How Many Pears Would a Pear Packer Pack if a Pear Packer Could Pack Pears at Quasi-Exogenously Varying Piece Rates?[1]

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Abstract

We examine labor supply using a unique dataset collected from a large pear-packing factory. Pear packers face both expected and unexpected shocks to their wages, and we use this to evaluate different models of inter-temporal labor supply. We find strong evidence for reference-dependent preferences, but only mixed support for models of rational-expectations-based targets.

1 Introduction

The way in which workers respond to a change in their wage rate is of interest to both academics and policy makers. Understanding how workers respond to wage changes determines the optimal incentive scheme that employers ought to provide (Prendergast, 1999). Moreover, the evaluation of government tax and transfer programs depends crucially on reliable estimates of how labor supply responds to wages (Farber, 2008).

In the absence of income effects, the neoclassical model of labor supply predicts a positive wage elasticity of work. But starting with work by Camerer et al. (1997), several empirical studies have challenged this prediction. Instead, they find evidence of negative temporal substitution in response to temporary wage shocks. Individuals seem to work less hard when their wages rise. These studies have suggested a model based on prospect theory, a model that combines neoclassical preferences with a reference point and loss aversion.[1] In such models, individuals are assumed to be more sensitive to changes in income below some reference point than above it. This creates a kink in preferences around the reference point that can lead to a negative wage elasticity, even in the absence of income effects.

Such models have inspired a number of empirical studies, but the importance of reference-dependent preferences in labor supply is still unclear. The literature on reference-dependent labor supply has focused exclusively on the labor supply of workers that are free to set their own hours.[2] It remains unclear whether reference-dependent preferences are an important factor in determining the labor supply of workers who work in an hours-constrained environment.

[1]See, for instance, Kahneman and Tversky (1979) and Tversky and Kahneman (1991).

[2]For instance, economists have studied the behavior of cab drivers (Camerer et al., 1997; Chou, 2000; Farber, 2005, 2008; Crawford and Meng, 2008), stadium vendors (Oettinger, 1999), bicycle messengers (Fehr and Götte, 2007), and fishermen (Giné et al., 2010).

This paper adds to this literature in three ways. First, we examine worker behavior in a setting where workers cannot choose their own hours, but can adjust their effort. Since relatively few professions allow workers to freely set their own hours, such an environment may be more representative of the general workforce. Second, the data we study allow us to explicitly test the role of cumulative worker fatigue in determining the labor supply of our workers. Third, we examine the role of both skill and experience in determining how workers respond to both predictable and unpredictable shocks. To our knowledge this paper is the first to examine reference-dependence in an hours-constrained environment, and the first to measure the effect of fatigue (increasing disutility of effort) in downward-sloping labor supply.

We analyze how workers respond to changes in their wage rate using a dataset of workers at a California firm that packages pears and ships them to retailers. We use a combination of worker-day-level payroll data as well as worker-minute-level data from a field-collection effort. The workers in this firm regularly face both expected and unexpected shocks to their wages, and we examine the workers' response to these shocks to directly test several models of labor supply.

The workers in our sample face two types of wage shocks. The first wage shock is driven by state laws regarding overtime. Workers are required to stay for an entire shift, but the length of a shift varies. Once a worker has worked eight hours in a given day or forty hours in a given week, the firm must increase compensation by fifty percent. Workers do not know the exact length of a shift on any given day, thus daily overtime represents a partially unexpected shock to wages. In contrast, weekly overtime is much more predictable, and represents a largely expected shock to wages.

The second type of wage shock is driven by the way work is organized on the factory floor. As workers package pears for shipping, they rotate across bins filled with pears of different sizes. Workers must pack a different number of pears into each box, depending on the size of the pear at their current bin. But workers are paid the same piece rate for each box packed. As such, when packing larger pears, a worker's implicit wage rises, because fewer pears need to be packed per box. Conversely, when assigned to pack smaller pears, their implicit wage falls. For the sake of fairness, the workers rotate across bins, spending roughly fifteen minutes at each bin. As a result, variation in pear size generates high-frequency, predictable variation in wages throughout the course of a workday.

