two, three, and four. If we think of workers in these middle quintiles as varying degrees of the medium ability workers outlined in the theoretical model, these results align the Hypothesis 2(a).

The estimates of the productivity responses of workers in these medium ability workers vary across year and quintile, ranging from -0.08 to -0.11. In 2013, the estimated productivity response is largest in magnitude for workers in the 4^{th} quintile. These workers decrease productivity by ten percent as an effect of the minimum wage increase. In 2015, workers in the 3^{rd} quintile are most responsive, decreasing productivity by eleven percent.

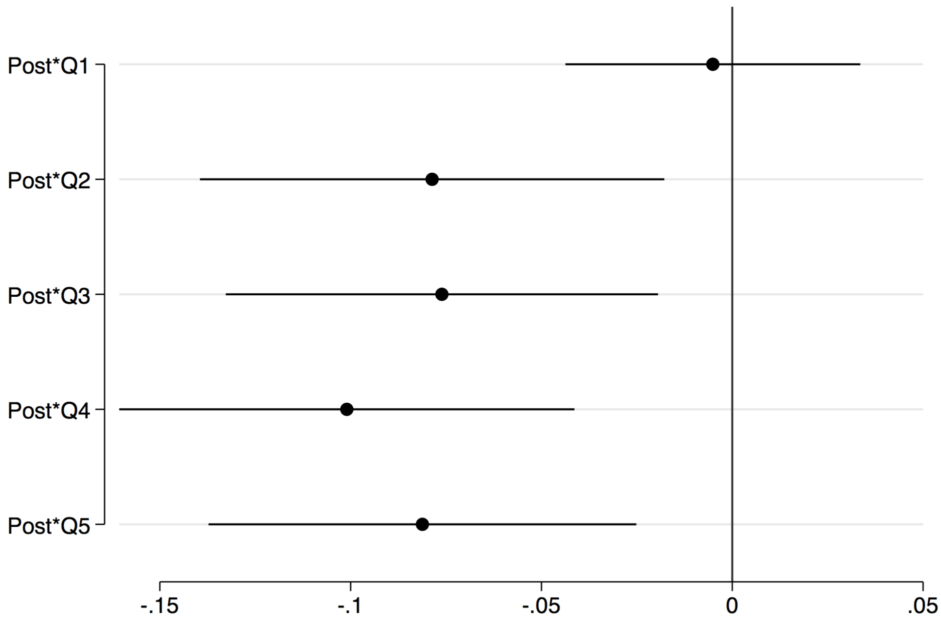
Finally, Table 5 shows that in 2015, workers in the 5^{th} (highest) quintile of the ability distribution do not change productivity significantly following the minimum wage change. This aligns with the theoretical prediction that high ability workers do not adjust productivity in response to the change. However, this is not the case in 2013. Even the most productive workers in 2013 become less productive following the minimum wage increase. These workers decrease productivity by eight percent following the increase.

Generally, the ability-specific regression results reveal some heterogeneity in the productivity responses of workers to the minimum wage increases. Figure 5 plots the regression coefficients with 95 percent confidence intervals. This figure shows that in 2015, workers in the second, third, and fourth quintiles are significantly more responsive to the minimum wage change than workers in the lowest quintile. This significant heterogeneity between workers at the bottom and in the middle of the ability distribution is consistent with Hypothesis 2(a), but the lack of significant differences with workers in the highest quintile is not.

