Temperature, Wages, and Agricultural Labor Productivity*

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Abstract

Agricultural laborers frequently work for piece rate wages – where they are paid per unit of output rather than per unit of time – based on the assumption that these wages incentivize productivity. In this paper, I exploit quasi-experimental variation to estimate the elasticity of labor productivity with respect to piece rate wages by analyzing a high-frequency panel of over 2,000 blueberry pickers on two California farms over three years. To account for endogeneity in the piece rate wage, I use the market price for blueberries as an instrumental variable. I find that picker productivity is very inelastic on average, and I can reject even modest elasticities of up to 0.7. However, this average masks important heterogeneity across outdoor working conditions. Specifically, at temperatures below 60°F, I find that higher piece rate wages *do* induce increases in labor productivity. This is suggestive evidence consistent with a model where at moderate to hot temperatures, workers face binding physiological constraints that prevent them from exerting additional effort in response to higher wages. This insight has important implications for understanding how climate change will affect the agricultural labor sector. (JEL codes: J24, J31, J43, Q12, Q54)

Keywords: Labor productivity, piece rate wages, climate change, agriculture

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1 Introduction

A canonical prediction of economic theory is that high wages increase labor productivity. In settings where workers are salaried or paid by the hour, this is the concept of efficiency wages (Akerlof and Yellen, 1986). In settings where workers are paid in proportion to their output (e.g. under piece rate wages), the theoretical connection between wages and productivity is even clearer.[1] However, it has proven difficult to empirically estimate the responsiveness of labor productivity to piece rate wages, since much of these wages' variation is driven by endogenous characteristics of the production process. In this paper, I provide the first quasi-experimental estimate of the elasticity of labor productivity with respect to piece rate wages. Specifically, I analyze a high-frequency panel of worker-level production data from over 2,000 California blueberry pickers paid by piece rates. Surprisingly, I find that on average, labor productivity is very inelastic with respect to wages.

Piece rate wages are interesting to study because they offer such a direct, clear, and salient link between a worker's effort and reward. In general, optimal labor contracts can be quite complex, as they must effectively incentivize worker effort while simultaneously accounting for issues like risk aversion, asymmetric information, and moral hazard (Hart and Holmström, 1987). However, these complications are less of a concern in settings where a firm can cheaply monitor both worker productivity and product quality. In such cases, theory suggests piece rate wages will outperform other common incentive schemes (Brown, 1990; Prendergast, 1999).[2] Understanding how workers respond to changes in a piece rate wage is important in sectors where these wages can vary over time, like in specialty agriculture, the auto repair industry, or the growing rideshare market (e.g. Uber and Lyft).[3]

Econometricians face a fundamental challenge when trying to estimate the causal effect of piece rate wages on labor productivity: these wages are inherently endogenous. As an example, consider blueberry picking. When ripe berries are scarce and spread out (at the beginning of the season), average worker productivity is low. When ripe berries are abundant and dense (at the peak of the season), it is easier for workers to pick berries quickly, and average productivity is markedly higher. Because farmers aim to keep their workers' average effective hourly pay relatively stable over time, they set piece rate wages higher when picking is more difficult, and lower when picking is easier.

[1] Piece rate wage schemes create "the clearest link between a worker's effort and the reward" (Billikopf, 2008). Specifically, a higher piece rate raises the marginal benefit of worker effort and therefore incentivizes workers to work harder.

[2] Empirical studies have confirmed that, under appropriate institutional circumstances, workers are indeed more productive under piece rate wages than under hourly wages (Lazear, 2000; Shearer, 2004; Shi, 2010; Billikopf and Norton, 1992).

[3] For recent analyses of the rideshare market, see Chen and Sheldon (2015) and Sheldon (2016).

In order to account for piece rates wages' endogeneity, I adopt a two-pronged identification strategy. First, exploiting the richness of my multidimensional panel data, I econometrically control for environmental factors like seasonality and temperature that directly affect the berry picking production function. Second, I use the market price for blueberries as an instrument for piece rate wages. This price is a valid instrument because it affects a farmer's willingness to raise piece rates (since it alters the value of workers' output), but is otherwise uncorrelated with picker productivity. Furthermore, the market price for California blueberries is set by global demand and global supply. As a result, individual farms are too small to directly affect the market price, and supply shocks at the farm level can be considered orthogonal to aggregate supply shocks.

I find that, on average, labor productivity is very inelastic with respect to piece rate wages, and I can reject even modest elasticities of up to 0.7. This finding contrasts with both canonical economic theory and previous structural estimates: relying on a calibrated structural model of worker effort, Paarsch and Shearer (1999) estimate a labor effort elasticity of 2.14 in the British Columbia tree-planting industry, and Haley (2003) estimates a labor effort elasticity of 1.51 in the U.S. midwest logging industry. Why, then, do blueberry pickers not seem to respond to changes in their wage? One explanation of my findings could be that blueberry pickers respond to average effective hourly wages rather than marginal piece rate wages, similar to how electricity consumers respond to average prices rather than marginal prices (Ito, 2014). This is unlikely, both because piece rate wages are highly salient in the context I study, and because my identification strategy specifically isolates marginal effects from average effects. Instead, I find suggestive evidence that blueberry pickers face some binding constraint on physical effort that is related to temperature.

Specifically, I find that at moderate to hot temperatures, I cannot reject that the piece rate wage level has no effect on labor productivity. However, at temperatures below 60 degrees Fahrenheit (15.6 degrees Celsius), a one cent per pound increase in the piece rate wage increases worker productivity by nearly 0.3 pounds per hour, implying a positive and statistically significant productivity elasticity of approximately 1.6. In other words, blueberry pickers respond to the piece rate wage level at cool temperatures, but seem not to respond to changes in their wage at higher temperatures.

Temperature also affects productivity *directly* in economically meaningful ways. Specifically, I find that blueberry pickers' productivity drops precipitously at very hot temperatures: workers are 12% less productive at temperatures above 100 degrees Fahrenheit (37.8 degrees Celsius) than they are at temperatures between 80 and 85 degrees Fahrenheit (26.7 and 29.4 degrees Celsius). However, I also find negative effects at cool temperatures. Workers are nearly 17% less productive at temperatures below 60 degrees Fahrenheit (15.6 degrees Celsius) than at temperatures in the low eighties. The most likely explanation of this finding is that berry pickers lose finger dexterity at cool temperatures and find it uncomfortable to maintain high levels of productivity. This hypothesis is supported by evidence from the ergonomics literature (Enander and Hygge, 1990), and highlights that temperature's effects on labor productivity depend on the particularities of the relevant production process.

To demonstrate the robustness of my findings, I address several threats to my identification strategy. First, I investigate berry pickers' labor supply on both the intensive (hours worked in a day) and extensive (probability of showing up to work) margins. I show that neither temperature nor wages have a statistically significant effect on these measures. Next, I address the fact that there exists a minimum hourly wage rule in the setting I study. This constraint binds for approximately 15.8% of my observations, raising concerns that workers falling below this threshold have an incentive to shirk or "slack off." I re-estimate my results using only those observations where workers earn more than the minimum wage and see no qualitative change in my findings. Finally, I confront the possibility of adverse selection in my sample by limiting my sample to only the observations from workers who work more than thirty days in a single season.

My results highlight the importance of environmental conditions in outdoor industries. Previous studies have shown, and I confirm, that temperature affects labor productivity directly.[4] However, I am the first to demonstrate that temperature also affects labor productivity indirectly by disrupting the economic relationship between wages and worker effort. As global temperatures rise, my findings suggest that firms in outdoor industries like agriculture and construction will have a reduced ability to effectively incentivize their employees' productivity. This can have large economic consequences. In the $76 billion U.S. specialty crop sector, for instance, harvest labor can account for more than half a farm's operating costs.[5] This is also a setting where piece rate wages are common: in California alone, over 100,000 specialty crop farm workers were paid by piece rates in 2012.[6]

My econometric estimates allow me to make several predictions about how rising temperatures will affect the agricultural labor sector. To do this, I develop a model of a firm choosing an optimal piece rate wage under some exogenous environmental condition (e.g. temperature).[7] My model produces two interesting sets of comparative statics. First, I show

[4]See, for instance, Adhvaryu et al. (2016b), Sudarshan et al. (2015), and Seppänen et al. (2006).

[5]Specialty crops are defined as "fruits and vegetables, tree nuts, dried fruits and horticulture and nursery crops, including floriculture" (United States Department of Agriculture, 2014). In 2012, US specialty crop farms sold over $76 billion of crops (National Agricultural Statistics Service, 2015). Jimenez et al. (2009) find that harvest labor accounts for over 50% of operating costs for a typical south California blueberry farm.

[6]Specialty crop farms in California employed 414,564 workers in 2012 (National Agricultural Statistics Service, 2015), and roughly one in four agricultural workers in the US west are paid piece rate wages (Moretti and Perloff, 2002).

[7]For a more general review of optimal contracts in agriculture, with special attention to transaction costs

that temperature's effect on the optimal piece rate wage depends on (1) how temperature affects labor productivity directly, and (2) how temperature affects labor productivity's responsiveness to the wage. Plugging my empirical estimates into this model, I find that an optimizing blueberry farm would pay its workers a higher piece rate wage on particularly cool days, *ceteris paribus*. Second, I show that temperature's effect on overall farm profits has the same sign as temperature's direct effect on labor productivity. In the case of California blueberry farms, where cool temperatures have meaningful negative effects on productivity, this suggests that the first-order effect of rising temperatures on profits is likely to be positive. However, in contexts where cool temperatures do not lower labor productivity, the opposite is likely to be true.

The remainder of this paper is organized as follows: in section 2, I develop a simple theoretical model of workers' optimal effort under a piece rate wage scheme. In section 3, I describe the institutional details of the two California blueberry farms I study in this paper. I then discuss my data and report summary statistics in section 4. Section 5 outlines my empirical strategy, and section 6 reports my results. I discuss my findings in section 7, giving particular attention to how rising temperatures are likely to affect the agricultural labor sector. Finally, in section 8, I conclude.

2 Theoretical Framework

In this section, I model a worker choosing to exert an optimal level of effort under a piece rate wage scheme.[8] Assuming a well-behaved production function, this framework predicts a positive elasticity of productivity with respect to the wage. I also allow worker effort to depend on exogenous characteristics of the production process, including an environmental condition (e.g. temperature). Doing so allows me to predict how changes in the environment will affect labor productivity. Later, in appendix A, I use these results to explore how rising temperatures may affect the agricultural labor sector.

2.1 A model of optimal effort under piece rate wages

Consider a setting where workers are employed to harvest some resource. Worker-level output is determined by a production function $f(e, \theta, T)$ that depends on the level of effort e expended by the worker, the abundance (or density) of the resource θ, and an environmental condition T. It is assumed that production is increasing in effort and resource abundance:

and risk, see Allen and Lueck (2002).

[8]The practice of modeling labor effort, rather than simply working hours, dates back to at least Robbins (1930).

$f_e > 0$, $f_\theta > 0$, with marginal production decreasing in e: $f_{ee} < 0$. Additionally, marginal production is assumed to be increasing across effort and resource abundance: $f_{e\theta} > 0$. Workers are paid a piece rate wage r per unit of output they produce. Workers also bear a cost of providing effort, $c(e, T)$, that is increasing in effort expended: $c_e > 0$. The marginal cost of effort is assumed to be increasing as well: $c_{ee} > 0$.

Workers therefore face the following utility maximization problem, where income enters utility linearly:

$$\max_e \quad rf - c, \tag{2.1}$$

which leads to the first-order condition:

$$rf_e - c_e = 0, \tag{2.2}$$

and the subsequent second-order condition:

$$rf_{ee} - c_{ee} < 0 \tag{2.3}$$

where the inequality follows from the assumptions on f_{ee} and c_{ee}. Equation (2.2) implicitly defines an optimal level of effort to expend as a function of the piece rate wage, resource abundance, and the environmental characteristic: $e(r, \theta, T)$. I now want to sign the following partial derivatives: e_r, e_θ, and e_T. To do so, I first note that in this case, $de/dr = e_r$, $de/d\theta = d_\theta$, and $de/dT = d_T$, since the worker takes r, θ, and T to be exogenous.

I calculate de/dr, $de/d\theta$, and de/dT by totally differentiating the first-order condition in equation (2.2) with respect to r, θ, and T respectively, and rearranging the resulting expressions. I obtain the following:

$$\frac{de}{dr} = -\frac{f_e}{rf_{ee} - c_{ee}} > 0 \tag{2.4}$$

$$\frac{de}{d\theta} = -\frac{f_{e\theta}}{f_{ee}} > 0 \tag{2.5}$$

$$\frac{de}{dT} = \frac{c_{eT} - rf_{eT}}{rf_{ee} - c_{ee}} \Longrightarrow \frac{de}{dT} < 0 \iff c_{eT} > rf_{eT}. \tag{2.6}$$

It is now clear that $e_r > 0$, $e_\theta > 0$, and that the sign of e_T depends on the nature and level of T.[9]

To determine a worker's optimized output, denoted by X, I simply plug the worker's optimal level of effort into the production function f:

$$X(r,\theta,T) \equiv f(e(r,\theta,T),\theta,T). \tag{2.7}$$

Time is not a choice variable in this model, so the function X can be interpreted as a worker's level of productivity given some piece rate wage r, resource abundance θ, and environmental condition T. I now directly derive expressions for X_r, X_θ, and X_{rr}:

$$X_r = f_e e_r > 0 \tag{2.8}$$

$$X_\theta = f_e e_\theta + f_\theta > 0 \tag{2.9}$$

$$X_{rr} = f_e e_{rr} + e_r^2 f_{ee}. \tag{2.10}$$

The signs for X_r and X_θ are immediate consequences of earlier assumptions on f and expression (2.5). The sign of X_{rr}, however, requires an additional condition. Rearranging equation (2.10) gives the following:

$$X_{rr} < 0 \iff e_{rr} < \frac{e_r^2 f_{ee}}{f_e} < 0. \tag{2.11}$$

That is, as long as marginal effort is decreasing severely enough with the piece rate wage r, laborers' marginal supply of output will also be decreasing in r. This condition is easy to swallow, since worker effort likely faces a finite psychological and/or physiological upper limit (Wyndham et al., 1965).

Figure 1 visualizes this model, holding θ and T fixed. Panel A summarizes the first-order condition in equation (2.2), where the value of marginal product of effort equals the marginal cost of effort, at three different piece rate wages (r_1, r_2, and r_3). Panel B translates the results of panel A into a relationship between piece rate wages and optimal effort. Finally, panel C shows how the production function f turns optimal effort e^* into productivity X. The

[9] A brief note is warranted about the sign of e_T. Expression (2.6) implies that if the marginal effort-cost of T is large enough relative to the marginal effort-product of T – as one could reasonably expect for "bad" environmental conditions like pollution or very hot temperatures – then optimal effort is decreasing in the environmental condition T. If we take T to represent very hot temperatures, then this condition appears to contradict the canonical finding of climate-change-adaptation models, where an increase in temperature leads to higher use of other inputs, thus mitigating the negative direct effect of temperature on output (Antle and Capalbo, 2010). Effort is different from other inputs in this case, since its cost *also* depends on temperature. In particular, as long as the numerator in expression (2.6) is positive, that is, $c_{eT} > rf_{eT}$, then optimal effort will decrease with T. One might term this phenomenon "negative adaptation."

figure is drawn such that condition (2.11) holds. The result, shown in panel C, is worker productivity X as a function of wage r.

Note that equations (2.8) and (2.10) imply that $X_r > 0$ and $X_{rr} < 0$, as long as condition (2.11) holds. That is, my model predicts that there is a positive elasticity of productivity with respect to the piece rate wage, and that this elasticity decreases as the wage increases. I focus on worker productivity X, rather than optimal effort e, because effort is fundamentally unobservable.

2.2 Previous literature on piece rate wages

There has been relatively little theoretical work done on piece rate wage schemes in the past, partly because their structure is so straightforward, and partly because they are so much less common than salaries or hourly wage schemes. Nonetheless, previous research has highlighted several important aspects of piece rate wages that are relevant to this paper. Prendergast (1999) and Brown (1990) both provide good summaries of when and where piece rates are likely to be effective. Specifically, in cases where firms can cheaply monitor productivity and ensure quality control, piece rates should correctly align workers' incentives with those of their employer, maximizing labor productivity.

Several papers have confirmed the prediction that, under the correct circumstances, piece rate wage schemes better incentivize labor productivity than do more traditional wage schemes. Lazear (2000), studying an auto glass company, finds that a switch from hourly to piece rate wages boosts output per worker by an average of 44%. Shi (2010), studying a tree-thinning company, estimates a more modest effect of 23%. Shearer (2004), studying tree-planters in British Columbia, also finds an effect near 20%. Bandiera et al. (2005) study agricultural workers in the United Kingdom and come to a similar conclusion, noting that piece rates based on individual production eliminate cross-worker externalities found in relative incentive schemes. In a non-causal study from California, Billikopf and Norton (1992) also provide evidence that piece rate wages boost vine-pruners' performance relative to hourly wages. Such increases in productivity under piece rates seem to come from increased worker effort, as Foster and Rosenzweig (1994) demonstrate by measuring workers' net calorie expenditures under different pay schemes.