Our empirical analysis leads to three main findings. First, workers respond to unexpected overtime by *decreasing* their effort. Second, workers respond to expected overtime by *increasing* effort, and this increase is larger for more experienced workers. Third, workers respond to bin rotation in a manner that differs by their skill level.[3] While the average worker responds by *decreasing* effort when facing a higher implicit wage, skilled workers respond with *increasing* levels of effort. The changes in effort we estimate are consistent with reference-dependent preferences, and suggest that reference dependence may be an important factor in the labor supply of hours-constrained workers. Specifically, we find that workers respond to overtime in a manner consistent with the work of Köszegi and Rabin (2006), and their model of reference-dependence based on rational expectations.[4] That is, workers exert less effort during overtime when that overtime is unexpected, even though it corresponds to a 50-percent increase in piece rates.

In contrast, the wage elasticity we estimate based on workers rotating across pears of different sizes depends on each worker's skill. Unskilled workers exhibit a negative wage elasticity when rotating across pears of different sizes, but skilled workers exhibit

[3]As described below, we measure the skill of each worker with their average packing speed.

[4]Köszegi and Rabin (2006) present a prospect-theory value function with a reference point determined by expectations. These expectations need not be "fully rational," but could be replaced by "any theory of how these expectations are formed." Following Köszegi and Rabin (2006), "as a disciplined and largely realistic first pass," we assume that expectations are fully rational throughout the paper.

a positive wage elasticity. Since these wage changes are predictable, this finding is consistent with rational-expectations-based targeting, but only for skilled workers. For unskilled workers, these results are consistent with neither a neoclassical model of labor supply nor rational-expectations-based targeting.

These findings paint a complex picture of how workers respond to wage changes. While workers appear to have reference-dependent preferences, learning or skill seems to be an important factor. While all workers respond to both expected and unexpected overtime in a manner that is consistent with rational-expectations-based daily targets, the difference in response to overtime predictability is markedly bigger for more experienced workers. In addition, in response to the fully predictable changes in wage associated with rotation across packing stations, only skilled workers exhibit behave in a manner consistent with the neoclassical model.[5] Our results are thus supportive of Köszegi and Rabin (2006) as well as the idea that experience can reduce or eliminate some observed behavior biases as in List (2011).

The paper is organized as follows. The subsequent section provides a brief review of the literature on labor supply and describes our contribution to that literature. Section 3 describes the pear-packing factory and the wage shocks experienced by the workers. Section 4 reviews the different labor-supply models and their implications in this context. Section 5 presents estimates of how workers react to wage changes driven by pear size, and section 6 presents empirical estimates of how workers react to wage changes driven by overtime. Section 7 concludes.

[5] And thus also consistent with rational-expectations based targets, since the two models generate identical predictions in a setting with no unexpected shocks.

2 Previous Research on Reference-Dependent Labor Supply

This paper contributes to a growing literature on the importance of reference-dependent preferences in labor supply. We focus on workers who do not control their schedules but do control their effort. In contrast, previous studies have focused on workers in occupations with flexible hours. Camerer et al. (1997), for instance, study the behavior of New York City cab drivers. The authors use the average daily wage of other drivers as an instrument for each driver's wage. They find that drivers work fewer hours when average wages are higher, a result consistent with reference-dependent preferences. Chou (2000) finds similar evidence among taxi drivers in Singapore.

Fehr and Götte (2007) run a field experiment on bicycle messengers and find that higher wages have a positive effect on the number of hours worked, but a negative effect on effort per hour. The authors argue that effort, and not hours, is the more accurate measure of labor in their setting and so conclude that workers have reference-dependent preferences.