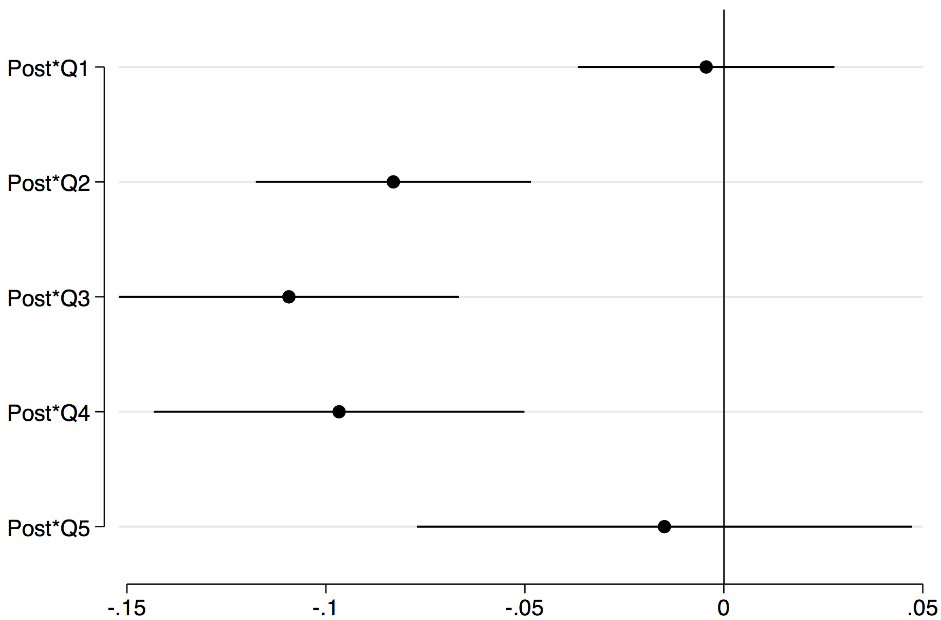
There are several potential explanations of the discrepancy between the estimates in 2013 and 2015. First, because the 2013 minimum wage increase occurs earlier in the season than the one in 2015, the worker fixed effects are estimated on a smaller sample of days, which reduces their precision. Second, workers in the 2013 season have more working days following the minimum wage increase than those in 2015. Workers in the 2013 season may be subject to more days with negative productivity shocks following the increase than their 2015 counterparts. Finally, in the theoretical section, worker abilities are relative to other workers and the minimum wage. A worker's quintile in the fixed effect distribution is an imperfect proxy for the abilities outlined in the theory.