None of the papers cited above, however, estimate how labor productivity responds to changes in a piece rate wage.[10] Among the most well-known papers that have attempted to do so are Paarsch and Shearer (1999) and Haley (2003). In both cases, the authors calibrate

[10] For yet another example, Dillon et al. (2014) derive a model of worker effort under piece rate wages that incorporates workers' health – as well as workers' perceptions of their health – to assess the labor productivity effects of a malaria testing policy in Nigeria. However, piece rates in their context are static.

a structural model of worker effort (motivated by Grossman and Hart (1983)) in order to address piece rates' endogeneity. They find positive elasticities of effort with respect to wages, of 2.14 and 1.51 respectively, in line with theoretical predictions (e.g. equation (2.8)).[11]

Other papers have relied on natural experiments or natural field experiments to try and recover the effect of piece rate wage levels on productivity. For instance, Treble (2003) exploits a natural experiment from the 1890s in an English coal mine to derive a near-unit-elastic productivity response. In a more recent setting, Paarsch and Shearer (2009) implement a natural field experiment with tree-planters in British Columbia and estimate a productivity elasticity of 0.39. While the authors note that this estimate is "substantially smaller" than that of Paarsch and Shearer (1999) and Haley (2003), it is unclear wether they think this result invalidates the earlier estimates.[12]

Despite the theoretical simplicity of a piece rate wage scheme, it is not immune to employees' behavioral responses. Even though a firm may be able to set a different piece rate every day, doing so may foment unrest among employees if the changes are seen as arbitrary (Billikopf, 2008). In other situations, high piece rates may operate as efficiency wages – à la Yellen (1984), Shapiro and Stiglitz (1984), and Newbery and Stiglitz (1987) – especially if a firm is trying to retain high-quality workers (Moretti and Perloff, 2002). An additional consideration is that variable piece rate wages may lead to a less reliable supply of labor on the intensive margin. In other words, piece rate employees may work fewer or more hours depending on the day's wage. Such behavior would be consistent with a reference-dependent preference model like that of Kőszegi and Rabin (2006) where workers have some internal reference point for how much money they intend to earn in a particular day.[13]

Finally, piece rate wages are much more common in seasonal specialty agriculture than in many other industries or settings. Tasks such as picking, pruning, or planting can be easily measured and tracked, making piece rates feasible. In these cases, productive workers

[11]Paarsch and Shearer (1999) argue that knowing this elasticity is important for firms, since the optimal (profit-maximizing) piece rate wage is increasing in this elasticity, as shown by (Stiglitz, 1975).

[12]The authors write both: "Given [our] identification results, this suggests that the values of $\bar{u}$ used by Paarsch and Shearer as well as Haley to identify γ were too low" (Paarsch and Shearer, 2009, p. 487), and "[O]ur results... [are] consistent with previous results obtained by Paarsch and Shearer (1999) as well as Haley (2003)" (Paarsch and Shearer, 2009, p. 493).

[13]Chang and Gross (2014) find evidence this sort of behavior in their study of pear packers. In particular, they observe that workers provide different amounts of effort when being paid overtime wages, and that this effect varies with whether overtime pay is expected or unexpected. They also find different effects for differently-skilled workers. Chang and Gross' research builds upon several studies that analyze workers who are free to set their own hours. The most well-known papers in this literature focus on New York City taxicab drivers (Camerer et al., 1997; Farber, 2005, 2008; Crawford and Meng, 2011), but other papers also explore stadium vendors (Oettinger, 1999), bicycle messengers (Fehr and Götte, 2007), and fishermen (Giné et al., 2010). Specialty agriculture may differ from these contexts in important ways, however. For instance, Billikopf (1995) finds that few agricultural workers in California reduce their work hours when paid according to piece rate wages.

can earn considerably higher incomes under a piece rate scheme than under an hourly wage scheme: Moretti and Perloff (2002) find that US agricultural workers paid by piece rate earn 26% more than their hourly counterparts. This number is slightly misleading, and certainly not causal, considering that workers select into particular work in part based on the compensation scheme. Rubin and Perloff (1993) note that piece rate workers tend to be disproportionately young or old: "[a]pparently, prime-age workers find that higher earnings in piece-rate jobs do not compensate for the difficulty of more intensive effort, more variable incomes, and possible greater injury risk or shortened farm-work career" (p. 1042). However, these selection issues are irrelevant if the goal is to understand how piece rates affect the productivity of workers who select into such work in the first place.

3 Context: California Blueberries

California is the fifth largest blueberry producer in the United States after Washington, Oregon, Georgia, and Michigan; the state grew over 31,000 tons of the fruit in 2015 alone (National Agricultural Statistics Service, 2016). Blueberries' popularity among California's specialty crop farmers is relatively new, and the California Blueberry Commission (CBC) was not established under the state's Food and Agricultural Code until 2010. I study two blueberry farms: an organic farm in San Diego County, and a conventional farm near Bakersfield. In order to protect the farms' identities, I cannot share their exact locations. However, figure 2 maps the approximate location of each farm within the state.

Harvesting fresh blueberries is a labor intensive process. Berries grow in small bunches and ripen at differing times. This means that a single blueberry bush can be harvested multiple times each season. However, since each berry-bunch contains both ripe and unripe berries, pickers must harvest fruit carefully by hand. Mechanized blueberry harvesters exist, but they are imprecise and are used primarily for harvesting berries destined for the processing (secondary) market.[14]

Berry-pickers collect fruit in small buckets fastened on the front of their bodies. Once the buckets are full, the workers carry their harvest to a weigh-station at the end of a field row. Workers pour their berries into standardized bins which are then weighed, packed into trucks, and driven to a refrigerated packing plant. Because blueberries are delicate and perishable, they must be refrigerated quickly after being picked. When workers bring their

[14] Gallardo and Zilberman (2016) conclude that in order for the current incarnation of mechanical blueberry harvesters to be profitable for fresh market producers, (1) the price gap between fresh market blueberries and processing market blueberries would have to shrink considerably, (2) labor wages would have to rise more than 60%, or (3) yield losses from mechanical harvesting would have to fall by over 60%. None of these changes are likely in the near future.

berries to be weighed, a foreman closely watches the process to ensure quality control. If a picker's fruit is intermingled with too many twigs, leaves, or unripe berries, the foreman will warn the picker that their quality must improve to keep their job.

The farms I study both utilize an automated system to track workers' productivity and calculate payroll.[15] Each picker is given a unique barcode that they wear as a badge, and each fruit tray is assigned its own barcode as well. When a picker brings their fruit to be weighed, the weigher scans both the picker's barcode and the tray's barcode to record the tray weight. The picker then receives a receipt of their weigh-in. The farmer likes the barcode system because it is quick, automatic, reliable, provides real-time data, and replaces a cumbersome paper-and-pencil system. Pickers like the barcode system because they are able to witness the fruit-weighing and are thus confident that the farmer is paying them honestly for the fruit they pick.

At the beginning of each work day, around 6:00 or 6:30 a.m., the farmer sets the day's piece rate wage and posts the wage in a public spot for all workers to see.[16] Workers are paid the piece rate for each pound of berries they harvest, and the rate does not change throughout the day. The piece rate does, however, change over the course of the season (mid-April to mid-June each year). As fruit becomes more abundant on the bushes through May and June, picker productivity rises. Farmers therefore generally lower the piece rate wage throughout the season as more and more berries ripen. Anecdotally, farmers say they lower their piece rates "when there's a lot of fruit in the field" with the goal of maintaining a relatively stable effective hourly wage for the average berry picker.[17]

If any one worker picks a small enough quantity of fruit that their effective hourly wage for the day falls below the legal minimum wage, the farmer pays them according to the

[15] PickTrace, Inc. (`http://www.picktrace.com/`)

[16] Blueberries cannot be picked when it is raining, or if it has recently rained, since moisture on the berries disrupts the packaging process. Workers will not even bother to show up at the farm if it is raining in the morning.

[17] As long as a farm's average effective hourly wage is somewhat competitive in the agricultural day-labor market, the farm has monopsony power to set its own particular piece rate wage. That is, the piece rate wage is not set directly by the labor market. Fisher and Knutson (2013) highlight the fact that US agricultural labor markets are fundamentally more localized and heterogeneous than many may think. Whether or not a farm faces a labor shortage depends on local labor market conditions and seasonality rather than on aggregate state or national statistics. Indeed, Fan et al. (2015) note that fewer agricultural laborers are migrants now than at any time in the recent past, meaning local labor conditions can vary significantly across space. In Kern and San Diego counties, where the farms I study are located, the blueberry season (mid-April through mid-June) competes with relatively few other crop harvest seasons (Kern County Department of Agriculture and Measurement Standards, 2016; San Diego Farm Bureau, 2016). Additionally, harvesting conditions on blueberry farms (where pickers spend the day standing upright) are less onerous than on strawberry farms, meaning a blueberry farmer can attract and maintain workers for lower wages than competing strawberry farms (Guthman, forthcoming). Finally, if farmers' concerns primarily relate to worker retention, Gabbard and Perloff (1997) suggest there is a higher return to extra money spent on benefits or improved working conditions than relative wages.

hourly minimum wage. In these cases, the farmer often then gives the picker in question additional training and a warning that they may be fired if they do not quickly improve. Anecdotally, the hourly minimum wage is most likely to bind during a new employee's first few days on the job as they develop their skills as a fruit picker. If a worker consistently falls below the minimum wage cutoff, they frequently quit on their own accord or are effectively fired and asked not to return the next day.

Because blueberries are delicate and highly perishable, they are not bought and sold in a central commodity market. Instead, individual producers set short-term contracts with different marketers or buyers to provide a certain quantity of berries in particular packaging at a particular time. These contracts are set on a near-daily basis, and prices can change quickly throughout the season. While there is certainly some quality differentiation within the blueberry market, buyers and marketers view different producers as close substitutes. This means that individual producers have relatively little, if any, market power. I thus take California blueberry contract prices as an accurate reflection of a competitive market price for blueberries in the state.

Blueberry prices in California are highly seasonal: prices are quite high at the beginning of the season in April, and much lower near the end of the season in June. This seasonality in price is largely explained by (1) variation in aggregate production throughout California, and (2) variation in the availability of blueberries from other global producers. In the early spring, the United States imports fresh blueberries at high prices from Mexico or other countries since domestic production is agronomically infeasible. By mid-to-late-June, farms in northern states such as Washington, Oregon, and Michigan begin to produce berries in large quantities, driving down the market price. California blueberry farmers therefore face a relatively short season when it is profitable to harvest and sell their fruit. While blueberry bushes continue to yield berries through June and into July, labor costs are too high relative to market prices at that time for California farmers to justify continued production. To summarize, the California blueberry season begins agronomically, but ends economically.

Organic blueberries regularly command a price premium of around two dollars per pound. While the harvesting process is identical for conventional and organic berries, organic bushes produce fewer berries per bunch. Thus, pickers of organic berries spend more time finding and harvesting berries than do their conventional counterparts. Additionally, fruit quality is more variable in organic blueberries. This leads to a smaller proportion of berries ultimately reaching market.

4 Data Sources and Description

I utilize data from three distinct sources: employee-level production and payroll figures, high-frequency temperature readings, and state-level market prices. I observe over 2,000 fruit pickers on 170 days over three growing seasons at two farms for a total of over 300,000 unique fruit weigh-ins.

4.1 Employee-level production figures

As described in the previous section, the farms I study use a digital fruit weigh-in system to track worker productivity and generate payroll data. I utilize data from these weigh-ins to conduct my analyses. In particular, I observe the weigh-in time, the berry picker's unique employee identifier, the field where the berries were picked, and the weight of the picker's harvest. I divide the harvest's weight by the time elapsed since the picker's previous weigh-in to obtain a weight-per-hour measure of worker productivity. For the first weigh-in of the day, I use time elapsed since morning check-in to calculate this measure.

As reported in table 1, average productivity pooled across both farms is just over nineteen pounds picked per hour. This number, however, masks significant heterogeneity across farm, day, and worker. At the San Diego farm, which grows organic berries, average productivity is slightly under fourteen pounds per hour, while at the Bakersfield farm, which grows conventional berries, average productivity is over twenty-two pounds per hour. Figure 3 plots the distribution of workers' average productivities, while figure 4 plots the distribution of each day's average productivity, in both cases separated by farm. These two figures highlight substantial variation in picker skill, as well as in daily productivity.

In southern California and the central valley, where the farms I study are located, temperatures peak in the mid-to-late afternoon. To avoid the hottest part of the day, most pickers begin work as early as 6:00 a.m. and end around 3:00 p.m. This pattern is reflected in figure 5: most fruit picking ends by mid-afternoon. The average picker works around eight hours each day, as shown in figure 6. Under California law in my sample period (2014–2016), agricultural workers do not earn overtime pay until after working ten hours in a single day. In my data, only the San Diego farm ever lets pickers work more than ten hours in any given day.

Farms employ pickers on a day-to-day basis, either directly or through a labor contractor.[18] Some pickers only work for a day or two, but others work continuously for several

[18] The San Diego farm (smaller, organic) hires pickers directly, while the Bakersfield farm (larger, conventional) uses a labor contractor. Previous research has suggested a farmer will use a labor contractor if they are particularly concerned about having workers when needed (Isé et al., 1996). The same authors also find suggestive evidence that larger farms are more likely to use a labor contractor.

weeks or months as shown in figure 7. A handful of pickers return to their respective farm each year. Indeed, several employees in my data work for a farm in two or all three of the years I study. Unfortunately, I do not observe each worker's initial date of hire, so I am unable to confidently measure lifetime worker tenure on either farm.

4.2 High-frequency temperature readings

I utilize high-frequency temperature data sourced from the MesoWest database maintained by the University of Utah.[19] In particular, for each year, I find the temperature monitor closest to each farm with hourly or finer temperature readings. In order to protect the identity of each farm, I cannot share the precise locations of these monitors, but they are all between 1.2 and 14.8 miles away from their respective farm. Temperature readings are available at least hourly, with some available at fifteen-minute intervals. I match temperature observations to each "picking period" – the span between two of a worker's sequential weigh-ins – using a time-weighted average of observed temperature. Figure 9 describes in detail how I calculate this time-weighted average. By using individual picking periods as my unit of observation, and matching these periods to time-weighted temperature measurements, I am able to exploit variation in temperature throughout each work day that accurately captures the heat exposure faced by outdoor laborers at different points of their shift. Figure 8 displays the distribution of time-weighted average temperatures within my data. There are few observations with extremely high temperatures, largely due to the fact that berry pickers usually end work in the mid-afternoon, before the hottest part of the day.

4.3 State-level market prices

While I know each farm's daily piece rate wage from the its payroll data, I obtain information on market prices for California blueberries from the Blueberry Marketing Research Information Center (BMRIC) of the California Blueberry Commission (CBC). As an official agricultural commission, the CBC legally requires all blueberry producers in the state to report daily production and sales figures. The CBC then publishes daily summary statistics of these data through BMRIC. Individual blueberry producers are able to access a daily BMRIC report online that summarizes the high, low, and weighted average prices received by blueberry producers throughout the state on the previous day. Separate statistics are provided for conventional and organic blueberries. In order to capture the information a farmer could have accessed on any particular day, I use each day's most recent *previous* BMRIC report as the relevant measure of market prices. Because BMRIC publishes a daily report each

[19] `http://mesowest.utah.edu/`

weekday except for holidays, the relevant market price data for harvest data collected on a Thursday is from the Wednesday prior. Similarly, the relevant market price data for harvest data collected on a Monday is from the Friday prior. Based on personal conversations, the blueberry farmers I study track these BMRIC reports quite closely throughout the season.

From April to June each year, both market prices and piece rate wages fall as the California blueberry season progresses. Figure 10 documents this relationship across the three years and two farms in my dataset. Recall that the San Diego farm grows organic blueberries while the Bakersfield farm grows conventional berries. This distinction accounts for why the two farms face differing market prices in the same year.

Market prices and piece rate wages are highly correlated over time, due in large part to seasonality in blueberry production. Figure 11 plots each farm's daily total production over time for each season. At times of high production, blueberry bushes are likely to be full of easily-pickable ripe berries. This abundance of fruit leads farmers to cut the piece rate as described in the previous section. In order to disentangle the various factors that affect farms' piece rate wages in my empirical exercises, I control both for seasonality in production as well as the field where berries are harvested.

4.4 Additional summary statistics

In my subsequent econometric analyses, I estimate the causal effects of piece rate wages and temperature on picker productivity. Figure 12, in contrast, plots the naïve relationship between average picker productivity and piece rate wages, temperature, and two other observable characteristics: time of observation and worker tenure by season. First, note that productivity and piece rate are negatively correlated, since farmers lower the piece rate when fruit is plentiful in the fields.[20] Second, note that there are no sharp decreases to average productivity at particularly high temperatures, as one may hypothesize. Finally, note that there is a clear increasing and concave relationship between worker tenure within a season and productivity. In other words, there is learning-by-doing in berry picking, and this learning has decreasing marginal returns over time.

While most employees out-earn the hourly minimum wage under the piece rate system, some fall below this threshold and are paid according to the minimum wage for the day. As Graff Zivin and Neidell (2012) note, if there is not a credible threat that these workers could be fired for their low output, they may shirk and provide less effort than they otherwise would. Figure 13 plots the distribution of normalized daily productivity that identifies those

[20] Paarsch and Shearer (1999) explain clearly why a simple covariance between piece rate wages and worker productivity would suggest a negative elasticity of effort with respect to piece rates: a firm sets piece rates endogenously in response to the difficulty of the work. In the terms of the model from section 2.1, $dr/d\theta < 0$.

picker-days where shirking could be a problem. Observations to the left of one are picker-days where the picker's effective hourly wage is below the minimum wage, and observations to the right of one are picker-days where the picker out-earns minimum wage under the piece rate scheme. A picker with a normalized productivity measure of two is earning twice the minimum wage. Productivity in this figure is normalized because both piece rate wages and the hourly minimum wage vary over the sample period.

Shirking, if it occurs, could bias my results. In particular, if high temperatures or low wages lead to more pickers earning the minimum wage, and these pickers subsequently shirk, my econometric estimates will be biased upward. I address this concern in section 6 by re-estimating my primary results using only those picker-days where employees out-earn the minimum wage. My findings do not change when I eliminate these observations, suggesting that the threat to a picker of being fired if they consistently slack off is a sufficient incentive to keep them from shirking.

5 Empirical Strategy

The model presented in section 2.1 motivates my empirical strategy. In particular, my goal is to estimate the relationship between piece rate wages and labor productivity (X_r). The primary challenges to this undertaking are twofold. First, many observable and unobservable factors contribute to worker productivity which – if unaccounted for – could lead to omitted variable bias in my estimates of temperature and wage effects. Second, piece rate wages are endogenous to labor productivity.