Other studies have not only documented reference-dependent preferences, but have tested how reference points are determined.[6] Farber (2005, 2008), for instance, calibrates a model of New York city cab drivers which incorporates a key distinction between unexpected and expected wages. He finds mixed evidence for reference-dependent preferences; drivers' stopping probabilities are significantly related to hours but not earnings. Crawford and Meng (2008) use Farber's data to estimate a model of reference-dependent preferences, and find strong support for rational-expectations-based targets. Similarly, Giné et al. (2010) find support for a model of reference-dependent preferences with rational-expectations-based targets among fishermen. And in a recent lab experiment, Abeler et al. (2011) directly ma-

[6] In addition, there exist studies that focus on reference dependence in contexts other than labor supply (Pope and Schweitzer, 2011).

nipulate the expectations of their subjects and finds that effort provision varies in a way consistent with rational-expectations-based targets.

In contrast, other studies have found results consistent with the neoclassical model of labor supply. Oettinger (1999) finds that stadium vendors are more likely to work on days when they can expect a higher wage, while Paarsch and Shearer (1999) measure a positive relationship between piece rate and productivity among workers at a tree-planting firm.[7] Similarly, Lazear (2000) finds that workers respond to a switch from fixed wages to piece rates by increasing effort.

A common characteristic of past studies is their focus on settings where workers are free to set their own hours.[8] The literature focuses on how the decision to stop working is affected by wage and hours targets. In contrast, the workers in our sample can neither choose what days to work nor how long to work on any given day. Instead they must attend all shifts and stay for the entirety of the shift length. Since most workers are not free to set their own hours, our findings extend this literature into an important segment of the labor market.

In addition, our data allow us to explicitly test for the role of cumulative fatigue (both within and across days), as well as worker skill and experience, in determining labor supply. Importantly, we are able to test whether fatigue drives the downward-sloping labor supply that much of the targeting literature has documented.[9]

Finally, we build on the work of Crawford and Meng (2008) by examining the relative importance of different reference points (e.g. daily hours, hourly rate) on

[7]Since the changes in wage studied by both Oettinger (1999) Paarsch and Shearer (1999) are anticipated by workers, their results are also consistent with reference-dependent preferences with rational-expectations-based targets.

[8]An exception is a paper by Dickinson (1999). In a laboratory experiment, the author finds that when hours are constrained, worker effort is positively correlated with wage. When subjects are allowed to set their own hours, however, some respond to higher wages by working longer but exerting less effort. Gill and Prowse (2012) also study a related laboratory experiment involving a simulated labor market and loss aversion.

[9]For example, while Camerer et al. (1997) argue that New York City cab drivers do not tire faster on high-wage days, they do not provide empirical evidence to support this position.

a worker's labor supply. Our data allow us to measure a worker's response to three different shocks to wages, an important source of variation that reveals that individual workers may simultaneously utilize different methods to set their reference points for different parameters.

3 How Pears are Packed

We examine the behavior of workers who package pears to be shipped to market at a large pear-packing facility in California. Due to the nature of the work, pear packers at the factory face both expected and unexpected shocks to implicit wages. This section describes how those shocks arise.

Because of their thin skin, pears do not respond well to bulk shipping. As a result, packers must wrap each pear individually in tissue paper and carefully arrange the pears in boxes. The procedure is labor intensive and must be done by hand. But such packaging allows the firm to ship pears directly to retail outlets and preserve the value of the fruit in transit.

Pears arrive at the factory each morning from farms throughout northern California. Once washed, the pears pass through a quality control process in which damaged pears are removed. The remaining pears then travel along a conveyor system that sorts the pears according to size into large rotating bins. Following industry standards, the pears are sorted into the following sizes: 60, 70, 80, 90, 100, 110, 120, 135, 150. The size of each pear indicates the number of pears that will fit into a standard, four-fifth-bushel box. For example, 100 "size 100" pears would be packed into a standard box.

Packers individually wrap and then carefully arrange pears in large cardboard boxes according to a pre-determined pattern based on pear size. Once a box is finished, the worker places the box on a conveyor belt that takes the box to a station where it is placed onto a pallet for shipping. A random subset of boxes is inspected to ensure that workers have taken sufficient care in packing each box. If a box is found deficient, the worker receives a lower piece rate for all boxes packed that day. Such fines are extremely uncommon in our data, with the median number of fines per worker-year equal to zero.