Figure 5: Ability Specific Coefficients

(a) 2013



(b) 2015

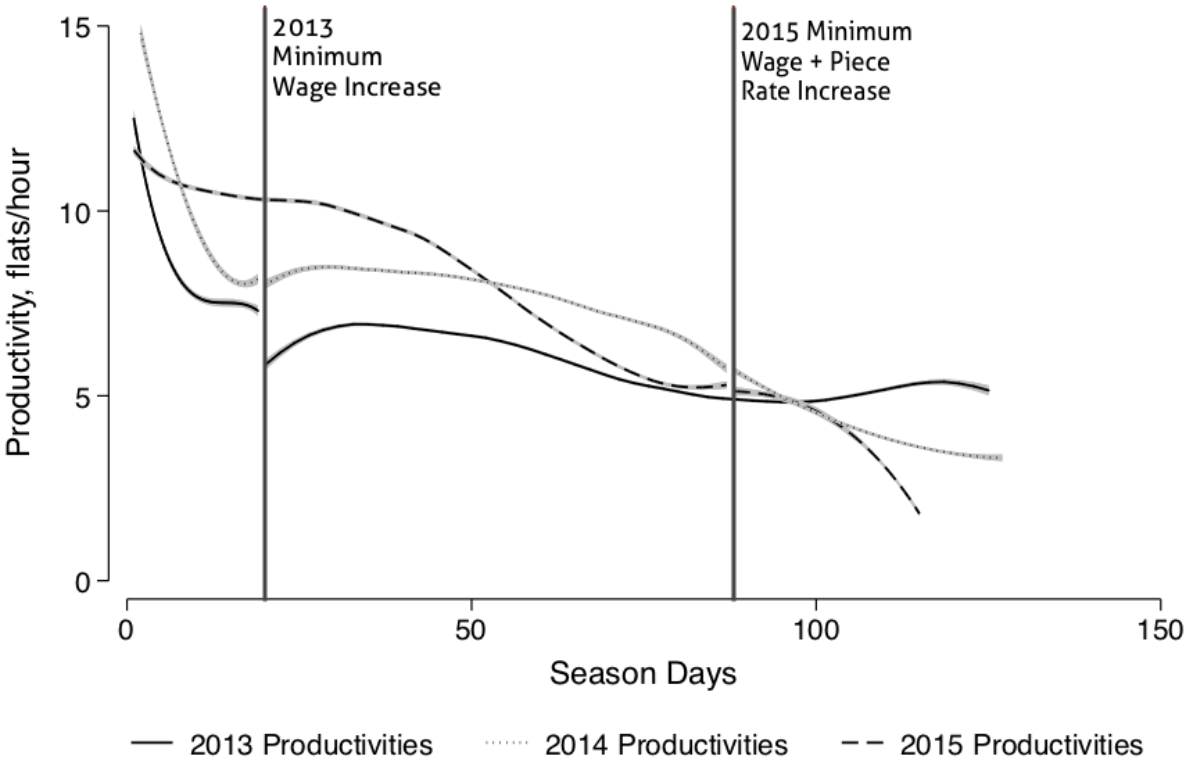


7 Robustness

The fixed effects model identifies the effect of minimum wage increases by comparing the productivity of the same worker before and after the increases, controlling for time trends, the piece rate wage, daily temperature, a worker's experience, and factors that are constant within fields and crews. The estimated effects could be biased if these controls fail to capture unobserved factors that cause productivity to fall over the season.

I address this concern in two ways. First, I use a placebo test to demonstrate that productivity does not change significantly when there is no increase in the minimum wage. Second, I narrow the window of focus and use a regression discontinuity in time (RDiT) design to estimate the immediate effects from the minimum wage increase.[7]

Figure 6: Smooth Polynomials of Worker Productivity, 2013-2015



[7]Hausman & Rapson (2018) draw a distinction between regression discontinuity designs (RDD) and RDiT designs, and provide suggested robustness checks for the RDiT approach.

To conduct the placebo test, I estimate the main fixed effects model, Equation 13, using the 2014 harvest season. Because the grower does not increase the minimum wage in 2014, the coefficient on the post indicator gives a placebo minimum wage effect, i.e. effects from unobserved productivity shocks that are not captured by controls. Placebo coefficients equal to zero would provide suggestive evidence that the estimated productivity effects in the 2013 and 2015 seasons are not the result of the timing of the minimum wage increases.

The ideal counterfactual would have productivity trends identical to the 2013 and 2015 seasons leading up to the minimum wage increases. This is not the case, but as shown in Figure 6, trends are similar. Figure 6 shows smoothed polynomials of daily worker productivities in the 2013, 2014, and 2015 seasons. The vertical lines denote the timing of the 2013 and 2015 minimum wage increases.

Figure 6 shows that leading up to the 2013 minimum wage increase, productivity trends in the placebo year are similar to trends in 2013. In both seasons, productivity decreases sharply leading up to the timing of the change. In the placebo year, there is no significant change in productivity immediately before and after the change. This provides a clear comparison to the discontinuity in the 2013 season. Around the time of the 2015 minimum wage increase, productivity levels in 2014 are similar to that in 2015, but the pre-change trends differ. While average productivity in 2015 stagnates leading up the the change, 2014 productivity is falling. Following the 2015 minimum wage change, there is no clear discontinuity in productivity in the placebo season.

Results in Table 6 show that there is no significant change in average productivity for either placebo minimum wage increase. In a model that only includes time trends, I find that productivity does not change significantly in the post 2013 increase period, and decreases significantly in the post 2015 increase period. After including all controls and worker-specific fixed effects, coefficients for both post indicators are precise estimates of no effect. This suggests that the time splines, fixed effects, and covariates explain most of the differences between worker productivities prior to and following the placebo increases. These results provide some evidence that the productivity decreases found in 2013 and 2015 are not driven by seasonal variation or unobserved shocks.