To address factors other than the piece rate wage that could drive labor productivity, I exploit the richness of my data and include (1) flexible controls for temperature, and (2) a host of fixed effects. Most importantly, I include time fixed effects to capture seasonality (week-of-year), work patterns (day-of-week, hour-of-day), and season-specific shocks (year). I also include field-level fixed effects to capture variation in the productivity of different varieties and plantings of blueberry bushes. The combination of time- and field-level fixed effects gives me a credible control for the average density of blueberries available for harvest at a given time in a given field. In other words, these fixed effects allow me to control for resource abundance (θ). Further, I include worker-specific fixed effects to capture heterogeneity in picker ability. Lastly, I include a quadratic of worker tenure to allow for learning-by-doing. When estimating the effect of temperature on productivity, my identifying assumption is that individual realizations of temperature are as good as random after including the controls described here and the piece rate wage.

To address the endogeneity of piece rate wages to labor productivity, I instrument for these wages using California market prices for blueberries. In order for these prices (described in section 4.3) to be a valid instrument for wages, they must be correlated with farms' piece rates, but not affect labor productivity through any other channel. Figure 10 plots piece rate wages and market prices over time and suggests a strong correlation between the two variables. I provide formal evidence of this relationship in table 4, which I describe in detail in the following section. As evidence that the exclusion restriction holds – that market prices do not affect labor productivity except through wages – I rely on the size and heterogeneity of the California blueberry industry. Statewide market prices capture supply shocks from growing regions around the globe, each with different weather, growing conditions, and labor markets. To the extent that environmental conditions agronomically drive blueberry production, they do so differentially across different growing regions of California. Therefore, any one farm's temperature shocks in a given growing season do not determine aggregate blueberry supply.[21] Additionally, both of the farms I study are quite small in comparison to the statewide market: they are price-takers and cannot independently affect average prices. As a result, market prices capture exogenous variation in aggregate supply shocks and serve as an effective instrument for piece rate wages.

Specifically, I estimate the following equation by two-stage least squares:

$$y_{itl} = \beta \hat{r}_{itl} + f(T_{tl}) + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \alpha_i + \boldsymbol{\delta}_t + \mu_l + \varepsilon_{itl} \tag{5.1}$$

where $\hat{r}_{itl}$ is estimated by the following first stage:

$$r_{itl} = bp_t + f(T_{tl}) + \boldsymbol{X}'_{it}\boldsymbol{g} + a_i + \boldsymbol{d}_t + m_l + \xi_{itl}. \tag{5.2}$$

In equations (5.1) and (5.2), y_{itl} is laborer i's production per hour at time t and location l. The piece rate wage is given by r, $f(T)$ is a flexible function of temperature, $\boldsymbol{X}$ is a vector of time-varying employee characteristics including days worked and days worked squared, α (a) is a worker fixed effect, $\boldsymbol{\delta}$ ($\boldsymbol{d}$) is a vector of time fixed effects (hour of day, day of week, week of year, year), μ (m) is a field fixed effect, and ε (ξ) is an error term.

In my baseline specification, I control for temperature with a series of five-degree temperature bins. In particular,

$$f(T_{tl}) = \sum_{i=0}^{10} \tau_{50+5i} \mathbb{1}(50 + 5i \le T_{tl} < 55 + 5i) \tag{5.3}$$

[21] The farms I study are located in San Diego and Kern Counties, which contain 0.1% and 14%, respectively, of all California blueberry acreage (California Blueberry Commission, 2015, p. 9).

where one of the eleven bins is omitted. I choose to omit the 80–85 degree bin. This approach allows me to remain agnostic to any particular functional parameterization of the temperature response function and capture any important non-linearities. It also is in line with previous research on the economic effects of temperature, and more precisely specified than some (very good) recent work.[22]

After estimating by baseline specification, I also estimate the effect of temperature on productivity using a piecewise-linear spline function with a single node at 88.5 degrees Fahrenheit:

$$f(T_{tl}) = \begin{cases} \tau_0 + \tau_1 T_{tl} & \text{if } T_{tl} \leq 88.5 \\ \tau_0 + \tau_1 88.5 + \tau_2 \left(T_{lt} - 88.5\right) & \text{if } T_{tl} \geq 88.5 \end{cases} \tag{5.4}$$

where the choice of 88.5 degrees is motivated by the results of my baseline specification.

In order to estimate how temperature affects productivity's responsiveness to piece rate wages, I estimate a variation of specification (5.1) without temperature controls on the observations in each five-degree temperature bin separately. I have too few observations to do this for the 50–55, 95–100, and 100–105 temperature bins, so I pool observations cooler than sixty degrees and hotter than ninety degrees, leaving me with eight separate estimates of how piece rate wages affect labor productivity across temperature.

In all my regressions, I two-way cluster my standard errors by day and worker to account for correlated error terms on the same day across different workers and for a single picker over time (Cameron et al., 2011).

6 Results

Table 2 presents the results of estimating my primary specification, equation (5.1), with different sets of controls. In column (1), I include only the instrumented piece rate wage and five-degree temperature bins. As expected, without controlling for seasonality or harvest field, I find a statistically significant negative effect of wages on productivity. I also find large and negative effects of cool (50–60 degree) temperatures on productivity. In each subsequent column, I add more controls: farm fixed effects, field fixed effects, worker tenure controls, time fixed effects (year, week-of-year, day-of-week, hour-of-day), and worker fixed effects. Including time fixed effects (moving from column (4) to column (5)) makes the largest difference to the sign and significance of my results. This makes sense, since seasonality and time-of-day dynamics are particularly relevant in the California blueberry context.

[22]Baylis (2016), as one example, uses temperature bins of five degrees Celsius. These are equivalent to bins of nine degrees Fahrenheit.

Column (6) of table 2 contains the results of my preferred specification using the temperature bins described in equation (5.3). By controlling for field and time fixed effects, (i.e. by controlling for resource abundance θ to the extent possible), the point-estimate for piece rate wages' effect on worker productivity switches from negative and statistically significant to positive but statistically indistinguishable from zero. The standard error on this effect is qualitatively small, meaning that I can reject even modest effects of wage on productivity.

I also find statistically significant negative effects of both cool temperatures (50–75 degrees Fahrenheit) and very hot temperatures (100+ degrees Fahrenheit) on picker productivity. The solid line in figure 14 plots this temperature-response function with a 95%-confidence interval. The relevant temperature point estimates (the τ_{50+5i} terms from equation (5.3)) represent the change in conditional average picker productivity (measured in pounds per hour) expected by replacing a picking period with a time-weighted average temperature between 80–85°F (the omitted temperature bin) with a picking period having a time-weighted average temperature within the corresponding temperature bin. I find that temperatures between 50 and 55 degrees lower productivity by 3.22 pounds per hour – a nearly 17% decrease, while temperatures over 100 degrees lower productivity by 2.33 pounds per hour – just over a 12% decrease.

Table 3 re-estimates my preferred specification using the piecewise-linear spline described in equation (5.4). I find that at temperatures below 88.5 degrees Fahrenheit, an additional degree of heat increases productivity by 0.088 pounds per hour, on average. At temperatures above 88.5 degrees, however, an additional degree of heat lowers productivity by 0.20 pounds per hour. The dashed line in figure 14 plots these effects, which are significant at the 0.001 and 0.05 levels, respectively.

In table 4, I provide evidence that blueberry market prices are an effective instrument for piece rate wages. Column (1) reports the results of estimating equation (5.1) by ordinary least squares without instrumenting for wages. While the estimated effect of wages on productivity in this specification is statistically insignificant, the point estimate is negative. Column (2) presents the results of regressing market prices, temperature, and other controls on the piece rate wage: my first stage. There is a large, positive, and statistically significant effect of prices on wages, while temperature has no meaningful effects on piece rates below 95 degrees Fahrenheit. Column (3) gives results from a reduced form specification regressing market prices and controls on worker productivity directly, and column (4) provides the results of my preferred two-stage least squares specification instrumenting for wages with market prices. When I instrument for wages, their effect on worker productivity remains statistically insignificant, but the relevant point estimate becomes barely positive. The temperature response function (as estimated by the point-estimates for each temperature bin) is quite stable across columns (1), (2), and (4), lending support to the conclusion that I accurately recover a true relationship.

While the richness of my data allows me to exploit intra-day variation in temperature, I can also collapse my data to the day-level and investigate how daily temperature affects daily worker productivity. Figure 15 reports the results of three different day-level temperature specifications. The first uses time-weighted average daily temperature experienced by each picker, the second uses daily maximum temperature, and the third uses daily minimum temperature. Overall, the results from these specifications support the qualitative results of my primary specification: extreme temperatures lower picker productivity, and cool temperatures are more damaging than very hot temperatures.

One threat to the credibility of my findings in tables 2 and 3 is that temperature and wages may affect workers' labor supply, both on the intensive and extensive margins. That is, workers may decide to work fewer hours on a particularly hot day, or choose not to come to work at all if the piece rate wage is particularly low.[23] Such behavior would bias my estimates of how temperature and wages affect productivity by introducing unobserved systematic selection into or out of my sample. I investigate this possibility in table 5 by regressing temperature, wages, and controls on both hours worked and the probability of working. In column (1), the dependent variable is the number of hours worked by a picker in a single day, and temperature is measured as a time-weighted average experienced by the picker during that (entire) day. Here, I control for a picker's start-time rather than their picking "midpoint." In column (3), the dependent variable is an indicator for whether a picker worked at all in a given day, and temperature is measured as a daily midpoint temperature: (Daily Max + Daily Min)/2. I use daily midpoint temperature in column (3) in order to provide a consistent comparison between employees who show up to work and employees who do not, since I do not know when or for how long these absent employees would have worked had they come to work. Figure 16 displays the relevant temperature results from columns (1) and (3) of table 5. Overall, table 5 reports that neither wages nor temperatures affect labor supply in a statistically significant way. Similar to Graff Zivin and Neidell (2012), I find the labor supply of agricultural workers to be highly inelastic in the short run. This also matches the findings of Sudarshan et al. (2015) for weaving workers in India. This evidence gives me confidence in the validity of my baseline results.[24]

[23]See Dickinson (1999) for an experimental treatment of these issues in a lab setting with both varying piece rates and labor supply choices.

[24]As an aside, the point-estimates in columns (1) and (2) of table 5, while not statistically significant, could be compared to the findings in Graff Zivin and Neidell (2014). These authors find that individuals reduce labor supply at hot temperatures and reduce time outside at cold temperatures. These same broad patterns, without statistical significance, appear at smaller magnitudes in my table 5.

I now turn to how temperature affects berry pickers' wage responsiveness. Table 6 reports the results of estimating a variant of equation (5.1) separately across eight temperature bins.[25] I find that wages have no meaningful effect on productivity at most temperatures, but have a statistically significant and positive effect on productivity at cool temperatures: those between 50 and 60 degrees. In particular, my estimate suggests an increase in the piece rate wage of one cent per pound at temperatures below 60 degrees increases average productivity by 0.28 pounds per hour. This reflects an elasticity of productivity with respect to the wage of roughly 1.6 at cool temperatures,[26] and an elasticity statistically indistinguishable from zero at other temperatures. This "productivity elasticity" is considerably smaller than the 2.14 number estimated by Paarsch and Shearer (1999).

Table 7, which repeats the analysis from table 6 using ordinary least squares (OLS), highlights the importance of instrumenting for piece rate wages. This table highlights two important things. First, the effects of wages on productivity at low temperatures do not show up in a statistically significant way without correctly instrumenting for wages with market prices. Second, I am able to rule out any dramatically large effect of wages on productivity at most temperatures.

Another threat to my findings is that workers who do not out-earn the hourly minimum wage in a given day may shirk ("slack off") when they know that additional productivity will not increase their take-home pay. Figure 13 reports the frequency with which workers fall below this minimum wage threshold. I face an econometric problem if the effects of temperature reduce workers' productivity, increase the probability that workers earn the minimum wage, and hence encourage shirking. To ensure my findings are not meaningfully altered by this phenomenon, I re-estimate my main results using only picker observations where the picker out-earns the minimum wage for the day. This procedure drops my number of picking period observations from 305,980 to 257,689: a decrease of 15.8%. Figure 17 and table 8 present the results of my main temperature and piece rate wage specifications using this subsample. My findings remain qualitatively stable and statistically significant.[27]

[25] As discussed in the previous section, I pool cool and very hot observations to achieve the sample size necessary to estimate effects. The eight temperature bins, measured in degrees Fahrenheit, are: [50, 60), [60, 65), [65, 70), [70, 75), [75, 80), [80, 85), [85, 90), and [90, 105).

[26] An increase in productivity of 0.28 pounds per hour reflects an approximately 1.6% increase in productivity from the average 18.0 pounds per hour at temperatures between 50 and 60 degrees (column (1) of table 6). An increase in the piece rate wage of one cent reflects an approximately 1.0% increase in wages from the average 97 cents per pound across all observations (see panel C in table 1).

[27] Graff Zivin and Neidell (2012) face a similar problem on a larger scale: over 60% of their observations face a binding minimum wage policy. In that case, as a robustness exercise, the authors apply a Tobit model to a normalized measure of productivity across different crops and confirm their full-sample findings. While Tobit models rely on strong distributional assumptions, they attempt to recover the true relationship between dependent and independent variables, even for observations below some cutoff (in this case, observations below the minimum wage cutoff). My decision to drop observations below the minimum wage threshold is

Finally, even if temperature and wages do not affect labor supply directly in a statistically significant manner, and even though worker-specific fixed effects capture individual workers' average productivity levels, I still face a potential adverse selection problem. Specifically, if variation in temperature and wages affects *which sorts* of workers choose to show up for work, my results may capture workforce compositional effects rather than individual productivity effects. To address this concern, I re-estimate my results only using observations from those workers who work more than thirty days in the relevant season. The intention here is to focus on workers who are likely to have the least elastic extensive labor supply. The results of this robustness exercise are presented in figure 18 and table 9. Taken together with the other available evidence, these results largely support my baseline findings.

7 Discussion

My results provide evidence of how blueberry pickers' productivity responds to piece rate wages and temperature, both independently and jointly. These findings have implications on several levels, each of which I address separately.

7.1 Wage effects

My primary finding is that labor productivity, on average, is very inelastic with respect to piece rate wages: I can reject with 95% confidence even modest positive elasticities of up to 0.7. This upper bound is considerably lower than the estimates derived by Paarsch and Shearer (1999) and Haley (2003). I show that, without controlling for seasonality, a regression of productivity on piece rate wages results in a negative and significant point estimate (see table 2). However, even once I control for seasonality, a naïve OLS regression of productivity on piece rate wage may be biased toward zero (see column (1) of table 4). By instrumenting for piece rate wages with the market price for blueberries, I can identify a precisely-estimated inelastic effect (see column (6) of table 2).

However, my primary specification makes the restrictive assumption that wages affect productivity linearly and in the same manner at all temperatures. Table 6 confirms that piece rates' effect on productivity is very much *non*-linear across different temperatures. Specifically, wages seem to spur productivity at cool temperatures (where workers' productivity is already depressed). At other temperatures, wages do not affect productivity in a statistically significant way. This empirical finding directly challenges one of the core as-

a more conservative approach that will understate the true relationship (if one exists) between independent and dependent variables. Thus, I remain confident in the results of my primary specifications.

sumptions of the model presented in section 2.1: that productivity always rises with the wage ($X_r > 0$). What is going on?

One possible explanation for my findings is that, at moderate to hot temperatures, workers' face some binding physiological constraint on effort that prevents them from responding to changes in their wage. Put bluntly, blueberry pickers in general may already be "giving all they've got" at the temperatures and wages I observe.[28] Figure 19 summarizes this possibility using the theoretical framework developed in section 2.1.

While the model in section 2.1 is straightforward and tractable, it is not the only way to conceptualize worker effort and productivity. In particular, rather than modeling effort as an unrestricted choice variable, one could assume each worker has a finite daily budget of effort that must be allocated across different activities throughout a day (for examples, see Becker (1965) and Becker (1977)). Such a model would allow X_r to be zero or even negative under certain conditions, implying a backwards-bending effort supply curve, somewhat analogous to the canonical backward-bending labor supply curve (Killingsworth, 1983). The downside of such models is that they fail to provide comparative statics that can be tested with the data I observe in this setting.

7.2 Direct temperature effects

My econometric analyses allow me to estimate the direct effects of temperature on California berry-pickers' labor productivity. These findings contribute to a large literature studying the effects of temperature and other environmental conditions on a variety of economic outcomes.

7.2.1 Existing literature on temperature and other environmental conditions

A growing literature has rigorously documented the non-linear impact of temperature on everything from corn yields (Schlenker and Roberts, 2009) to cognitive performance (Graff Zivin et al., 2015), but has not focused specifically on how temperature affects agricultural workers.[29] Nevertheless, several recent papers in this literature seem particularly relevant to my findings. One strand of research has investigated how temperature affects labor productivity in a variety of different industries. Adhvaryu et al. (2016b) show that factory workers in India produce more output when heat-emitting conventional light bulbs are replaced LED

[28]I am not suggesting that blueberry pickers spend most of their working time on the brink of physiological exhaustion. Rather, I interpret my findings as evidence that most pickers spend most of their working time at or near a "maximum *sustainable* level of effort." Consider the analogy of a marathon runner: such a runner could certainly increase their speed for any arbitrary short distance if given a compelling incentive. However, maintaining that increased speed for the entire race would be physiologically impossible.