Packers are paid the same piece rate for each box regardless of the number of pears it contains. Workers thus face a higher implicit wage when packing larger pears. For instance, while a worker must exert fifty percent more effort to fill a box with 120 small pears than with 80 large ones, the worker will be paid the same piece rate for both boxes.[10] For that reason, the firm requires packers to rotate across packing stations, so that each worker spends the same amount of time with each pear size. Typically, workers spend fifteen minutes at each station and then switch to the next-larger size. When they reach the end of the line, the workers switch back to the station with the smallest pears. If a worker is part way through a box when it is time to rotate, the worker finishes the box before moving to the next bin. The bins are large enough that two workers can have simultaneous, unrestricted access to a single bin. Standard pear sizes vary from 70 to 150, so the number of pears that must be packed in a standard box varies by more than a factor of two. Thus a worker will experience a change in piece rate at regular intervals (every fifteen minutes) throughout each shift. If a worker's piece rate earnings for a single day implied a wage lower than the California minimum wage, then the worker was paid minimum wage.[11]

In addition, the firm provides packers with overtime pay in accordance with California law. Packers received overtime wages when they had been working for more

[10] The pears weigh very little, approximately 4–6 ounces. Thus the physical effort required to pack a single pear does not vary by size.

[11] In general, the minimum wage constraint applied only to new workers as they learned to pack, and affects only a small fraction of our sample. All empirical results are unaffected by removing such 'hourly' days from our sample.

than 8 hours in any given day or for more than 40 hours in any given week. Wages increased by 50 percent when the overtime limits were reached. For example in 1990, overtime increased a worker's piece rates from 43 cents to 64.5 cents a box.[12] Packers generally work 6 days per week, Monday through Saturday, and are expected to work for an entire shift, regardless of the work day's duration.

The "just-in-time" nature of pear packing leads to significant daily variation in shift length. Given limited cold storage space, pears at the plant are generally packed within 24 hours of being picked. Figure 1 plots the daily shift lengths over the 2002 season, and demonstrates that the variance in hours is large. This subjects the plant's daily production to fluctuations both due to supply and demand. Demand from individual retailers can vary in response to idiosyncratic sales conditions, while the supply of pears to be packed on a given day is affected by the productivity of farms currently being harvested.

In summary, pear packers are subject to several wage changes. The first is caused by variation in pear size; the packers' implicit wage changes every fifteen minutes. Second, packers' wages change when overtime begins. In particular, overtime leads to two types of wage shocks. Early in the week, a worker will receive overtime pay for any work done after the eight-hour mark. Workers arrive each day with no knowledge of the length of that day's shift.[13] As such, daily overtime represents a partially unexpected, fifty percent increase in wages. Towards the end of the week, the 40-hour-a-week overtime constraint will bind. Weekly overtime is highly predictable. For example, if workers have put in a total of 38 hours from Monday through Friday, then they know that when they come in Saturday morning, overtime will begin after 2 hours. Thus weekly overtime represents a largely expected 50 percent increase in

[12]One of the authors, Chang, worked as a pear packer in 1990 and 1991.

[13]During lunch, some workers may ask the shift supervisor whether the work day will last into overtime. But often the supervisor may not know.

wage.

We collected two types of data at the firm. First, the firm's personnel department provided payroll records for the 2001, 2002, and part of the 2003 packing seasons. For each season, the payroll data list each worker's total boxes packed during regular hours, total boxes packed during overtime, regular hours worked, and overtime hours worked.[14] Turnover among workers is high; roughly 70 percent of workers in one year did not return the next year.

The payroll data do not indicate the size of the pears packed in each box, because such information is not relevant to the workers' pay. As such, we cannot use the payroll data to examine how workers respond to the high-frequency wage changes associated with rotating from one bin to another.

For that reason, we collected data on output for a small set of workers on the factory floor during the summer of 2007. A research assistant monitored workers along one production line (row of bins) and recorded the time each worker spent packing each box. Over the course of four weeks, the research assistant measured the output of workers for 20 shifts; this generated data on 3,967 boxes packed by 70 packers.[15]

4 Models of Labor Supply

This section presents a simple model of a worker's labor supply decision to illustrate the response of workers with neoclassical and reference-dependent preferences in the context of pear packing.