Table 6: 2014 Placebo Results

Outcome variable:	2013 Placebo Change		2015 Placebo Change	
log(flats/hour)	Time Splines	All Controls + FE	Time Splines	All Controls + FE
Post	-0.0137	-0.0038	-0.0482***	-0.0104
	(0.00844)	(0.00723)	(0.00872)	(0.00737)
log(piece rate)		1.640***		1.541***
		(0.1060)		(0.0842)
R^2	0.461	0.553	0.464	0.546
N	30,228	30,228	37,916	37,916
Time splines	yes	yes	yes	yes
All Controls	no	yes	no	yes
Individual FE	no	yes	no	yes

Standard errors in parentheses, clustered at worker

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

As additional evidence that these productivity decreases are not driven by seasonal variation, I now turn to the RDiT design. A benefit to this approach is that the seasonal trends in harvest conditions are less prominent over short time spans. Thus estimating the effect of a minimum wage increase over a small window removes bias from large changes in harvest conditions. A drawback to this approach is that the small window removes variation in the piece rate wage. For the 2015 season, this challenges identification of productivity effects because the minimum wage and piece rate are increased simultaneously. Finally, results from this approach should be interpreted differently than results from the main analysis. Theory suggests that productivity effects will persist for the remainder of the season and can even be magnified by the falling harvest abundance. The RDiT approach will not capture productivity changes that occur later in the season. Results should be interpreted as short-run effects from the minimum wage increases.

Table 7: RDiT Summary Statistics

	2013			2015		
	Pre-change	Post-change	Difference	Pre-change	Post-change	Difference
# Pickers	488	488	–	616	616	–
# Picking days	12	12	–	12	12	–
# Picker-day obs	2,206	1,740	466	4,871	4,154	717
Average picking hours	6.18	7.03	0.85***	8.00	8.25	0.25***
	(1.03)	(1.06)	(0.03)	(1.50)	(1.45)	(0.03)
Average productivity	7.54	6.08	−1.46***	5.12	4.69	−0.43***
	(1.86)	(1.85)	(0.06)	(2.35)	(2.60)	(0.05)
% Receiving min wage	8.39	34.94	26.55***	65.41	66.47	1.06***
	(0.27)	(0.48)	(0.01)	(0.48)	(0.47)	(0.01)
Average hourly earnings	13.29	11.27	−2.02***	11.12	11.76	0.64***
	(3.09)	(2.54)	(0.09)	(2.61)	(3.55)	(0.18)
Average daily earnings	82.35	79.54	−2.81***	88.69	95.44	6.75***
	(23.81)	(22.93)	(0.751)	(25.38)	(26.69)	(0.55)
Daily high temperature	68.74	69.21	0.47	75.03	79.04	4.01
	(4.02)	(4.96)	(1.84)	(2.81)	(6.85)	(2.14)
Daily low temperature	49.09	49.60	0.51	57.15	56.51	−1.00
	(3.59)	(3.07)	(1.36)	(2.27)	(3.09)	(1.107)
Minimum Wage Increase (%)		2.84			2.56	

Standard deviations in parentheses. Differences are post-change minus pre-change means, standard errors and significance come from a two sample t-test, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The sample is restricted to pickers who work at least one day in the pre-change period and at least one day in the post-change period.

To employ the RDiT design, I narrow the window of focus to the two weeks before and after each of the minimum wage increases. Pickers work 6 days each week, making this a 24 day window that includes 12 picking days on either side of the minimum wage increases. Considering productivity over this small window substantially reduces effects from harvest conditions. Table 7 shows summary statistics for the pre and post change periods over the 24 day windows in 2013 and 2015. In both years, pickers work significantly more hours, are significantly less productive, and are more likely to earn the minimum wage in the post-change period, compared with the pre. In 2013, average hourly and daily earnings are lower after the minimum wage increase, while in 2015, earnings are higher in the post-change period. Following the 2013 minimum wage increase, productivity decreases by almost 20 percent and the proportion of workers earning the minimum wage increases by 26 percent. Following the 2015 minimum wage and piece rate increase, the changes are much smaller. Productivity decreases by eight percent, and the proportion of workers earning the minimum wage increases by one percent. Another notable difference between the two years is in the change in hourly and daily earnings. In 2013, both of these are lower in the post-increase period because of the large decrease in productivities. In 2015, both of these increase despite the fall in productivity, implying that the piece rate and minimum wage increase compensated workers for the fall in productivity.

Figures 7 and 8 show linear trends and daily averages of worker productivity over this window. Figure 7 shows that, in 2013, average productivity is fairly stable in the two weeks prior to the minimum wage increase, decreases immediately following the increase, and continues to decline over the subsequent two weeks. Productivity trends around the 2015 minimum wage and piece rate increase differ. Figure 8 shows that average productivity is increasing leading up to the 2015 change, does not change significantly immediately after the change, and decreases for the remaining two week period.