[29]For useful reviews of the economic literature on temperature, see Carleton and Hsiang (2016), Kahn (2016), and Heal and Park (2016).

lighting, especially on hot days. Sudarshan et al. (2015) find similar evidence that temperature reduces worker productivity in a variety of Indian manufacturing firms. Finally, Seppänen et al. (2006) show that temperature even has large effects on the productivity of office workers.[30]

Other researchers have asked broader questions about how temperature affects aggregate production or labor decisions at the county- or country-level. The growing consensus is that weather shocks – particularly exposures to extreme heat – reduce aggregate production in a wide variety of settings. For instance, Hsiang (2010) exploits natural variation in cyclones to find negative impacts of high temperatures in both agricultural and non-agricultural sectors at the country-level. Deryugina and Hsiang (2014) and Park (2016) find similar county-level effects of daily temperature in the United States, despite widespread adoption of air conditioning. Heal and Park (2014) document relevant findings throughout the economics literature and provide a useful theoretical link between heat's physiological effects and aggregate economic activity.[31] Extreme heat may reduce aggregate production through several channels. The first possibility, discussed at length in the previous paragraph, is that employees are less productive while working at high temperatures. Another possibility is that employees may choose to work fewer hours when temperatures are particularly high. In other words, there may be a labor supply response to temperature on the extensive margin. Graff Zivin and Neidell (2014) provide support for this hypothesis by analyzing data from the American Time Use Survey. They find that at high temperatures, individuals reduce the time they spend working and increase the time they spend on indoor leisure. Finally, temperature can affect even broader aspects of the labor market like aggregate demand for agricultural labor in India (Colmer, 2016), or the composition of labor in urban vs. rural regions of Eastern Africa (Dou et al., 2016).

While this paper examines how a particularly salient environmental condition, temperature, affects labor productivity, previous research has shown that other environmental factors matter as well. Chang et al. (2016a), for instance, find that outdoor air pollution negatively affects the indoor productivity of pear packers. The same authors conduct a similar exercise using data from Chinese call-centers (Chang et al., 2016b) and find comparable results.

[30] In a recent and extensive summary of the economic risks of climate change, Houser et al. (2015) highlight that relatively little is known about how temperature affects worker effort: "While we consider the effects of temperature on the number of hours worked, we do not assess the effects on the intensity of labor during working hours" (p. 167).

[31] There is a vast medical, physiological, and ergonomic literature documenting the ways in which temperature affects the human body. Hot temperatures consistently tax individuals' endurance, exacerbate fatigue, and diminish cognitive performance in a variety of experimental settings. For evidence on endurance and fatigue, see Nielsen et al. (1993), Galloway and Maughan (1997), and González-Alonso et al. (1999). For evidence on cognitive performance, see Epstein et al. (1980), Ramsey (1995), Pilcher et al. (2002), and Hancock et al. (2007).

Adhvaryu et al. (2016a) find a steep pollution-productivity gradient in the context of an Indian garment factory, and Graff Zivin and Neidell (2012) find large damages from ozone in an agricultural context somewhat similar to my own. In an older case study, Crocker and Horst, Jr. (1981) study seventeen citrus pickers in southern California and find negative effects of both high temperatures and air pollution. It is useful to think of temperature not as a single sufficient statistic to describe environmental quality, but rather as one condition among many that is relevant for understanding labor productivity.

This paper makes several important contributions to the literature discussed above. First, because I observe berry-pickers' productivity multiple times during a single day, the variation I observe in both productivity and temperature is much more temporally precise than in many previous studies. Additionally, since I use temperature observations that are taken hourly, and sometimes more frequently, I do not need to interpolate temperature over time. Second, I study a setting where both very hot and cool temperatures have negative effects on productivity, highlighting the particularities of different production processes when it comes to temperature impacts. Third, and most importantly, I look at how how environmental conditions and incentive schemes interact.[32]

7.2.2 Temperature effects on California blueberry pickers

Table 2 and figure 14 provide my estimates of the direct effects of temperature on labor productivity in the California blueberry industry. Whereas most previous studies have focused on the negative effects of extreme heat (Dell et al., 2012; Heal and Park, 2014; Deryugina and Hsiang, 2014), I find that cool temperatures (50–60 degrees Fahrenheit, in particular) have just as large negative effects as very hot temperatures, if not larger. While this may appear counterintuitive at first, two insights help to explain this result. First, blueberry farmers have already adapted to hot temperatures: pickers generally finish picking around 3:00 p.m. and avoid the hottest parts of the day. This means that I do not observe how workers would perform under temperatures above 100–105 degrees.[33] And looking at the temperature response function in figure 14, it is easy to imagine due to its overall inverse-parabolic shape that there would be even larger productivity losses at such high temperatures. Second, blueberry picking is a highly dextrous job requiring workers to use their bare hands to pick only ripe

[32]An early ergonomic laboratory experiment (Mackworth, 1947) found that incentivizing subjects to improve their performance on a simple physical task increased their physiological endurance at both normal and hot temperatures. However, incentives were not able to eliminate a stark performance drop-off as temperatures increased. More recently, Park (2016) noted that temperature's effect on labor productivity should be expected to vary with the incentive scheme: "...the optimal [temperature] response for someone who is paid a piece rate wage contract... will differ from someone who is paid on a fixed annual contract or simply by the hour" (p. 350).

[33]In fact, all the temperature observations in my 100–105 degree bin are below 102 degrees Fahrenheit.

berries from the bush. At cooler temperatures, berry pickers lose finger dexterity and find it uncomfortable to maintain the same levels of productivity as at warmer temperatures.[34] Indeed, Enander and Hygge (1990) note that manual dexterity can start to be impaired at temperatures in the range of 12–15 degrees Celsius (53.6–59 degrees Fahrenheit).[35]

7.3 Implications for California blueberry growers

My empirical findings explain (1) how blueberry pickers respond to changes in their piece rate wage, (2) how temperature directly affects these pickers' labor productivity, and (3) how temperature affects these pickers' wage responsiveness. Combining these effects, I can predict how rising temperatures will affect labor market outcomes in the California blueberry picking sector. In appendix A, I develop a model of a firm choosing an optimal piece rate under some environmental condition. That model produces two particularly interesting comparative statics results.

First, condition (A.10) predicts that farmers should increase their piece rate wage in response to an increase in temperature if and only if $X_T < (p - r)X_{rT}$, where X is worker productivity, T is temperature, p is the market price of blueberries, and r is the piece rate wage. Using the results of my linear spline specification (table 3), I find that, at temperatures below $88.5°F$, $X_T = 0.088$ pounds per hour for a one-degree-Fahrenheit increase in temperature. Furthermore, for temperatures between 50 and 65 degrees, I estimate $X_{rT} \approx -0.035$ pounds per hour for an increase of one degree.[36] Thus, $X_T/X_{rT} \approx -2.5 < 0 < p - r$, and a profit-maximizing farmer would choose to decrease the wage r for temperature increases at these temperatures.[37] Put more clearly, my results suggest that an optimizing farmer would pay pickers higher piece rate wages at particularly cool temperatures than at more moderate temperatures.

At warmer levels, between 90 and 105 degrees Fahrenheit, I am unable to repeat the analysis of the previous paragraph since the condition in expression (A.10) is only valid when $X_r > 0$. Therefore, I rely on more basic economic intuition when analyzing behavior at these temperatures: since there is no discernible benefit of higher wages at higher temperatures, an optimizing farmer would not raise piece rates at particularly hot temperatures.

[34] Ambient temperature is not the only consideration here. Berries themselves are cool to the touch each morning and compound the effect of air temperature on pickers' hand dexterity.

[35] The authors also write: "Tasks involving fine movements of the fingers and hands or manipulation of small objects are particularly sensitive to cold effects. Slow cooling, as found in many occupational settings, is more detrimental to manual performance than rapid cooling" (Enander and Hygge, 1990, p. 46).

[36] I calculate this figure by subtracting the point estimate in column (2) of table 6 from the point estimate in column (1) of the same table and dividing by 7.5 (degrees). Specifically, $(0.28 - 0.015)/-7.5 \approx -0.035$.

[37] If $X_{rT} < 0$, as it is here, then the condition $dr/dT > 0 \iff X_T < (p - r)X_{rT}$ can be rewritten as $dr/dT > 0 \iff X_T/X_{rT} > (p - r)$.

The analyses of previous paragraphs relied on the important assumption that farmers are able to set piece rates that vary with temperature. In reality, a farmer only sets a single piece rate wage for the entire day. As a result, the entire distribution of expected temperature throughout a day is what matters to the farmer. Since most days during the blueberry season in California include a wide range of temperatures, farmers are likely already close to a second-best optimum given the constraint of a single daily wage.[38] Nonetheless, farmers may be able to boost profits by increasing their piece rates on particularly cool "cold snap" days, especially if the presence of such a premium could be tied to an external authority (i.e. *"I pay 2 ¢ per pound extra on days when the daily high temperature in the local newspaper is predicted to be below 75° F"*).

The second interesting prediction from the model in appendix A (see equation (A.13)) is that, at the margin, farm profits will move with X_T. Therefore, at low temperatures, a warming climate may increase California blueberry farms' profitability. However, if farm workers are then also exposed to higher, more extreme temperatures, profits may decrease at such temperatures.

How then, in sum, could climate change affect the California blueberry industry? My results suggest that average picker productivity would likely increase as workers face fewer "cold" hours in the fields. This effect will almost certainly dominate the marginal decreases in productivity at very hot temperatures, given the distribution of temperature to which pickers are currently exposed (see the lower panel in figure 14). Therefore, as far as labor considerations are concerned, moderate climate warming may increase profits for California blueberry growers. However, if pickers begin working in extreme heat conditions that they currently avoid, there may be significant negative impacts that are not captured by my analysis. From the farmer's perspective, an ideal response to climate concerns would be to hire more employees for fewer hours each day, focusing on times when temperatures are most amenable to high productivity. This is impractical, though, since many fruit pickers expect a full day's work and would likely look for other employers if a farmer failed to provide the opportunity for an eight-hour work day. As a final caveat, this paper explores only the effects of temperature on labor productivity. A changing climate is also likely to have important agronomic consequences (à la Schlenker and Roberts (2009)) that I do not address here.

[38]It is not even clear that an unconstrained variable piece rate wage regime would dominate the *status quo*, since a varying rate would introduce incentives for workers to manipulate that system, or horde fruit until times of the day when wages are highest. The behavioral losses incurred by such a system could easily outweigh its theoretical benefit.

8 Conclusion

In agriculture – as in many other industries – labor is a primary input, pay is tied to worker output, and firms cannot completely control important workplace environmental conditions like temperature. How do agricultural workers respond to changes in their piece rate wage? How does temperature affect this wage responsiveness? And what are the net effects of temperature on agricultural labor productivity? This paper addresses these questions in the context of California blueberry farmers and provides the following answers: (1) on average, blueberry pickers' productivity is very inelastic with respect to wages; (2) workers seem to face binding constraints on effort at moderate to hot temperatures, but display an elastic response to wages at cool temperatures; and (3) both very hot and cool temperatures have negative direct effects on berry pickers' productivity.

This paper makes a meaningful contribution to the empirical understanding of how wages affect worker productivity. While the basic theoretical prediction is straightforward (under piece rate wages, a higher wage should encourage more effort and higher output), previous studies have struggled to test this hypothesis directly. Doing so is difficult since, in settings where piece rates vary over time, their variation is endogenous to worker productivity. To isolate wages' effect on productivity, I instrument for blueberry pickers' piece rate wage using the market price for California blueberries. I find that on average, pickers' productivity is very inelastic with respect to piece rate wages, and I can reject even modest elasticities of up to 0.7. However, this finding hides important heterogeneity in the relationship across different temperatures. In particular, only at cool temperatures (50–60 degrees Fahrenheit) do higher wages have a statistically significant and positive effect on worker productivity. This result suggests that at most temperatures and wages, blueberry pickers face some sort of binding constraint on effort and cannot be incentivized to increase their productivity.

This research raises questions for future research both about firms' responses to changing temperatures and their choice of an optimal payment scheme. For instance, it would be helpful to analyze a different industry to see how temperature response functions differ across tasks. It would also be interesting to analyze, both theoretically and empirically, a varying wage scheme tied directly to exogenous factors such as market prices, resource abundance, and environmental conditions. With the advent of cheap, sophisticated monitoring technology, more and more industries are candidates for adopting piece rates, raising the importance for economists to deepen our understanding of the forces at work in such wage schemes.

Appendix A A Model of Optimal Piece Rate Wages

In this appendix, I develop a simple model of a firm employing workers under a piece rate wage. This framework generates comparative statics on the firm's optimal piece rate wage with respect to output prices, resource abundance, and environmental conditions, which will allow me to predict how rising temperatures will affect the California blueberry industry.[39]

Consider a firm that produces output by employing labor to harvest some resource. In the short-run, the total amount of the resource, B, is fixed. Let θ be the abundance or density of the resource, such that $B = b\theta$ for some constant b. Because B is fixed in the short-run, the firm's only discretionary input is labor. The firm chooses both the number of workers to hire, n, and a piece rate wage r. The workers then each produce output X, which the firm sells at market price p. The firm is assumed to be a price-taker in the output market, but to have at least some monopsony power in the labor market to set r.[40] Also, if there exists a minimum hourly wage below which laborers cannot be paid, this constraint is assumed not to bind in equilibrium (i.e., all laborers working for the piece rate wage end up earning more than they would under the hourly minimum wage).

Employed laborers observe the piece rate wage r, the abundance of the resource θ, and an environmental condition T. They then endogenously select an unobserved level of effort that results in output $X(r, \theta, T)$ as described in section 2.1.[41] Laborers' supply of output, X, is increasing in r, since higher piece rate wages incentivize higher levels of effort holding θ and T constant. X is also increasing in θ, since a more abundant resource is easier to harvest. The effect of T on laborers' supply of output is ambiguous *a priori*, and depends both on the environmental condition in question and its level.[42] Finally, the workers' productivity function is assumed to be concave in r. To summarize, $X_r > 0$, $X_\theta > 0$, and $X_{rr} < 0$. The firm is assumed to be sufficiently knowledgeable about its production process that it knows

[39] Heal and Park (2014) have previously considered the relationship between temperature and effective labor supply, deriving theoretical predictions based on worker-level micro-foundations. My model differs by directly accounting for wages that may also adjust to changing environmental conditions.

[40] In the California blueberry market, there is certainly competition between farms in the labor market. However, different farms provide different work environments and require workers to perform different physical tasks, meaning potential workers have *a priori* preferences over different possible employers. As long as a farmer offers a wage that is considered relatively comparable to what other farmers offer, conditional on the nature of the work, the farmer has some latitude to choose the particular wage level.

[41] Laborers may also differ in individual ability or skill ϕ. If skill simply affects optimized production multiplicatively, (i.e., $\phi X(r, \theta, T)$), then it will have no impact on the results derived in this model. My empirical strategy controls for individual fixed effects to address this concern.

[42] If T is a measure of air pollution, one would expect $X_T < 0$ since pollution reduces both the productivity of laborers' effort as well as their willingness to provide it (Graff Zivin and Neidell, 2012). Similarly, if T is temperature, one would expect $X_T < 0$ for hot temperatures (Adhvaryu et al., 2016b; Sudarshan et al., 2015). However, at low temperatures, additional heat may be welcome and actually increase laborers' supply of output: $X_T > 0$ (Seppänen et al., 2006; Meese et al., 1984).

the function $X(r, \theta, T)$.[43]

I assume the firm must choose n before choosing r, and that the realization of n is somewhat stochastic. This closely matches reality in the California blueberry industry: a farmer considers how many berries will be ripe on the following day, and determines the ideal number of pickers he would like to hire. The farmer then calls workers directly or calls a labor contractor to coordinate the right number of pickers to show up the next day. However, the number of pickers who arrive the next morning may not exactly match the farmer's expectations. Once the farmer observes how many pickers show up, he *then* sets the daily piece rate wage. I further assume the farmer pays some constant per-worker cost h, to reflect various managerial costs that scale with the size of the farm workforce.

The firm faces the following "day-ahead" profit maximization problem:

$$\max_{n,r,\lambda} \quad (p - r)nX - hn + \lambda(b\theta - nX), \tag{A.1}$$

which implicitly gives an expected (non-binding) piece rate wage $\mathbb{E}[r^*]$ and the following optimal n:

$$n^* = \frac{b\theta}{\sqrt{hX_r}}. \tag{A.2}$$

Here, the labor participation constraint is $\mathbb{E}[r^*]X(\mathbb{E}[r^*]) > w_0$ where w_0 is a worker's daily reservation wage. Note that in equation (A.2), the optimal number of workers is mainly driven by resource abundance θ and labor costs h.

Once workers arrive for a day's work, n (which may differ somewhat from n^*) is fixed. The farmer then sets r to maximize daily profits:

$$\max_{r} \quad (p - r)nX - hn, \tag{A.3}$$

which gives the following first-order condition:

$$(p - r)X_r - X = 0. \tag{A.4}$$

Equation (A.4) implicitly defines an optimal piece rate wage as a function of three exogenous parameters: output price, resource abundance, and the environmental characteristic:

[43] In my empirical setting, this is close to true. Farmers understand particularly well the relationship between the density of ripe berries in the field and worker output: $X(\theta)$. Additionally, employers in other piece rate settings clearly acknowledge the negative effect of temperature on output: "Managers claimed that during the hottest months, daily wage workers preferred to go home to their villages... rather than work under the much more strenuous conditions at the factory. Some owners said they were actively considering the possibility of combating this preference for less taxing work by temporarily raising wages through a summer attendance bonus" (Sudarshan et al., 2015, p. 44).

$r(p, \theta, T)$. Differentiating equation (A.4) once more by r gives the following second-order condition:

$$(p - r)X_{rr} - 2X_r < 0 \tag{A.5}$$

where the inequality follows from the earlier assumptions that $X_{rr} < 0$ and $X_r > 0$.

Now, I investigate the comparative statics of the optimal piece rate wage $r(p, \theta, T)$. I begin by analyzing the effects of output price p on r. Totally differentiating equation (A.4) with respect to p and rearranging gives:

$$\frac{dr}{dp} = \frac{-X_r}{(p - r)X_{rr} - 2X_r} > 0 \tag{A.6}$$

where the inequality comes from the facts that the denominator in equation (A.6) is simply the second-order condition from expression (A.5), and that X_r is assumed to be positive.