[14] Workers were given unique employee identifiers for each calendar year, but those identifiers are not unique across years. For that reason, we linked workers across years based on their full names.

[15] We had hoped to collect payroll data on the same workers as in the on-site sample. Unfortunately, the factory has closed, and we were unable to procure that data.

4.1 Basic Model

An agent can work for up to two periods, and must choose her effort at the start of each period. The worker's expected utility at the start of period 1 is:

$$E\left[u(e_1, e_2)\right] = e_1 - \frac{1}{2}e_1^2 + \rho \cdot \left[\omega e_2 - \frac{1}{2}\left(e_2 + \gamma e_1\right)^2\right]. \tag{1}$$

In this utility function, e_t represents the effort exerted in period t and ω represents the ratio of period-1 wages to period-2 wages. The parameter $\rho \in [0, 1]$ represents the workers' belief that work will continue into period 2. The parameter $\gamma \geq 0$ represents cumulative fatigue, whereby effort exerted in period 1 increases the dis-utility of effort in period 2.

Consider the wage shocks experienced by pear packers. First, consider the case of a worker rotating across bins containing different sizes of pears. Each period in equation (1) then represents the 15 minutes spent at each particular bin. In this setting, packers expect period 2 to occur ($\rho = 1$), fatigue should have little effect across such short time periods ($\gamma = 0$), and ω is equal to the ratio of implicit wages driven by the difference pear sizes in the two bins.

Next, consider the effect of overtime. Here we treat regular hours as period 1 and overtime hours as period 2. The parameter ρ then captures whether or not overtime is expected, and $\omega = 1.5$. In our setting, weekly overtime is largely expected, but daily overtime is only partially predictable. In our empirical analysis we utilize an instrumental variables technique similar to that of Crawford and Meng (2008) to separately identify predictable daily overtime from unpredictable daily overtime.

4.2 Neoclassical Preferences

At the start of period 1, the worker's expected utility is given by equation (1) above, and worker utility at the start of period 2 is:

$$E\left[u(e_1, e_2)\right] = \omega e_2 - \frac{1}{2}\left(e_2 + \gamma e_1\right)^2. \tag{2}$$

Workers with neoclassical preferences choose effort by maximizing equations (1) and (2). Their optimal effort is thus

$$(e_1^*, e_2^*) = (1 - \rho\omega\gamma,\ \omega - \gamma e_1^*) = (1 - \rho\omega\gamma,\ \omega - \gamma(1 - \rho\omega\gamma)). \tag{3}$$

First, consider packer response to bin rotation. Since period 2 is expected ($\rho = 1$) and fatigue is not a significant factor ($\gamma = 0$), equation (3) implies that $e_2^*/e_1^* = \omega$. That is, when period 2 is expected and the effect of fatigue is negligible, then workers' effort in each period is proportional to their wage.

Second, consider the case of overtime. In this case, period one represents eight hours of work, and thus fatigue is potentially an important factor ($\gamma > 0$). In addition, the likelihood of overtime (period 2) occurring is uncertain.

When period 2 is expected (workers expect overtime), $\rho = 1$, and equation (3) implies that $e_2^* > e_1^*$ if and only if $\omega > \frac{1+\gamma}{1+\gamma+\gamma^2}$. In such a case, workers will exhibit a positive wage elasticity for any $\omega > 1$. In contrast, when overtime is completely unexpected ($\rho = 0$), $e_2^* > e_1^*$ if and only if $\omega > 1 + \gamma$.