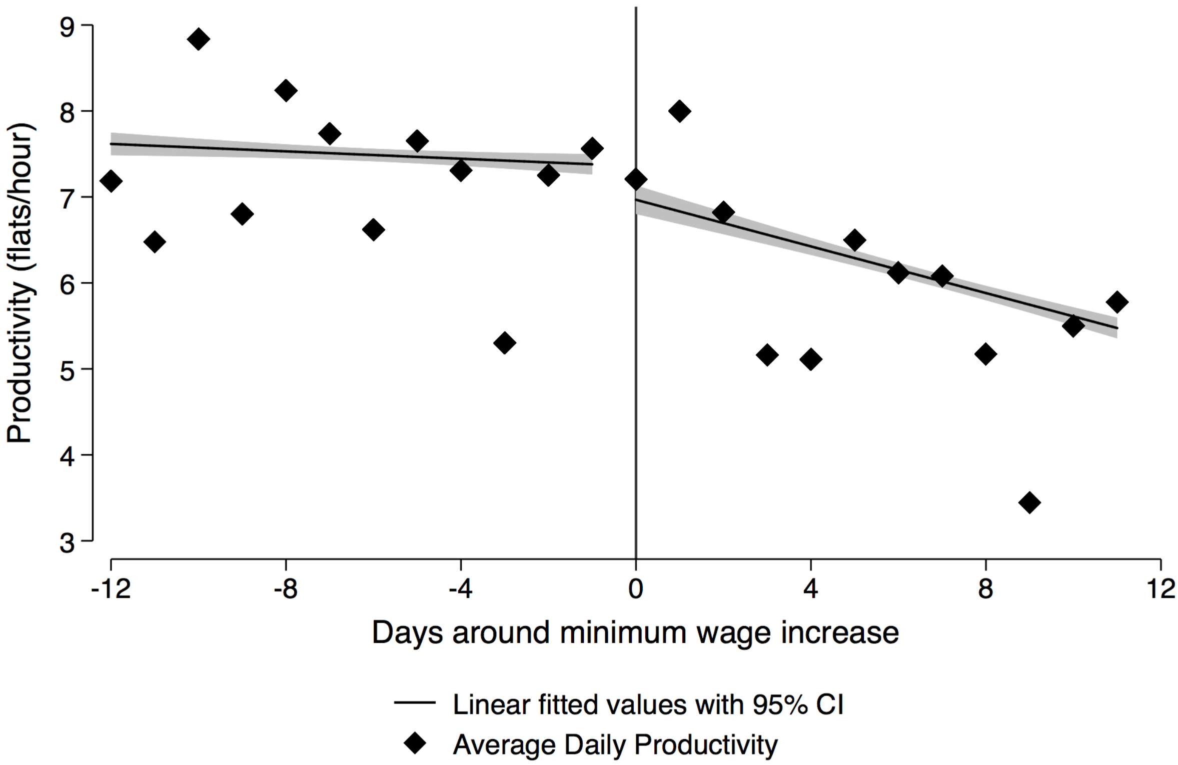
The RDiT estimating equation can be written:

$$y_{it} = \alpha_i + \mu_1 \text{Post}_t + \mu_2[\text{Post}_t \cdot (t_t - t_0)] + \beta_1(t_t - t_0) + \beta_2 w_t^h + \lambda_c + \lambda_d + \lambda_f + \epsilon_{it}. \quad (15)$$

Where $(t_t - t_0)$ is the time trend relative to the minimum wage increase, i.e. the implementation of the new minimum wage occurs at t_0. w_t^h is the daily high temperature, and λ_c, λ_d, and λ_f are crew, day of week, and field fixed effects, respectively. For this small window I omit cumulative worker experience, because it changes little over the window, and daily low temperatures, because they are highly correlated with daily high temperatures. As is common in RDiT approaches, I include day of week fixed effects so that worker productivities are compared before and after the increases, on the same working day, i.e. productivity on the two Mondays prior to the increase are compared with productivity on the two Mondays after.