Next, I consider resource abundance θ. Totally differentiating equation (A.4) with respect to θ and rearranging gives:

$$\frac{dr}{d\theta} = \frac{X_\theta - (p - r)X_{r\theta}}{(p - r)X_{rr} - 2X_r}. \tag{A.7}$$

Again, note that the denominator in equation (A.7) is the second-order condition from expression (A.5), and therefore negative. Thus, the sign of $dr/d\theta$ depends on the numerator of equation (A.7). In particular,

$$\frac{dr}{d\theta} < 0 \iff X_{r\theta} < \frac{X_\theta}{p - r}. \tag{A.8}$$

This gives the sufficient condition that if $X_{r\theta} < 0$, then $dr/d\theta < 0$. The condition $X_{r\theta} < 0$ implies that the marginal increase in output induced by an increase in r is decreasing in the resource's abundance. This may or may not be a reasonable assumption.[44]

Finally, I consider the environmental condition T. Totally differentiating equation (A.4) with respect to T and rearranging gives:

$$\frac{dr}{dT} = \frac{X_T - (p - r)X_{rT}}{(p - r)X_{rr} - 2X_r}. \tag{A.9}$$

As before, the denominator in equation (A.9) is the second-order condition from expression (A.5) and thus negative. Consequently, the sign of dr/dT depends on the numerator of equation (A.9). In particular,

$$\frac{dr}{dT} > 0 \iff X_T < (p - r)X_{rT}. \tag{A.10}$$

[44] In my empirical setting, I observe $dr/d\theta < 0$.

This implies that, in general, the sign of dr/dT is ambiguous and therefore an empirical question.

In addition to the above exercises, I also analyze how changes in the three truly exogenous variables – p, θ, and T – affect farm profits Π:

$$\frac{d\Pi}{dp} = \frac{dr}{dp}\underbrace{((p-r)X_r - X)}_{=0 \text{ by envelope thm}} + 1 = 1 > 0 \tag{A.11}$$

$$\frac{d\Pi}{d\theta} = \frac{dr}{d\theta}\underbrace{((p-r)X_r - X)}_{=0 \text{ by envelope thm}} + (p-r)X_\theta = (p-r)X_\theta > 0 \tag{A.12}$$

$$\frac{d\Pi}{dT} = \frac{dr}{dT}\underbrace{((p-r)X_r - X)}_{=0 \text{ by envelope thm}} + (p-r)X_T = (p-r)X_T. \tag{A.13}$$

Equation (A.13) implies that the sign of $d\Pi/dT$ will match the sign of X_T. All three results match intuition.

The model outlined above produces two particularly interesting predictions. First, equation (A.10) suggests that the impact of environmental conditions (such as temperature) on the optimal piece rate wage r can be determined by estimating two effects – X_T and X_{rT} – over wide supports of r, θ, and T.[45] Second, equation (A.13) states that the effect of the environmental condition T on firm profits will have the same sign as X_T. Thus, by credibly estimating X_T, I am able to provide a prediction on how changing levels of T will affect firm profits.

[45] The model also highlights the need to control for r's endogeneity. In particular, equation (A.7) suggests that r will depend on resource abundance θ. However, equation (A.6) also suggests that r will be positively correlated with output price p, justifying my use of the market price p as an instrument in my empirical strategy.

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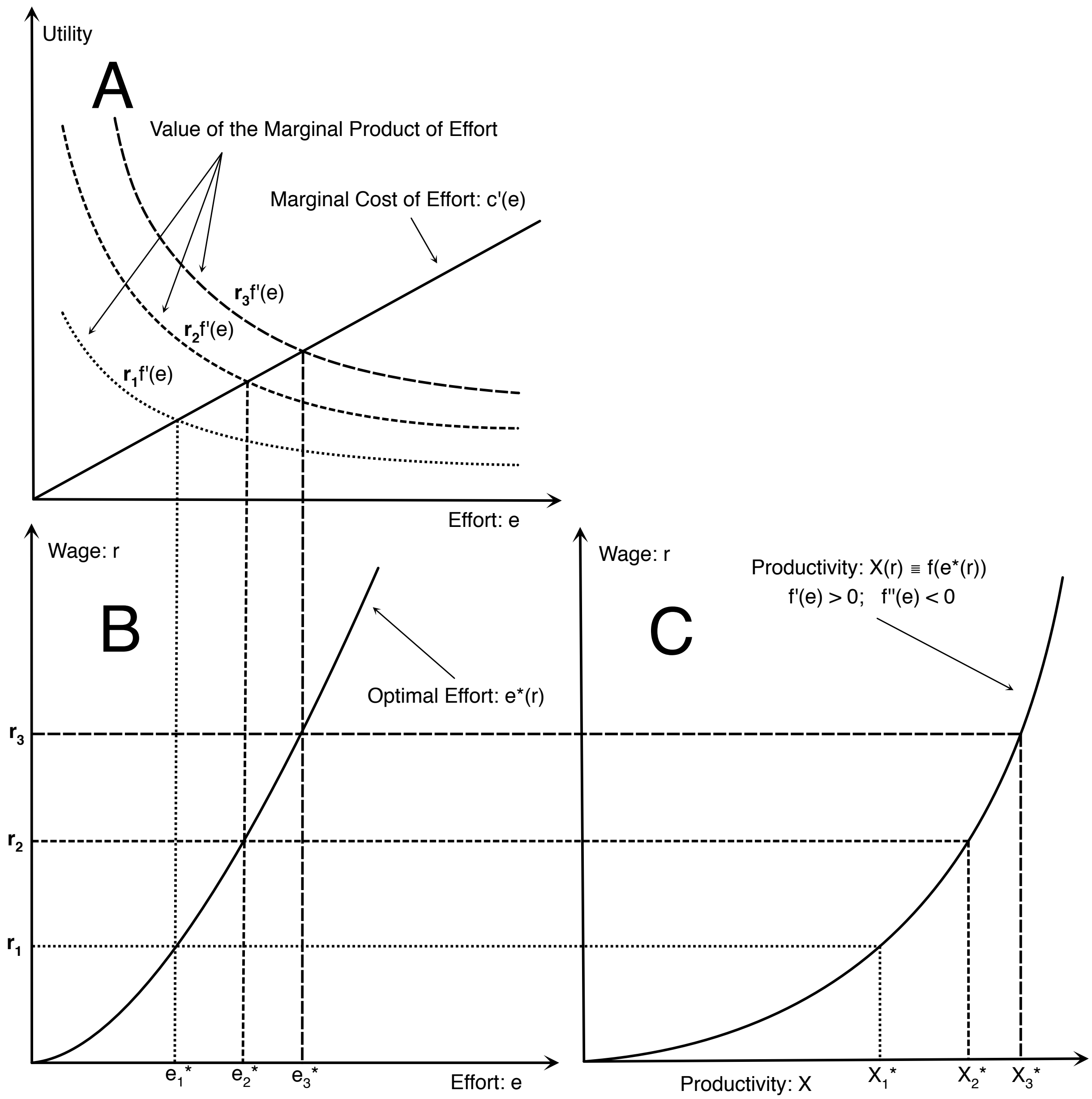
Figure 1: A Model of Optimal Worker Effort

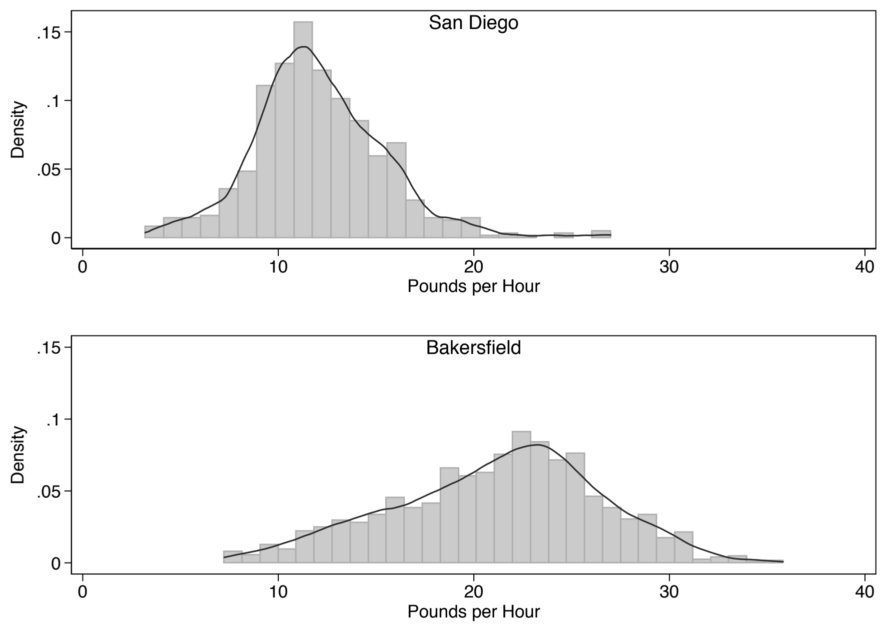


This figure illustrates the model developed in section 2.1, holding resource abundance (θ) and environmental conditions (T) constant. Panel A summarizes a worker's utility maximization process where the optimal level of effort is determined by the intersection of the value of marginal product of effort and the marginal cost of effort. This is drawn at three different piece rate wages: r_1, r_2, and r_3. Panel B translates the information from panel A into an optimal effort curve that is a function of the piece rate wage: $e^*(r)$. Finally, panel C turns the optimal effort curve into a productivity curve by plugging effort into the production function f. The result is productivity as a function of piece rate wage: $X(r)$. As drawn, $X_r > 0$ and $X_{rr} < 0$, as discussed in section 2.1. Empirically, I cannot observe effort e, but I can and do estimate X_r.

Figure 2: Farm Locations

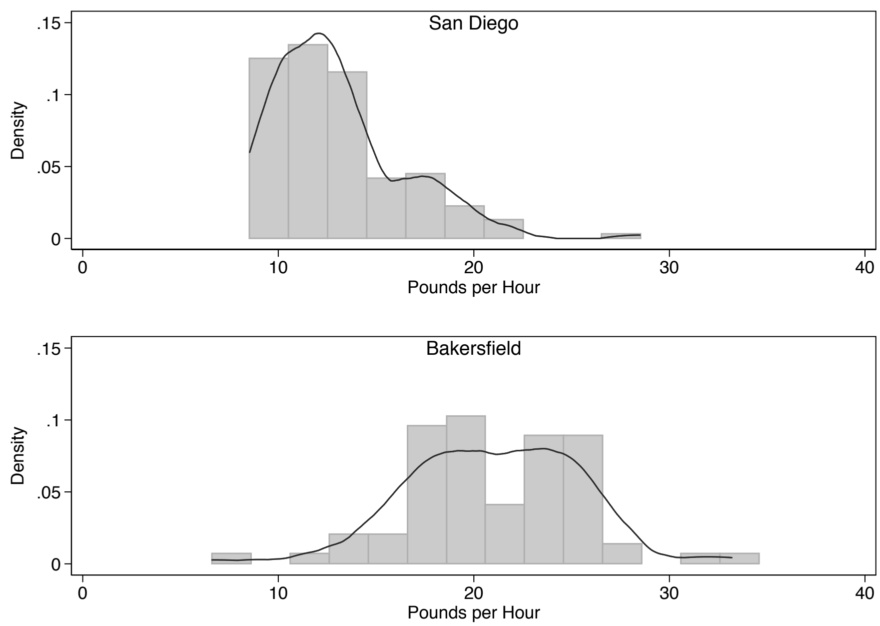
This figure maps the approximate locations of the farms studied. In order to protect the farms' identities, exact locations cannot be shared. The San Diego farm grows organic blueberries while the Bakersfield farm grows conventional blueberries. Source: author's spatial approximation.

Figure 3: Average Productivity by Picker



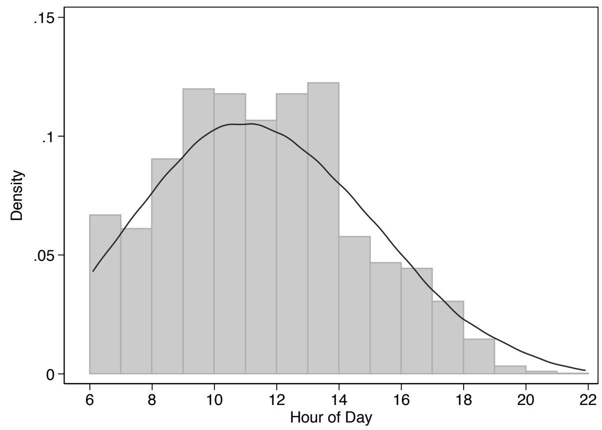
This figure plots the distribution of each picker's average productivity measured by pounds of blueberries picked per hour at two farms over three growing seasons. The San Diego farm (top panel) grows organic blueberries while the Bakersfield farm (bottom panel) grows conventional blueberries. The kernel density estimates use an Epanechnikov kernel. Source: proprietary payroll data.

Figure 4: Average Productivity by Day



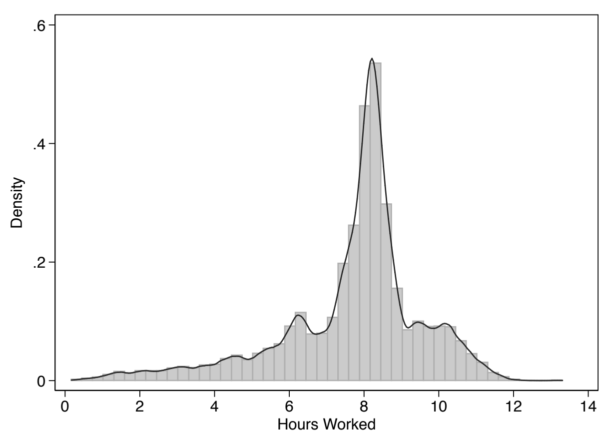
This figure plots the distribution of all pickers' productivity – measured by pounds of blueberries picked per hour and averaged over each day – at two farms over three growing seasons. The San Diego farm (top panel) grows organic blueberries while the Bakersfield farm (bottom panel) grows conventional blueberries. The kernel density estimates use an Epanechnikov kernel. Source: proprietary production data.

Figure 5: Time of Production



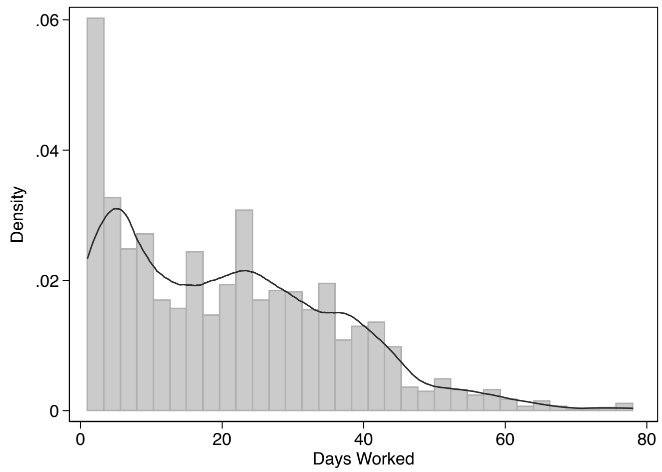
This figure plots the time distribution of blueberry pickers' "picking periods" at two California blueberry farms over three growing seasons. An observation in this distribution is the midpoint in time between when a picker begins filling a single tray of berries and when they weigh that tray. A single picker will have several "picking periods" within a single day. The kernel density estimate uses an Epanechnikov kernel with a bandwidth of two hours. Note that most weigh-ins occur before 3:00 p.m., as farmers and pickers avoid the hottest part of the day. Source: proprietary production data.

Figure 6: Hours Worked



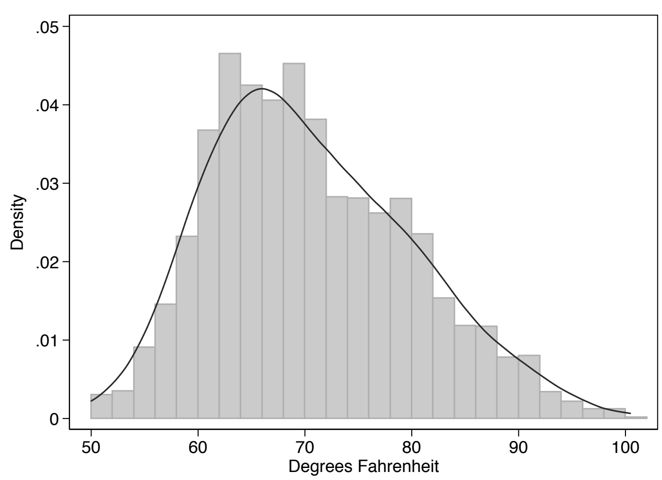
This figure plots the distribution of daily hours worked by blueberry pickers on two farms over three growing seasons. An observation is a picker-day. The kernel density estimate uses an Epanechnikov kernel. Under California law at the time of this study, agricultural laborers do not earn overtime pay until after working ten hours in a day. All observations in this figure with more than ten hours worked come from a single farm (San Diego). Source: proprietary payroll data.