Note that since $\frac{1+\gamma}{1+\gamma+\gamma^2} \leq 1 + \gamma$ for all $\gamma \geq 0$, there exist a set of wage and fatigue parameters (ω, γ) such that workers will exhibit a positive wage elasticity in response to overtime when overtime is *anticipated*, but a negative wage elasticity when overtime is *unanticipated*. Thus, neoclassical preferences can generate behavior consistent with reference-dependent preferences (described below).[16]

Specifically for values of ω and γ that satisfy the condition $\omega > \frac{1+\gamma}{1+\gamma+\gamma^2}$, workers will always exhibit a positive wage elasticity with respect to overtime pay regardless of whether it is anticipated or not. In contrast, for values of $\omega \in \left(\frac{1+\gamma}{1+\gamma+\gamma^2}, 1+\gamma\right)$ workers will exhibit a positive wage elasticity when overtime is expected, but a negative wage elasticity when overtime is completely unexpected.

Intuitively, consider the case when overtime comes as a surprise. In that case, a worker may exert a great deal of effort in period 1 without regard for the deleterious effects period 1 effort has on period 2 effort. Then, when overtime arrives, they may exert less effort due to exhaustion, even though the wage rate is higher. In this sense, a negative wage elasticity with response to overtime alone is not evidence that workers are irrational.

Nevertheless, since wages increase a great deal during overtime ($\omega = 1.5$), fatigue would have to be an extremely large factor to generate negative wage elasticities. Such a possibility though should not be ruled out a priori, but rather ruled out by the data.

Fortunately, the model provides a test of the extent to which unexpected shocks affect labor supply. Worker effort in period 1 should decrease as the probability of overtime increases ($\partial e_1^*/\partial \rho < 0$). That is, if fatigue is a factor, when workers expect overtime, they should exert less effort during regular time to save their strength for the more lucrative overtime period. The results of such a test are presented in Section 6.

[16]See Camerer et al. (1997) for a discussion of the fatigue hypothesis as potential source of the observed negative wage elasticities in cab drivers.

4.3 Reference-Dependent Preferences

Models of targeting assume that workers choose a level of some parameter as a goal, beyond which they become less responsive to changes in their wage. That is, their preferences depend on some target or reference level. For example, according to models of daily income targeting, workers hold a specific dollar value as a daily target income level. Under this model, workers may work less when their wage is higher, because the higher wage allows them to reach their income targets more quickly.

Following Köszegi and Rabin (2006), we incorporate reference dependence into our model by adding an additional term to the agent's utility function.[17] Equation (1) becomes:

$$v\left(e_1, e_2; y^R\right) = u\left(e_1, e_2\right) - I\left\{y_t > y_t^R\right\} \cdot \lambda \cdot \left[e_1 + \omega e_2\right]. \tag{4}$$

Here, y is the value of a target variable, y^R is its target value, and $\lambda \geq 0$ represents the relative importance of the "gain-loss utility" that captures the behavioral bias brought about by exceeding the target level. In this context, y_t is the number of hours that a packer has worked in a day, and y^R is the number of hours they expect to work. We discuss this further, below.

A challenge for researchers in this area is determining which parameters are targeted (e.g. daily hours, weekly income, hourly rate), and how the targets are set (e.g. heuristics, rational expectations). For example, taxicab drivers may have a daily hours target, while a CEO might have a quarterly earnings target. Knowing what parameters are targeted, and how those targets are set, is central to measuring the

[17] In the general Köszegi and Rabin (2006) model, there would be a third term associated with the gain-loss utility that occurs if workers expect to work longer than they do. While this third term would affect worker utility, since workers cannot set their own hours, we are able to exclude it from equation (4) as it affects worker preferences only in situations in which there is no observed worker effort.

impact (if any) of reference-dependent preferences.

Following Köszegi and Rabin (2006), we model targets as set equal to the agents' rational expectations: $y^R = E(y)$. This implies that changes in the target variable must be unanticipated to generate behavior that differs from the neoclassical model. Packers will thus only deviate from the neoclassical model when events are *unanticipated*. For example, if packers can perfectly anticipate the length of a shift, $y \leq y^R$, then the gain-loss term drops out of their utility function and does not affect their decisions. In contrast, if workers set targets by some other means, then even fully anticipated changes may affect decisions. We refer to such targets as heuristics-based.