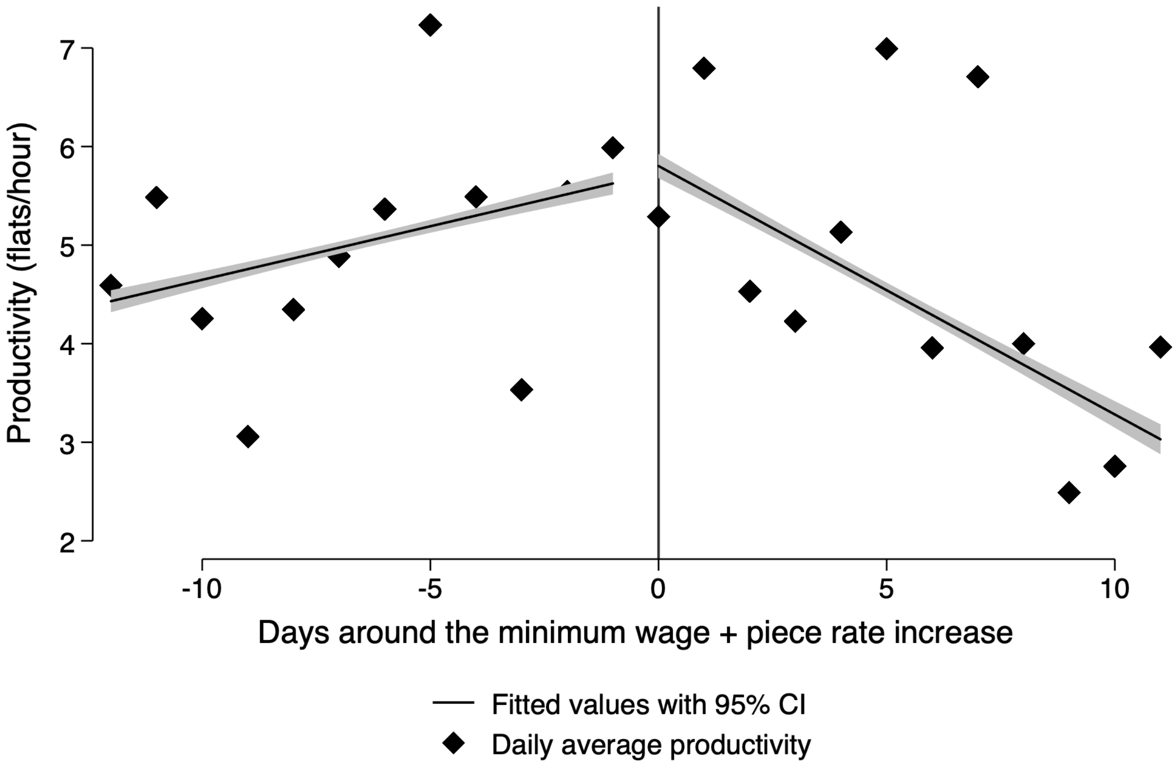
Table 8 shows results from this specification. These indicate that the short-run effects of the minimum wage increase are negative and significant in both 2013 and 2015. Columns

Figure 7: Worker Productivities Around the 2013 Minimum Wage Increase



(1), (2), and (3) of Table 8 shows results for the 2013 minimum wage increase, and columns (4), (5), and (6) show results for 2015. Columns (1) and (4) show results from a model that includes all controls and a linear time trend, columns (2) and (5) show results after adding the post minimum wage indicator, and columns (3) and (6) are the preferred specifications, which include a linear time trend, the post indicator, and the post-trend interaction term. The shift in productivity immediately following the minimum wage increase is represented by the coefficient on the Post indicator. In 2013, this coefficient ranges from -0.072 in column (2), to -0.035 in the preferred specification, shown in column (3). This indicates that the average worker reduces productivity by four percent immediately following the 2013 minimum wage increase. In 2015, this coefficient is -0.02 in both models and is significant at the five percent level. This suggests that workers decrease productivity immediately after the 2015 minimum wage and piece rate increase, but the change is smaller than in 2013.