Figure 7: Days Worked



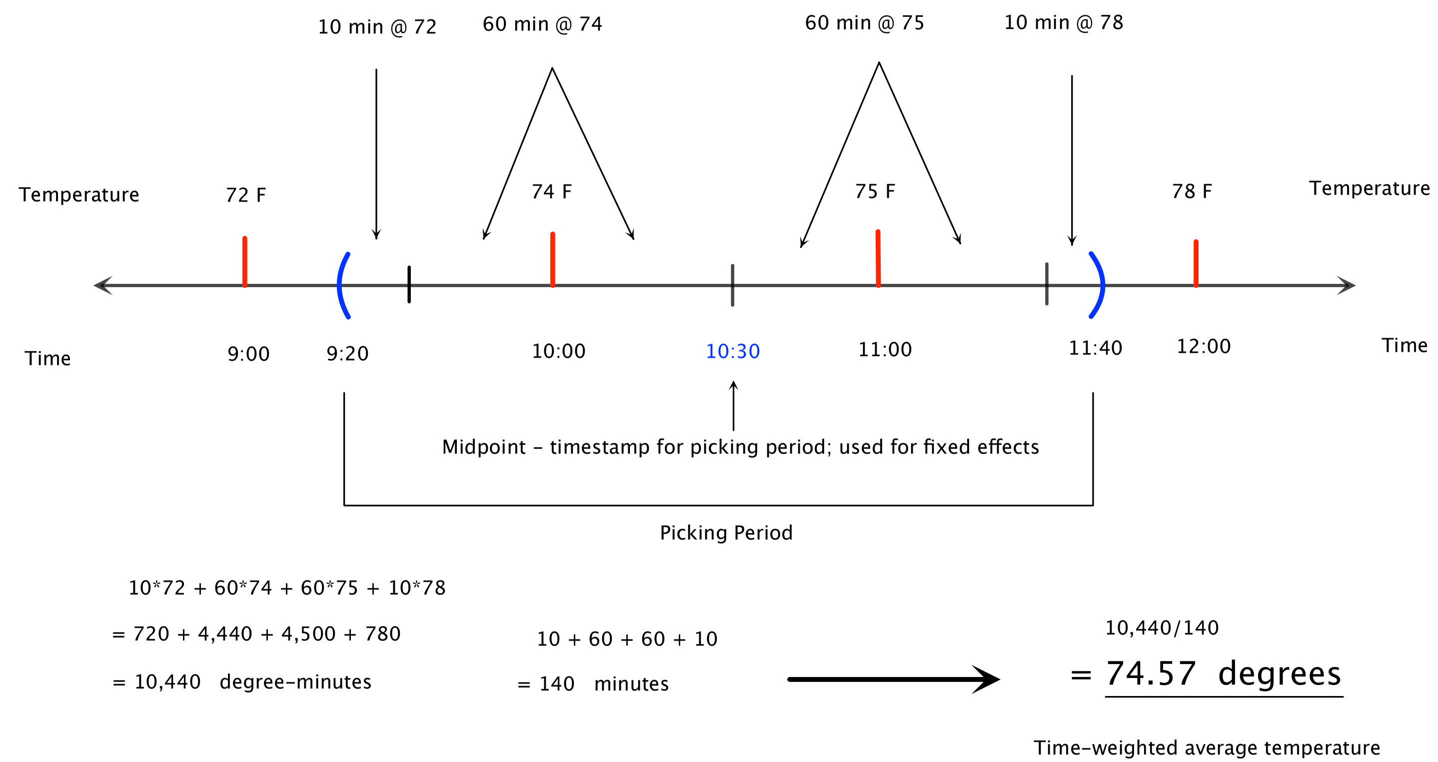
This figure plots the distribution of days worked in a single season by blueberry pickers on two farms over three growing seasons. An observation is a picker-season. The kernel density estimate uses an Epanechnikov kernel. Source: proprietary payroll data.

Figure 8: Temperature at Time of Production



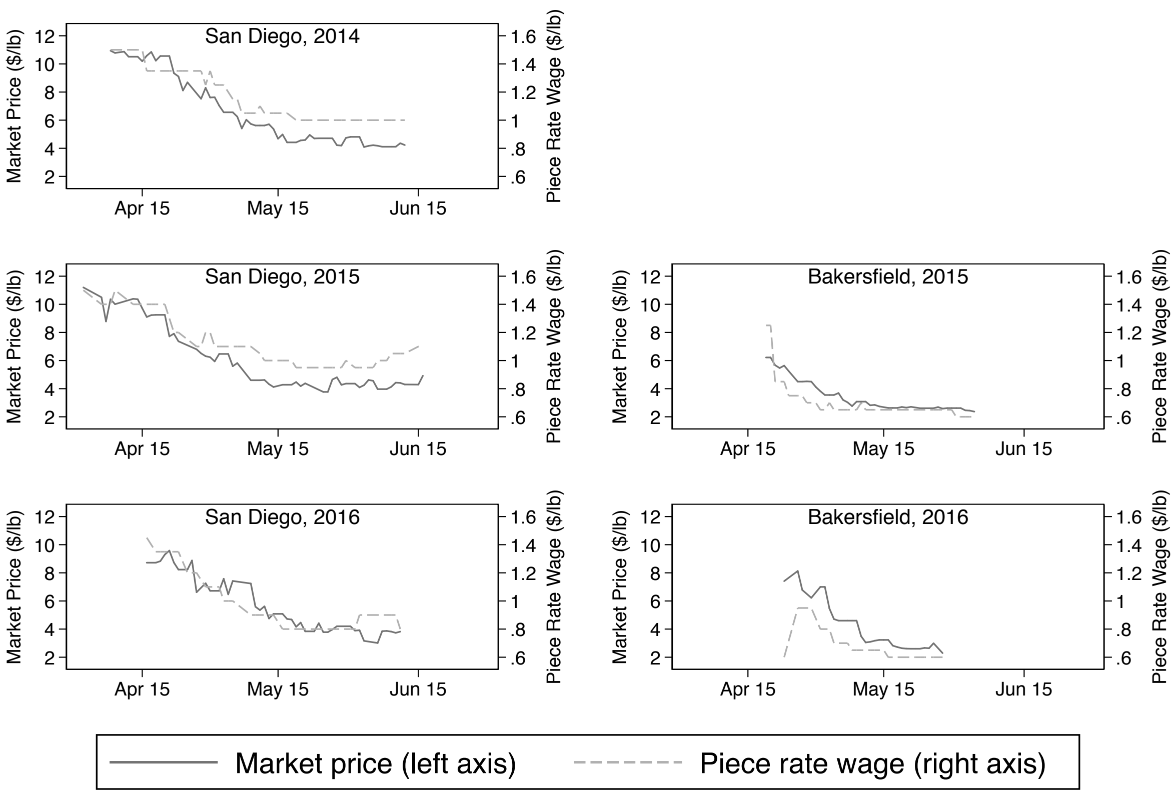
This figure plots the distribution of time-weighted average temperature in degrees Fahrenheit for each "picking period" at two California blueberry farms over three growing seasons. The kernel density estimate uses an Epanechnikov kernel with a bandwidth of three degrees. Sources: proprietary production data, MesoWest (temperature).

Figure 9: Time-Weighted Average Temperatures



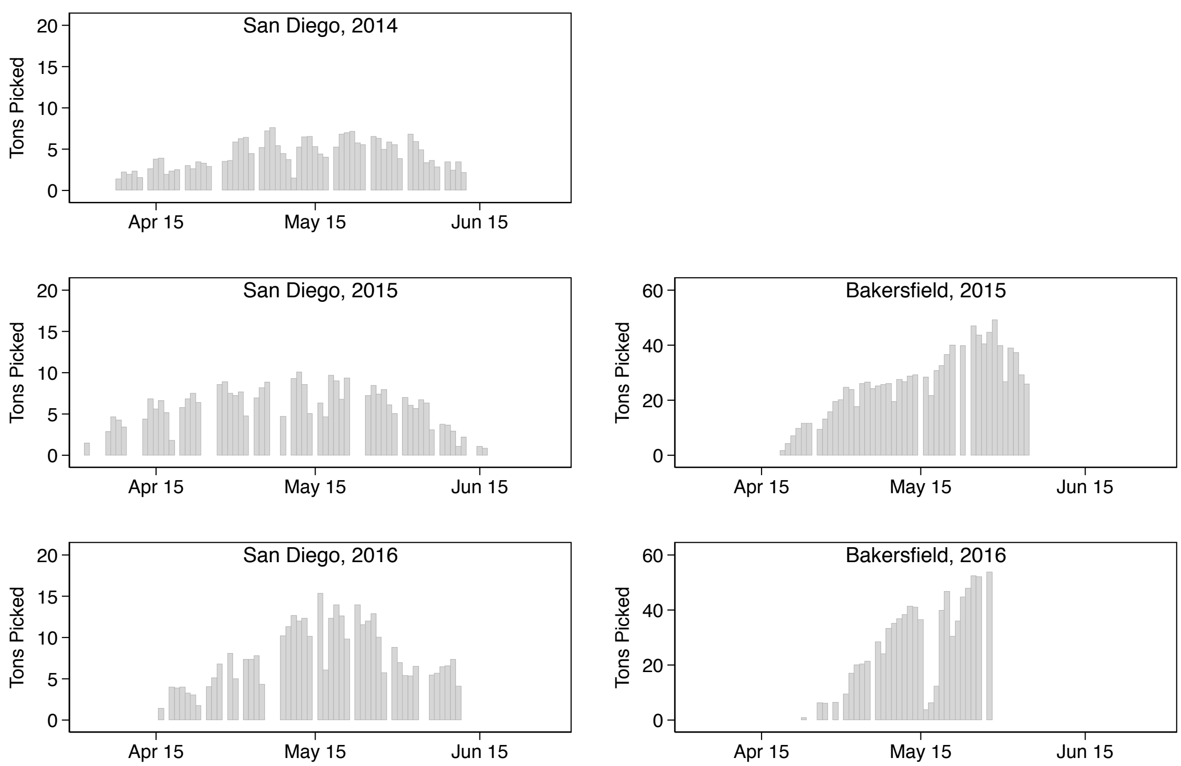
This figure describes the method I use to match temperature observations to a single "picking period" using hypothetical data. In particular, I calculate a time-weighted average of temperature observations during or near the time a picker is actively picking. Source: author's illustration.

Figure 10: Market Prices and Piece Rate Wages



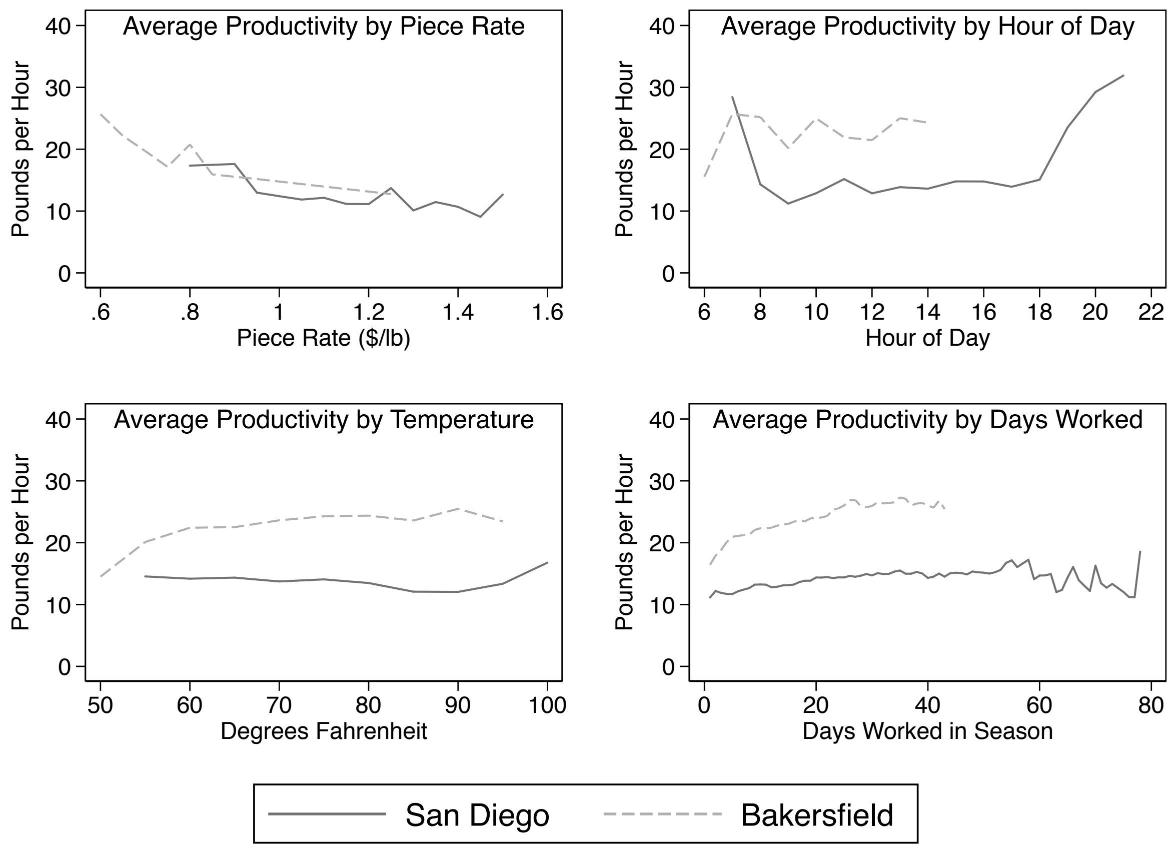
This figure plots the market price of California blueberries and the piece rate wage paid to berry pickers by two farms over the span of three growing seasons. The San Diego farm (left column) grows organic blueberries while the Bakersfield farm (right column) grows conventional blueberries. This explains the difference in the market price faced by the two farms. Sources: Blueberry Marketing Research Information Center, California Blueberry Commission (market prices); proprietary payroll data (piece rate wages).

Figure 11: Daily Blueberry Production



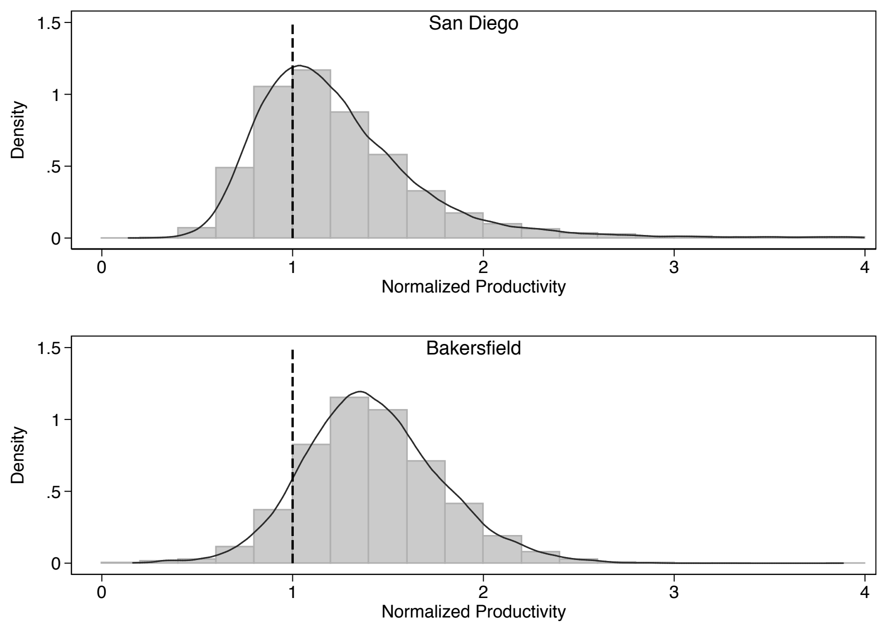
This figure plots production at two California blueberry farms over three growing seasons. Production is measured in tons, and observations are daily. Transitory gaps in production are generally weekends (especially Sundays) or rainy days. The San Diego farm (left column) grows organic blueberries while the Bakersfield farm (right column) grows conventional blueberries. Production ends abruptly as competition from northern producers (Washington, Oregon, and Michigan) pushes the market price for blueberries below profitable levels for California producers. Source: proprietary production data.

Figure 12: Average Productivity Across Observable Variables



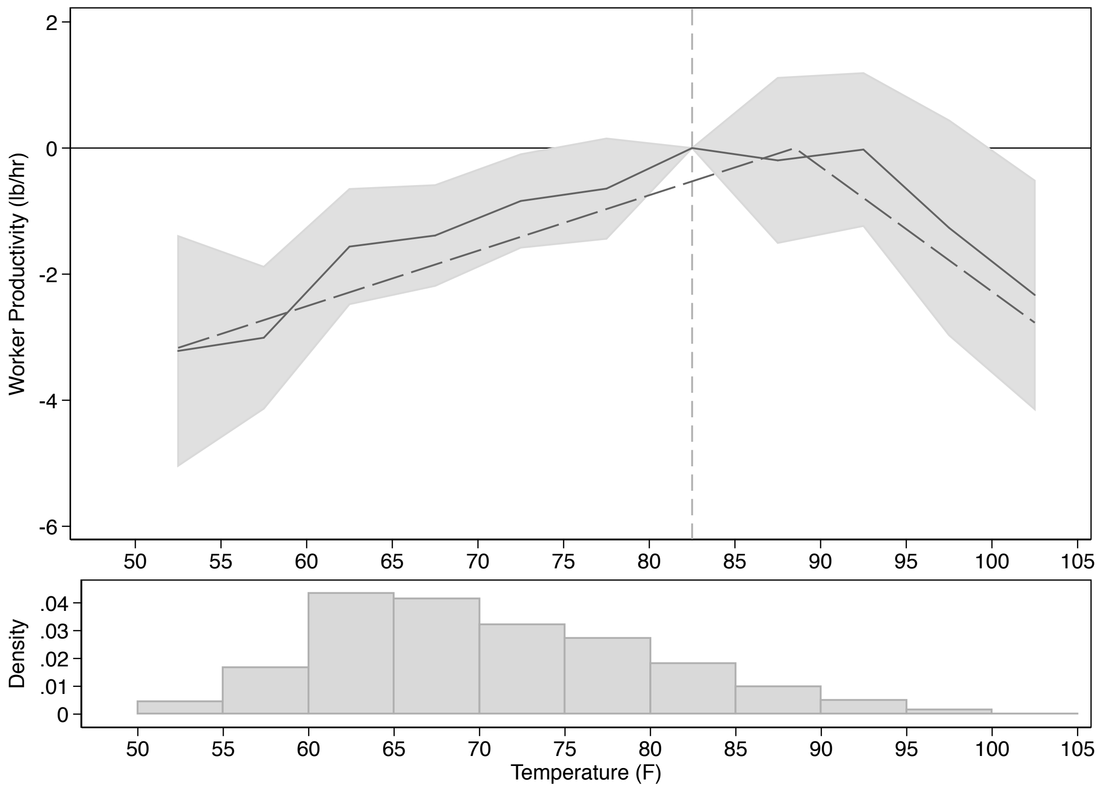
This figure plots average worker productivity – pounds of blueberries picked per hour – for two California blueberry farms over three growing seasons and across four observable variables: the piece rate wage, hour of day, temperature, and worker tenure. The San Diego farm (solid lines) grows organic blueberries while the Bakersfield farm (dashed lines) grows conventional blueberries. For the temperature plot, observations are grouped into five-degree bins beginning at 50 degrees Fahrenheit. None of these plots is adjusted for seasonality. Sources: proprietary payroll and production data, MesoWest (temperature).