Consider then the case of a packer rotating from one bin to another ($\rho = 1$ and $\gamma = 0$). Workers can perfectly anticipate the move to the next bin. Thus if workers set their targets via rational expectations, the preferences above mirror the neoclassical case. If, on the other hand, workers' targets are not set via rational expectations, then their response to changes in their implicit piece rate can differ from the neoclassical case.

Similarly, when workers fully anticipate overtime, their response will be identical to the neoclassical case. But when overtime is unanticipated, the hours target is exceeded ($y_t > E(y_t)$), and so workers are affected by two countervailing forces. First, workers are induced to exert more effort during overtime, because their wage (ω) increases. But since the overtime is unexpected, the dis-utility of effort increases by λ, since they have exceeded their target hours ($y_t > y_t^R$). Given a sufficiently large λ relative to ω, workers may actually decrease their effort during overtime and exhibit the characteristic negative wage elasticity found in much of the targeting literature.

Sections 5 and 6 describe empirically how workers react to expected and unexpected shocks. In Section 7 we summarize the extent to which the results suggest workers' preferences are reference-dependent.

5 The Reaction of Workers to Pear Size

Every fifteen minutes, workers rotate across bins into which pears of different sizes have been mechanically sorted. Workers are paid the same piece rate for each box regardless of the number of pears they are required to pack into the box. As a result, the size of the pears determines the implicit piece rate. At each fifteen-minute mark, workers rotate to the next larger pear size until the largest size is reached. If a worker is at the last station when it is time to rotate, she moves back to the station carrying the smallest pear. In this way, workers experience an increase in their piece rate of approximately 12.5 percent each time they move down the line and a decrease of approximately 50 percent when they rotate from the back of the line to the front of the line.[18]

5.1 How does packing speed vary across pear sizes?

Table 1 presents sample statistics for the on-site data. We observe 3,960 boxes packed by 70 workers. Workers take an average of 2.4 seconds for each pear, with a standard deviation of 0.856. The remainder of Table 1 suggests that workers increase their effort as their implicit wage decreases. For instance, workers take an average of 2.6 seconds to pack each of the largest type of pear, but only 2.0 seconds for each of the smallest pears. That difference alone suggests that workers exert more effort for the smaller pears, when the incentive to pack is weakest.

Table 1, however, does not control for variation that stems from worker- or day-specific shocks. To account for worker- and day-specific variation, we regress the packing speed of packer i when packing box b on day t on the size of the pear.

[18]The exact values depend on the range of pear sizes packed on a given day, which varies with availability.

Specifically, we estimate the regression:

$$
\begin{aligned}
\text{Seconds per Pear}_{ibt} &= \alpha_0 + \beta_{90} \cdot I\{\text{Pear Size 90}\} \\
&\quad + \beta_{100} \cdot I\{\text{Pear Size 100}\} + \beta_{110} \cdot I\{\text{Pear Size 110}\} \\
&\quad + \beta_{120} \cdot I\{\text{Pear Size 120}\} + + \gamma_b + \alpha_i + \alpha_t + \varepsilon_{ibt}, \qquad (5)
\end{aligned}
$$

where γ_b is a dummy equal to one if the box packed is a "Costco box,"[19] α_i is a worker fixed effect and α_t are date fixed effects.

Table 2 presents estimates of equation (5) with size-80 pears as the omitted category. Size-80 pears are the largest pears and therefore involve the largest implicit piece rate.[20] The estimates of β_i decrease monotonically as the pears become smaller, meaning that workers take *less* time to pack a pear as their effective piece rate decreases. Compared to the smallest pears (120 count), workers take an additional half second (or 17 percent more time) to pack the largest pears. The third and fourth columns of Table 2 present similar estimates, but include only a single variable representing pear size. Such a model imposes a linear functional form on size. That specification leads to the same conclusion: workers pack smaller pears faster.

Table 2 presents estimates for all workers. We next explore heterogeneity in these effects amongst workers. The workers differ in skill; some pack much more quickly than others. Table 3 presents a similar model as that presented in columns 3 and 4 of Table 2, but divides workers by their packing speed. We rely on two methods of dividing workers by skill. First, we calculate each worker's packing speed, and normalize it to be between zero and unity. Second, we create a binary variable, that indicates whether workers are in the top decile of packing speeds.