Figure 8: Worker Productivities Around the 2015 Minimum Wage Increase



The coefficient on the Post indicator interacted with the time trend gives the change in the linear trend in productivity following the minimum wage increase. In 2013, this coefficient is negative and significant (-0.016). This means that the average worker continues to decrease productivity by one to two percent each day following the minimum wage increase. In 2015, this coefficient is negative, significant, and larger in magnitude than in 2013 (-0.035). This means that the average worker continues to decrease productivity by three to four percent each day following the minimum wage and piece rate increase.

Because these minimum wage increases occur in different seasons and at different points during the season, interpretation of the productivity effects in percentages differs in levels. Around the 2013 minimum wage increase average productivity is almost seven flats per hour, whereas in 2015 it is roughly five flats per hour. In 2013, this implies that the immediate effect of the minimum wage increase is the average worker picking one less flat every four hours, i.e. a decrease of 0.25 flats per hour. The time trend indicates that each day after the 2013 minimum wage increase, workers continue to slow down by about 0.10 flats per hour. In 2015, the effect is an immediate decrease of 0.10 flats per hour and a subsequent decrease of 0.20 flats per hour each day following the change. In the 2013 season, the RDiT results show that workers respond immediately to the minimum wage increase. This suggests that the main results are driven by more than seasonal harvest trends. The results for the 2015 season are less clear, but still show evidence of short-run decreases in productivity. These short-run effects support the main analysis and show that even in a narrowed window, worker productivities are significantly different after the changes in compensation policies.

Table 8: Regression Discontinuity in Time Design, 4 Week Window

Outcome variable:	2013 RDiT			2015 RDiT		
log(flats/hour)	(1)	(2)	(3)	(4)	(5)	(6)
Trend	-0.0143***	-0.0101***	-0.0045***	-0.0061***	-0.0046***	0.0093***
	(0.0004)	(0.0007)	(0.0011)	(0.0006)	(0.0010)	(0.0013)
Post		-0.0724***	-0.0347***		-0.0210*	-0.0232*
		(0.0102)	(0.0092)		(0.0096)	(0.0093)
Post*Trend			-0.0158***			-0.0348***
			(0.0018)			(0.0016)
R^2	0.489	0.498	0.517	0.521	0.521	0.551
N	3,946	3,946	3,946	9,025	9,025	9,025
Time trend	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Worker FE	yes	yes	yes	yes	yes	yes

Standard errors in parentheses, clustered at worker

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

8 Discussion and Conclusion

This paper presents the first empirical evidence that increases in the minimum wage can cause workers to decrease productivity. This finding is specific to a compensation policy where workers are paid piece rate with a floor on earnings. Here I study the productivity of strawberry harvesters who are paid per flat delivered, subject to an hourly minimum wage. This empirical example is in an almost ideal setting for studying the incentive effects of this compensation policy. Productivity is easily observed, workers are not fired for earning the minimum wage, and there is no technology to mediate effects from a worker's ability or chosen effort.

Piece rate payments are the norm for many jobs in U.S. agriculture and, as a low-wage industry, the earnings floor is often set at the state minimum wage. My results have direct policy implications for U.S. agricultural employers. and bear similar importance in other low-wage industries where this payment scheme is common — e.g. construction and automotive services. There are also many jobs in high-wage industries where this type of contract is the norm, e.g. insurance agents, real estate agents, and car salespeople. For these workers, my findings have implications for optimal raise structures. Namely, when employers in these industries raise the hourly floor without a contemporaneous increase in the piece rate, they may see decreases in workforce productivity.

In this paper, I use a theoretical model to show how, under this compensation policy, increases in the minimum wage can affect productivity. In particular, I show that for some workers the wage floor removes the incentives provided by the piece rate and creates the opportunity to shirk, i.e. to reduce effort a lot in exchange for a little decrease in pay. In the empirical application, I find evidence that supports the theory. My analysis follows the productivity of workers over two separate harvest seasons during which the employer raises the minimum wage and the piece rate. I show that in both seasons, minimum wage increases cause workers to slow down and piece rate increases cause workers to speed up. Both changes in the minimum wage are roughly three percent increases and cause the average worker to decrease productivity by seven percent. The piece rate is increased several times in both seasons, allowing for estimation of a piece rate-productivity elasticity. I estimate elasticities that range from 1.2 to 1.6. These suggest that a four to six percent increase in the piece rate would offset the productivity losses from the observed minimum wage increases. I replicate this analysis over a season with no changes in the minimum wage and find precise estimates of no effect from placebo increases and similar estimates of the piece rate-productivity elasticity (1.5 to 1.6).