Figure 13: How Frequently Does the Minimum Wage Bind?



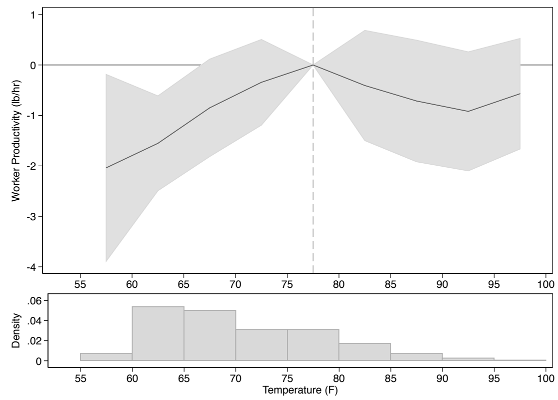
This figure plots the distribution of pickers' daily productivities over three growing seasons, normalized by the productivity necessary to exceed the hourly minimum wage rate. Normalization is necessary because both piece rate wages and the hourly minimum wage vary over the sample period. Pickers with a normalized productivity measure greater than one will earn more per hour than the minimum wage, while pickers with a normalized productivity measure less than one will be paid the hourly minimum wage. Pickers who consistently fall below this threshold receive additional training and are in some cases fired. The San Diego farm (top panel) grows organic blueberries while the Bakersfield farm (bottom panel) grows conventional blueberries. The kernel density estimates use an Epanechnikov kernel. Source: proprietary payroll data.

Figure 14: Effect of Temperature on Worker Productivity

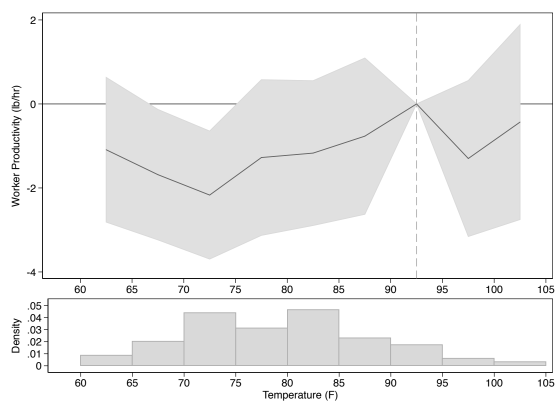


This figure plots the relationship between temperature and worker productivity (pounds of fruit picked per hour) while controlling for instrumented piece rate wages, worker tenure, worker tenure squared, field fixed effects, time fixed effects (year, week-of-year, day-of-week, hour-of-day), and worker fixed effects. The solid line in the top panel displays the point-estimates for the five-degree temperature bins in specification (6) of table 2 with an omitted temperature bin of 80–85 degrees. The light gray region surrounding this line signifies a 95% confidence interval, two-way clustered on date and worker. The dashed line in the top panel displays a piecewise linear specification of the relationship between temperature and worker productivity with a single node at 88.5 degrees Fahrenheit as in table 3. Below $88.5°F$, an additional degree in temperature elicits an 0.088 lb/hr increase in worker productivity. Above $88.5°F$, however, an additional degree in temperature reduces worker productivity by 0.20 lb/hr. These effects are statistically significant at the 0.001 and 0.05 levels, respectively, again two-way clustering on date and worker. Finally, the bottom panel displays a histogram of temperature observations in my data.

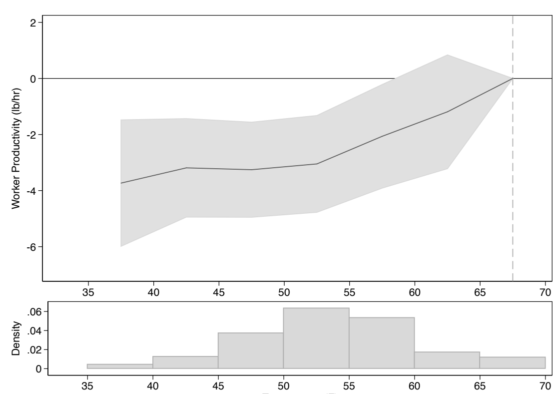
Figure 15: Effects of Daily Temperature on Daily Productivity



(a) Time-Weighted Daily Average Temperature



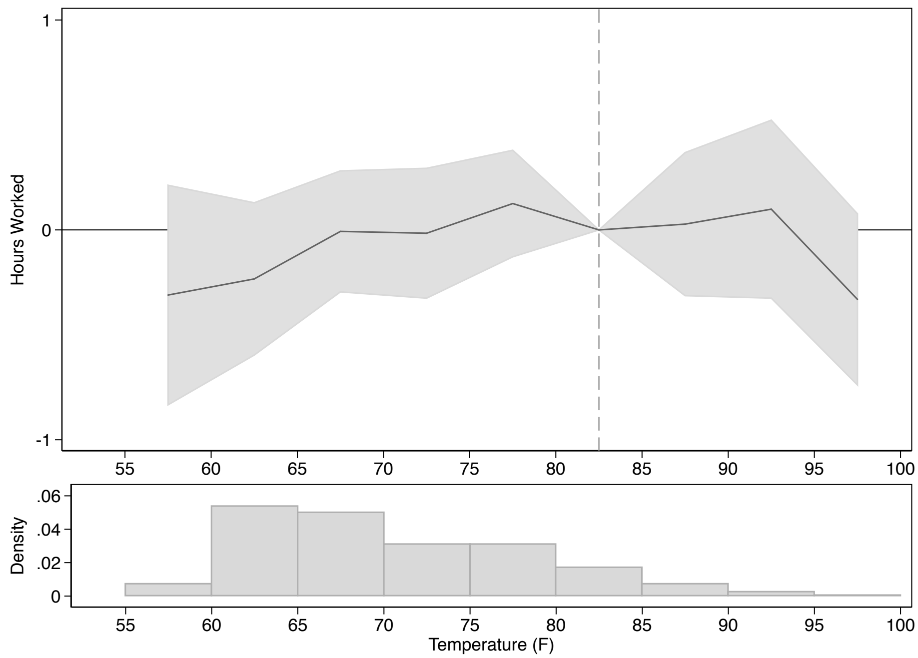
(b) Daily Maximum Temperature



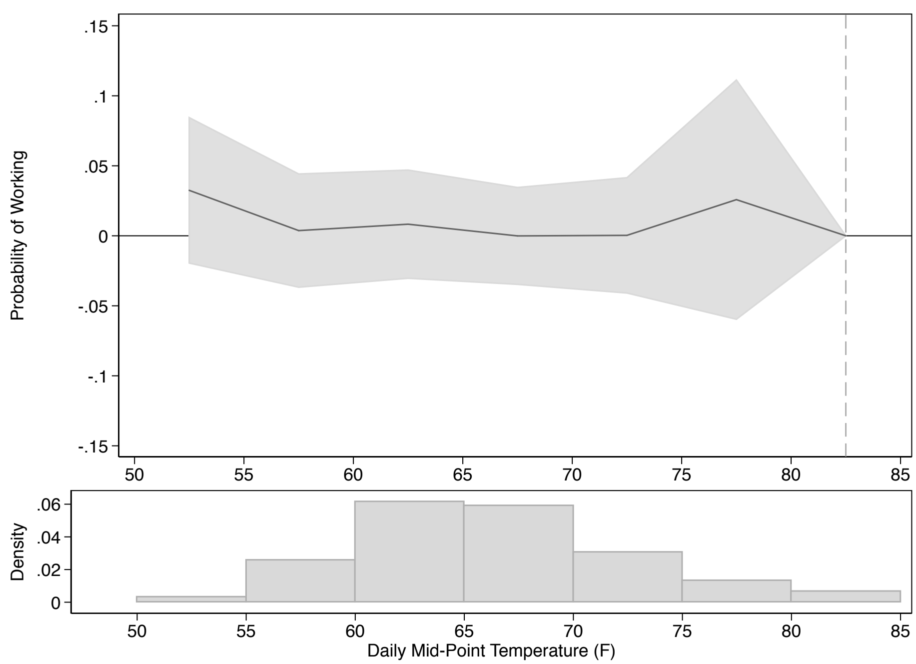
(c) Daily Minimum Temperature

These figures repeat the analysis from figure 14, using different measures of daily temperature. Panel (a) reports the effect of time-weighted average daily exposed temperature on daily picker productivity, panel (b) reports the effect of daily maximum temperature on daily picker productivity, and panel (c) reports the effect of daily minimum temperature on daily picker productivity. These results are qualitatively similar to those in figure 14.

Figure 16: Effects of Daily Temperature on Labor Supply



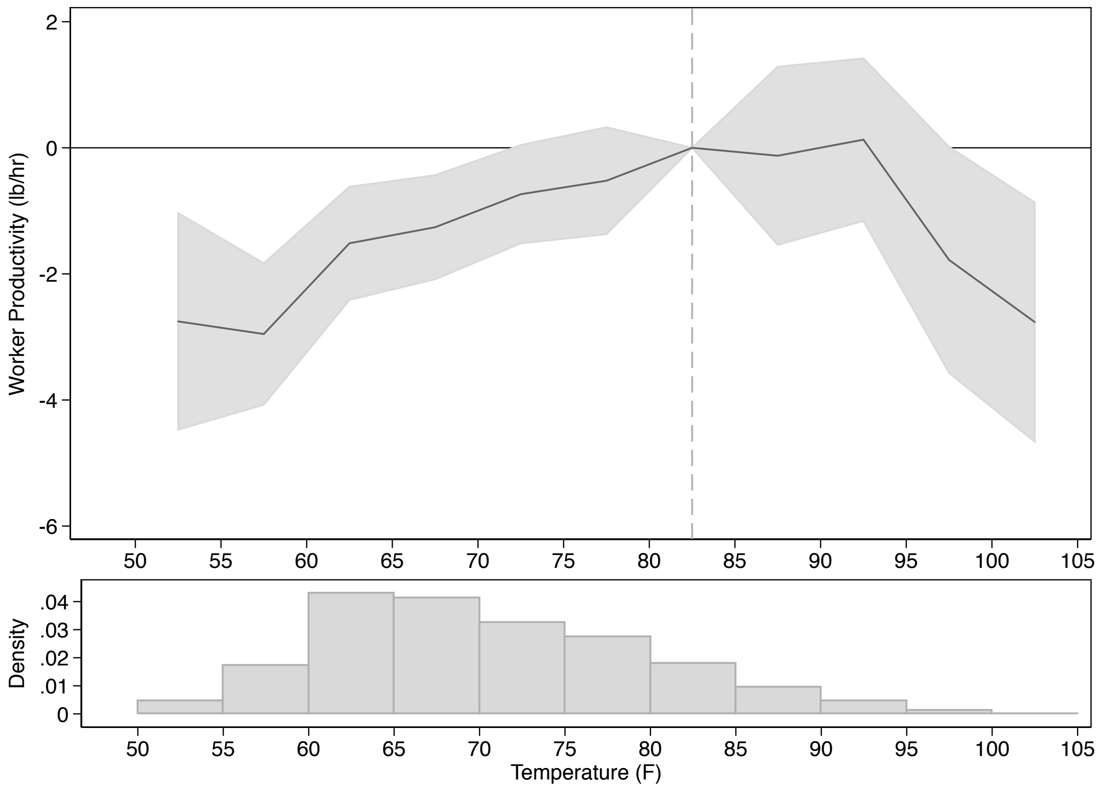
(a) Effect of Temperature on Hours Worked (Intensive Labor Supply)



(b) Effect of Temperature on Probability of Working (Extensive Labor Supply)

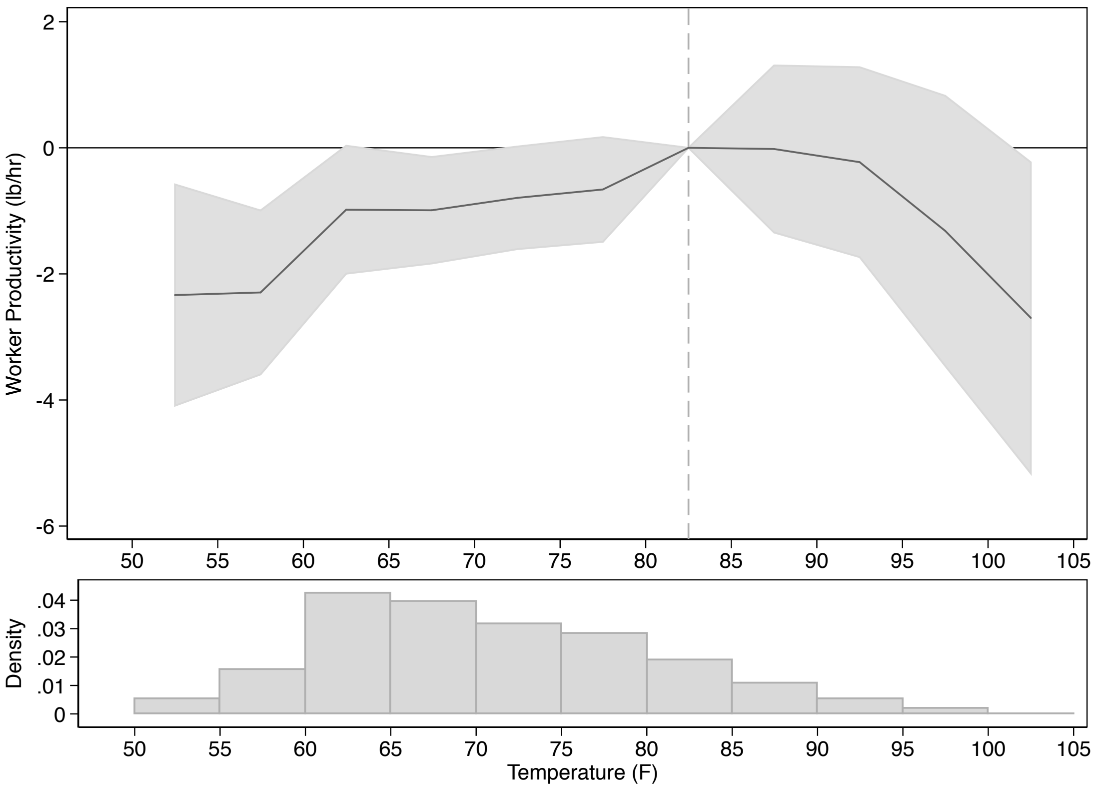
These figures display the results from table 5. Panel (a) reports the effect of temperature on pickers' intensive labor supply (the number of hours they work), and panel (b) reports the effect of temperature on pickers' extensive labor supply (the probability they show up to work on a given day). These results show that blueberry pickers have very inelastic labor supplies with respect to temperature.

Figure 17: Effect of Temperature on Worker Productivity Without Possible Shirkers



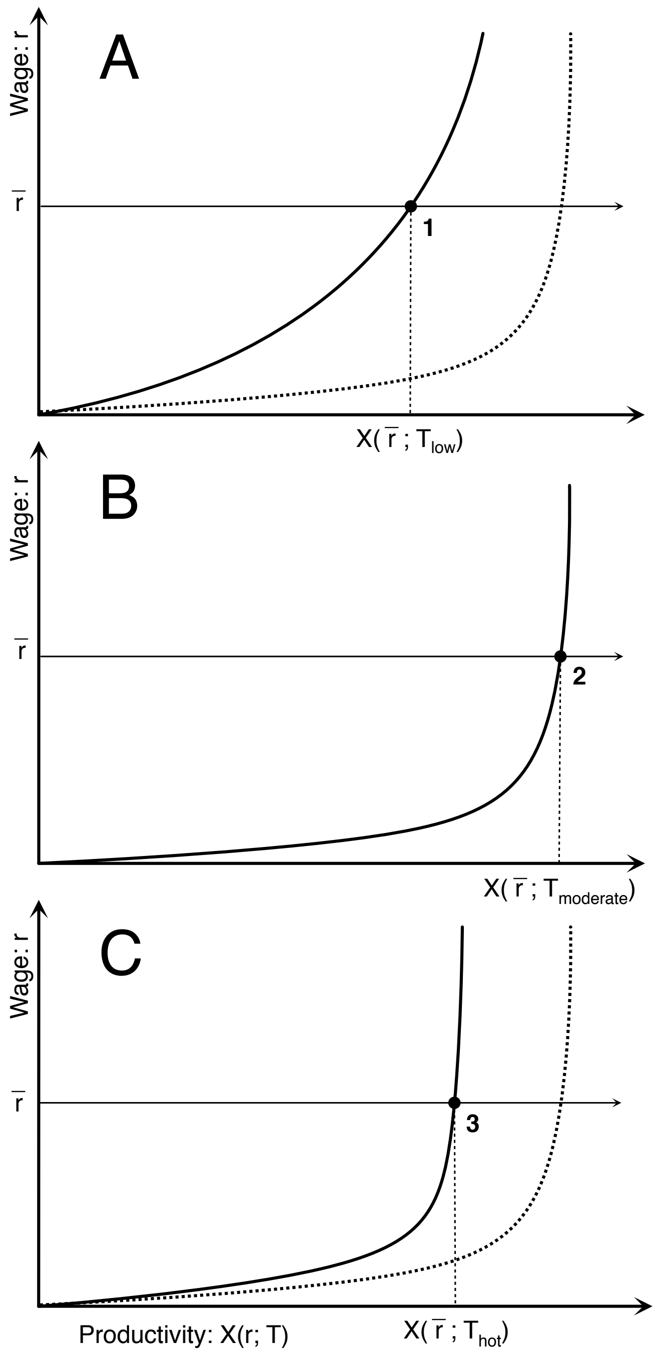
This figure plots the relationship between temperature and worker productivity (pounds of fruit picked per hour) while controlling for instrumented piece rate wages, worker tenure, worker tenure squared, field fixed effects, time fixed effects (year, week-of-year, day-of-week, hour-of-day), and worker fixed effects. This figure is estimated using only picker-day observations where pickers earn more than the hourly minimum wage. The top panel displays the point-estimates for the five-degree temperature bins as in specification (6) of table 2, while the bottom panel displays the support of temperature observations. The light gray region in the top panel signifies a 95% confidence interval, two-way clustered on date and worker. The omitted temperature bin is 80–85 degrees Fahrenheit.