I explore heterogeneity in responses to the minimum wage increases by grouping workers based on relative productivity levels. I find that the most responsive workers are in the center of the the productivity distribution and the least responsive are at the bottom. Following the minimum wage increase, workers in the center of the distribution decrease productivity by ten to eleven percent, while workers at the bottom do not change productivity significantly. Theory predicts that both low and high ability workers do not change productivity in response to the minimum wage increase. My results are only partially consistent with this prediction. While I find evidence that low ability workers do not adjust productivity following the minimum wage increase, both medium and high ability workers in my sample significantly decrease productivity. This is likely because empirically estimated worker abilities are an imperfect map to abilities defined in theory.

Finally, I use two approaches to explore the robustness of the main results. I use a placebo test to show that the productivity effects are not driven by the timing of the minimum wage increases, and I use a regression discontinuity in time design to show that effects are not driven by seasonal harvest trends. Results from the placebo test show precise estimates of no effect from placebo minimum wage increases in a season with similar harvest trends, but no change in the minimum wage. In the RDiT, I compare worker productivities in the two weeks before and after the minimum wage increases. Results show that workers immediately decrease productivity by two to four percent and continue to decrease productivity by one to three percent each day. Results from these robustness checks support the main results and suggest that the estimated effects are unlikely to be driven by either the timing of the minimum wage increases or seasonal harvest trends.

The average effects estimated in this paper are in line with previous estimates of the productivity effects of a switch from hourly to piece rate pay. This literature provides estimates of productivity gains from incentive pay that range between 8 to 60 percent. The productivity decreases I document reflect a temporary switch from piece rate to hourly pay that only affects a subset of the workforce on some working days. Because of this, my estimates should (and do) fall below or at the lower end of this range. My results add to the empirical evidence that piece rate wages encourage higher productivity than hourly wages. Further, my results demonstrate how an hourly wage floor can remove some of the incentives provided by the piece rate. While prior work has important implications for employers choosing between hourly and piece rate compensation policies, my findings are most important for employers who choose to pay by the piece and are legally bound to pay at least the state minimum wage. My results suggest that rising state minimum wages may result in productivity losses in industries where this contract structure is common.

I find evidence that employers can offset these losses by raising the piece rate. Estimates indicate that a four to six percent increase in the piece rate would offset the productivity losses from the examined increases in the wage floor. Though outside the scope of this paper, there are other strategies for mitigating these productivity losses. For example, employers may consider alternative contract structures or adopting new technologies that enhance productivity. Piece rate pay has well documented productivity gains compared with hourly pay, but alternative contract structures, such as hourly wages with daily, weekly, or seasonal bonuses, provide comparable incentives. Another potential strategy comes from technological innovation. The productivity decreases I find are an effect of piece rates and productivities that are low enough so that the minimum wage is desirable for some workers. Employer practices that increase productivity by lowering worker disutility from exerting effort are clear options for mitigating these effects. Technological innovations, such as picking assist for strawberry harvesters, are one way employers can do this. Future research can build on this by examining the economic viability of alternative compensation policies and mechanization for reducing the productivity effects from minimum wage increases.

In the next few years, the California minimum wage is scheduled to increase incrementally until reaching $15 per hour, a 40 percent increase from current levels. My results suggest that the farmer I study will need to increase the piece rate by 50 to 80 percent to prevent productivity losses from these minimum wage increases. Though my results are unlikely to translate linearly to large, statewide policy changes, these predictions are not unreasonable. Based on the productivity and piece rate in the 2015 season, the piece rate would need to increase by 20 percent for the average worker to earn $15 per hour. These piece rate increases can prevent productivity losses, but will substantially raise the marginal cost of producing strawberries. This farmer, and many other employers in low-wage industries who pay by the piece, face substantial increases in payroll costs from rising state minimum wages.

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