Figure 18: Effect of Temperature on Worker Productivity Without Transient Workers



This figure plots the relationship between temperature and worker productivity (pounds of fruit picked per hour) while controlling for instrumented piece rate wages, worker tenure, worker tenure squared, field fixed effects, time fixed effects (year, week-of-year, day-of-week, hour-of-day), and worker fixed effects. This figure is estimated using only picker-day observations for workers who work more than thirty days in the relevant season. The top panel displays the point-estimates for the five-degree temperature bins as in specification (6) of table 2, while the bottom panel displays the support of temperature observations. The light gray region in the top panel signifies a 95% confidence interval, two-way clustered on date and worker. The omitted temperature bin is 80–85 degrees Fahrenheit.

Figure 19: Graphical Summary of Findings



This figure uses the productivity curve derived in panel C of figure 1 to qualitatively describe my empirical findings. At moderate temperatures (panel B of this figure), I find that berry pickers are very inelastic to the piece rate wages they face. That is, the slope at point **2** is close to vertical. At very hot temperatures (over 100°F; panel C of this figure), productivity is similarly inelastic to wages (point **3**). However, these extreme temperatures have a direct negative effect on productivity (**3** is to the left of **2**). Finally, at cool temperatures (under 60°F; panel A of this figure), I find a positive elasticity of productivity with respect to the piece rate wage. That is, the slope at point **1** is less than vertical. However, cool temperatures also have a large direct negative effect on productivity (**1** is to the left of both **2** and **3**).

Table 1: Summary Statistics

	Pooled Sample			San Diego Farm			Bakersfield Farm		
Variable	Observations	Mean	SD	Observations	Mean	SD	Observations	Mean	SD
Panel A: variables that vary by weigh-in									
Worker productivity (lb/hr)	305,980	19.09	9.86	122,549	13.87	8.76	183,431	22.58	8.97
Temperature (°F)	305,980	70.63	9.31	122,549	72.34	9.27	183,431	69.48	9.17
Effective hourly wage ($/hr)	305,980	14.35	7.20	122,549	13.90	9.09	183,431	14.64	5.58
Panel B: variables that vary by worker-day									
Hours worked	47,939	7.71	1.90	23,026	7.71	2.50	24,913	7.72	1.06
Worker tenure by season (days)	47,939	17.75	13.04	23,026	22.07	14.68	24,913	13.75	9.74
Hourly minimum wage binds (proportion)	47,939	0.21	0.41	23,026	0.32	0.47	24,913	0.11	0.31
Panel C: variables that vary by day									
Piece rate wage ($/lb)	229	0.97	0.26	156	1.10	0.20	73	0.69	0.13
Market price ($/lb)	229	5.37	2.35	156	6.14	2.30	73	3.71	1.44
Total production (tons)	229	12.61	12.81	156	5.86	2.96	73	27.03	13.82
Number of workers	229	209.34	120.23	156	147.60	41.00	73	341.27	127.46
Female workers (proportion)	229	0.65	0.17	156	0.72	0.15	73	0.49	0.05
Panel D: number of days and employees									
Unique days in sample	170			156			73		
Unique employees in sample	2,022			655			1,367		

Note: SD: standard deviation. "Hourly minimum wage binds" is an indicator variable equal to one for a worker-day if the worker in question picked enough fruit per unit of time to earn more money under the piece rate wage than under the hourly minimum wage. "Worker tenure by season" is a variable that counts the number of days (inclusive) that a single employee has worked at a given farm in a given year. On a worker's first day of work in a season, this variable equals one. On their second, it equals two. And so on. The San Diego farm grows organic blueberries while the Bakersfield farm grows conventional blueberries. This explains the difference in mean market price faced by the two farms.

Table 2: Effects of Wage and Temperature on Worker Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Piece Rate Wage (¢/lb)	-0.20***	-0.14***	-0.16***	-0.074***	0.019	0.020
	(0.013)	(0.016)	(0.021)	(0.017)	(0.049)	(0.060)
Temperature $\in$ $[50, 55)$	-8.68***	-9.36***	-9.46***	-9.62***	-2.93***	-3.22***
	(0.87)	(0.86)	(0.81)	(0.74)	(0.94)	(0.93)
Temperature $\in$ $[55, 60)$	-2.78***	-3.09***	-3.37***	-3.34***	-2.78***	-3.01***
	(0.93)	(0.90)	(0.84)	(0.77)	(0.60)	(0.57)
Temperature $\in$ $[60, 65)$	-1.34*	-1.23	-1.37*	-1.25*	-1.39***	-1.56***
	(0.76)	(0.75)	(0.71)	(0.67)	(0.49)	(0.47)
Temperature $\in$ $[65, 70)$	-1.18	-1.09	-1.30*	-1.15*	-1.25***	-1.39***
	(0.73)	(0.72)	(0.67)	(0.65)	(0.43)	(0.41)
Temperature $\in$ $[70, 75)$	-0.23	-0.37	-0.53	-0.54	-0.73*	-0.84**
	(0.58)	(0.54)	(0.52)	(0.48)	(0.38)	(0.38)
Temperature $\in$ $[75, 80)$	-0.14	-0.056	-0.23	-0.22	-0.52	-0.64
	(0.67)	(0.65)	(0.61)	(0.59)	(0.43)	(0.41)
Temperature $\in$ $[85, 90)$	-0.53	-0.69	-0.67	-0.70	-0.26	-0.20
	(0.90)	(0.90)	(0.87)	(0.80)	(0.68)	(0.67)
Temperature $\in$ $[90, 95)$	-0.49	-0.38	-0.30	-0.59	-0.14	-0.024
	(0.93)	(0.83)	(0.77)	(0.70)	(0.65)	(0.62)
Temperature $\in$ $[95, 100)$	-2.05**	-1.37*	-1.38	-2.15***	-1.06	-1.27
	(1.01)	(0.78)	(0.84)	(0.78)	(0.86)	(0.87)
Temperature $\in$ $[100, 105)$	-1.40**	0.34	-0.64	-0.82	-1.62*	-2.33**
	(0.62)	(0.61)	(0.94)	(0.98)	(0.91)	(0.93)
Worker Tenure				0.36***	0.35***	0.36***
				(0.034)	(0.027)	(0.047)
Worker Tenure^2				-0.0051***	-0.0045***	-0.0052***
				(0.00068)	(0.00058)	(0.00071)
Number of Observations	305980	305980	305980	305980	305980	305980
Mean of Dependent Variable	19.1	19.1	19.1	19.1	19.1	19.1
Farm FE		X				
Field FE			X	X	X	X
Time FE					X	X
Worker FE						X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: In all specifications, the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Results are estimated by two-stage least squares (2SLS) instrumenting for the piece rate wage with the market price for blueberries. Temperature is measured in degrees Fahrenheit, and the omitted temperature bin is 80–85 degrees. Worker tenure is the number of days an employee has worked in the current season at the time of weigh-in. Time fixed effects include year, week-of-year, day-of-week, and hour-of-day fixed effects. Standard errors are two-way clustered on date and worker.

Table 3: Piecewise Linear Effect of Temperature on Worker Productivity

	(1)
Piece Rate Wage (¢/lb)	0.026
	(0.060)
Temperature, $< 88.5°F$	0.088***
	(0.019)
Temperature, $> 88.5°F$	-0.20**
	(0.100)
Worker Tenure	0.36***
	(0.047)
Worker Tenure^2	-0.0052***
	(0.00070)
Number of Observations	305980
Mean of Dependent Variable	19.1
Field FE	X
Time FE	X
Worker FE	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents results of a piecewise linear relationship between temperature and worker productivity with a single node at 88.5°F. The dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Results are estimated by two-stage least squares (2SLS) instrumenting for the piece rate wage with the market price for blueberries. Worker tenure is the number of days an employee has worked in the current season, measured on the day of an observation. Time fixed effects include year, week-of-year, day-of-week, and hour-of-day fixed effects. Standard errors are two-way clustered on date and worker.

Table 4: Testing Market Price as an Instrument for Piece Rate Wage

	(1) OLS	(2) First Stage	(3) Reduced Form	(4) 2SLS
Piece Rate Wage (¢/lb)	-0.015			0.020
	(0.023)			(0.060)
Market Price ($/lb)		4.97***	0.100	
		(0.64)	(0.30)	
Temperature $\in$ $[50, 55)$	-3.26***	-1.21	-3.24***	-3.22***
	(0.93)	(1.39)	(0.93)	(0.93)
Temperature $\in$ $[55, 60)$	-3.03***	-1.22	-3.03***	-3.01***
	(0.57)	(1.13)	(0.57)	(0.57)
Temperature $\in$ $[60, 65)$	-1.60***	-1.46*	-1.59***	-1.56***
	(0.45)	(0.85)	(0.45)	(0.47)
Temperature $\in$ $[65, 70)$	-1.41***	-1.02	-1.41***	-1.39***
	(0.40)	(0.72)	(0.40)	(0.41)
Temperature $\in$ $[70, 75)$	-0.85**	-0.52	-0.85**	-0.84**
	(0.38)	(0.58)	(0.38)	(0.38)
Temperature $\in$ $[75, 80)$	-0.65	-0.19	-0.65	-0.64
	(0.41)	(0.43)	(0.40)	(0.41)
Temperature $\in$ $[85, 90)$	-0.21	0.66	-0.18	-0.20
	(0.66)	(0.73)	(0.68)	(0.67)
Temperature $\in$ $[90, 95)$	0.0038	1.39	0.0044	-0.024
	(0.62)	(0.88)	(0.63)	(0.62)
Temperature $\in$ $[95, 100)$	-1.20	2.36**	-1.22	-1.27
	(0.87)	(0.96)	(0.88)	(0.87)
Temperature $\in$ $[100, 105)$	-2.22**	6.25***	-2.20**	-2.33**
	(0.91)	(1.70)	(0.95)	(0.93)
Number of Observations	305980	305980	305980	305980
Mean of Dependent Variable	19.1	80.5	19.1	19.1
Controls for Worker Tenure	X	X	X	X
Field FE	X	X	X	X
Time FE	X	X	X	X
Worker FE	X	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: In specifications (1), (3), and (4), the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). In specification (2), the dependent variable is piece rate wage in cents per pound (¢/lb). All specifications include my preferred set of controls as in specification (6) from table 2. Temperature is measured in degrees Fahrenheit, and the omitted temperature bin is 80–85 degrees. Standard errors are two-way clustered on date and worker.

Table 5: Effects of Wage and Temperature on Labor Supply

	(1) Hours Worked	(2) Hours Worked	(3) Probability of Working
Piece Rate Wage (¢/lb)	0.0100		0.000078
	(0.014)		(0.0015)
Market Price ($/lb)		0.049	
		(0.070)	
Worked the Previous Day			0.72***
			(0.018)
Temperature $\in$ $[50, 55)$			0.031
			(0.026)
Temperature $\in$ $[55, 60)$	-0.31	-0.32	0.0030
	(0.27)	(0.27)	(0.021)
Temperature $\in$ $[60, 65)$	-0.23	-0.26	0.0072
	(0.19)	(0.19)	(0.020)
Temperature $\in$ $[65, 70)$	-0.0071	-0.036	-0.00059
	(0.15)	(0.15)	(0.018)
Temperature $\in$ $[70, 75)$	-0.016	-0.026	-0.0019
	(0.16)	(0.16)	(0.021)
Temperature $\in$ $[75, 80)$	0.13	0.11	0.024
	(0.13)	(0.13)	(0.044)
Temperature $\in$ $[85, 90)$	0.028	0.044	
	(0.17)	(0.18)	
Temperature $\in$ $[90, 95)$	0.099	0.11	
	(0.22)	(0.22)	
Temperature $\in$ $[95, 100)$	-0.33	-0.31	
	(0.21)	(0.21)	
Number of Observations	47919	47919	201966
Mean of Dependent Variable	7.71	7.71	0.24
Controls for Worker Tenure	X	X	X
Start Hour FE	X	X	
Time FE	X	X	X
Worker FE	X	X	X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the effects of temperature and wages on workers' labor supply, both on the intensive margin (hours worked) and on the extensive margin (probability of working). In specifications (1) and (2), the dependent variable is the number of hours worked by a picker in a single day, and temperature is measured as a time-weighted average experienced by the picker during that day. In specification (3), the dependent variable is an indicator for whether a picker worked at all in a given day, and temperature is measured as a daily midpoint temperature: (Daily Max + Daily Min)/2. Temperature is measured in degrees Fahrenheit, and the omitted temperature bin is 80–85 degrees. Specifications (1) and (3) are estimated by 2SLS, instrumenting for the piece rate wage with the market price for blueberries. Time fixed effects include year, week of year, and day of week. Standard errors are two-way clustered on date and worker.

Table 6: Effect of Piece Rate Wage on Worker Productivity by Temperature

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[50, 60)	[60, 65)	[65, 70)	[70, 75)	[75, 80)	[80, 85)	[85, 90)	[90, 105)
Piece Rate Wage (¢/lb)	0.28***	0.015	0.063	-0.029	-0.18	0.22	0.094	-0.29
	(0.097)	(0.091)	(0.083)	(0.073)	(0.13)	(0.15)	(0.091)	(0.19)
Number of Observations	32668	66265	63640	48915	41617	27912	15046	9917
Mean of Dependent Variable	18.0	18.9	19.1	20.1	19.7	19.1	17.9	17.7
Controls for Worker Tenure	X	X	X	X	X	X	X	X
Field FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Worker FE	X	X	X	X	X	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: In all regressions, the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Each column reports the effect of piece rate wages (instrumented by market prices via two-stage least squares) on worker productivity for a different range of temperature. Temperatures are pooled between 50 and 60 degrees and between 90 and 105 degrees to ensure a sufficient sample size to estimate effects in those ranges. Standard errors are two-way clustered on date and worker.

Table 7: Effect of Piece Rate Wage on Worker Productivity by Temperature: OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[50, 60)	[60, 65)	[65, 70)	[70, 75)	[75, 80)	[80, 85)	[85, 90)	[90, 105)
Piece Rate Wage (¢/lb)	0.100*	-0.028	0.020	-0.032	-0.059	0.074	0.13	-0.19
	(0.050)	(0.048)	(0.041)	(0.031)	(0.054)	(0.063)	(0.078)	(0.15)
Number of Observations	32668	66265	63640	48915	41617	27912	15046	9917
Mean of Dependent Variable	18.0	18.9	19.1	20.1	19.7	19.1	17.9	17.7
Controls for Worker Tenure	X	X	X	X	X	X	X	X
Field FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Worker FE	X	X	X	X	X	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates table 6 without instrumenting for piece rate wages. Instead, I run each regression using ordinary least squares (OLS). By comparing these results to those in table 6, it is clear that OLS biases my estimates toward zero. In all regressions, the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Each column reports the effect of piece rate wages on worker productivity for a different range of temperature. Temperatures are pooled between 50 and 60 degrees and between 90 and 105 degrees to ensure a sufficient sample size to estimate effects in those ranges. Standard errors are two-way clustered on date and worker.

Table 8: Piece Rate Wage Effect Without Possible Shirkers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[50, 60)	[60, 65)	[65, 70)	[70, 75)	[75, 80)	[80, 85)	[85, 90)	[90, 105)
Piece Rate Wage (¢/lb)	0.27***	0.013	0.047	-0.065	-0.20	0.20	0.014	-0.44
	(0.10)	(0.079)	(0.080)	(0.067)	(0.12)	(0.16)	(0.098)	(0.27)
Number of Observations	28494	55311	53630	41517	35300	23367	12192	7878
Mean of Dependent Variable	19.0	20.6	20.7	21.8	21.4	20.9	19.9	19.8
Controls for Worker Tenure	X	X	X	X	X	X	X	X
Field FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Worker FE	X	X	X	X	X	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table is analogous to table 6, with the distinction that here I include only those picking period observations for workers who earn more than the hourly minimum wage for the day. In all regressions, the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Each column reports the effect of piece rate wages (instrumented by market prices via two-stage least squares) on worker productivity for a different range of temperature. Temperatures are pooled between 50 and 60 degrees and between 90 and 105 degrees to ensure a sufficient sample size to estimate effects in those ranges. Standard errors are two-way clustered on date and worker.

Table 9: Piece Rate Wage Effect Without Transient Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[50, 60)	[60, 65)	[65, 70)	[70, 75)	[75, 80)	[80, 85)	[85, 90)	[90, 105)
Piece Rate Wage (¢/lb)	0.45***	0.090	0.21**	0.13	0.25	0.39***	0.19***	-0.86***
	(0.11)	(0.090)	(0.099)	(0.10)	(0.21)	(0.13)	(0.052)	(0.18)
Number of Observations	16672	33872	31918	25130	22500	15136	8543	5973
Mean of Dependent Variable	17.8	17.3	17.8	18.3	18.0	17.0	15.6	15.8
Controls for Worker Tenure	X	X	X	X	X	X	X	X
Field FE	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X
Worker FE	X	X	X	X	X	X	X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table is analogous to table 6, with the distinction that here I include only those picking period observations for workers who work more than thirty days in the relevant season. In all regressions, the dependent variable is worker productivity measured in pounds of fruit picked per hour (lb/hr). Each column reports the effect of piece rate wages (instrumented by market prices via two-stage least squares) on worker productivity for a different range of temperature. Temperatures are pooled between 50 and 60 degrees and between 90 and 105 degrees to ensure a sufficient sample size to estimate effects in those ranges. Standard errors are two-way clustered on date and worker.