[19]During the period in which we gathered data, workers packed both standard 4/5th bushel boxes and a smaller "Costco box."

[20]We exclude size 60, 70, 135, and 140 pears as they are rarely observed in the data.

Table 3 presents estimates of the previous specification stratified by worker packing speeds. Both columns of the table demonstrate that fast (skilled) workers have less of a perverse response to increases in the implicit wage. As the pears per box rises, and thus the implicit wage falls, workers on average pack more quickly. That effect is clear in Table 2, and in the first row of Table 3. But the fastest workers do not exhibit such an effect. The interaction between pears per box and either measure of packer skill is positive and statistically significant. The magnitudes are such that, for the fastest packers, the general pattern shown in Table 2 reverses, and workers pack the larger, higher-piece-rate pears at a faster rate than the smaller ones. This pattern suggests that less-skilled packers exhibit behavior more consistent with heuristics-based targeting, but the behavior of the most-skilled packers is consistent with rational preferences.

5.2 Alternative Explanations

We interpret Table 2 as a test of the models presented in Section 4. But that interpretation must address several concerns.

First our results may be driven by the discrete nature of boxes and bins. Perhaps packers do not want to be in the middle of packing a box when it is time to rotate to the next, more lucrative bin. As such, they may rationally adjust their effort so as to be ready to rotate when the time comes. An anonymous referee has suggested that this might account for the findings above.

To explore such an explanation, we have run regressions that include two additional variables: the order of the box packed at the bin and an indicator for whether each box is the last box a worker packs at the current bin. Those results are presented in Appendix Table 1. We find no statistically significant effect of box order on packing speed. Workers do not seem to pack boxes faster (or slower) the longer they stay at a bin. Workers do, however, pack the last box much faster than all other boxes. In addition, we have run regressions that include an interaction term between box order and a measure of packing skill. Those results, presented in Appendix Table 2, demonstrate that this last-box effect disappears for the most-skilled workers.

These results suggest that less-skilled workers "hurry up" in packing their last box, so that they can get to the next bin. These workers do not calibrate their effort at each bin, so as to finish the bin without having to hurry through the last box. Such a pattern is inconsistent with a rational smoothing of effort. In contrast, skilled workers exhibit both a positive wage elasticities across bins and smooth provision of effort within bins.

A second concern is that the workers' effort may be determined, in part, by peer pressure. A growing literature demonstrates the importance of social networks in determining how workers respond to incentives (Mas and Moretti, 2009; Bandiera et al., 2010). The concern is that packers pressure each other to exert less effort when packing larger pears, as the opposite could be seen as strategic or selfish. But the nature of pear packing makes it unlikely that workers collude in such a fashion. In most settings in which network effects are discussed, the workers either directly collaborate (Bandiera et al., 2010) or can easily observe co-workers (Mas and Moretti, 2009). In contrast, pear packers work alone at each station, and it is difficult for them to monitor each other. The distance between packers, the noisiness of the factory floor, and the fact that packing requires their full attention, means that passive monitoring is quite difficult.

One potential source of less-costly peer monitoring is the presence of a fellow packer at the start of any 15-minute period. Workers must finish their last box before rotating, and so occasionally two workers may share a bin until one of them finishes their last box and switches to the next bin. While such overlap is normal, perhaps workers do not want to be seen as spending extra time at the bins with the larger (more lucrative) pears. This, however, seems unlikely to affect our results. With the exception of the largest pears, workers rotate from smaller to larger pears. As such, workers have little incentive to linger at any given bin. In contrast, we find a consistent effect of pear size on effort across even the smallest pears.

And finally, smaller pears may simply require less effort to pack. In that case, workers may speed up as they pack smaller pears, not due to reference-dependent preference, but because of the change in the difficulty of packing. Given the fact that more skilled workers do exhibit a positive wage elasticity, under this interpretation more skilled workers are either able to overcome the weight effect, or weight is disproportionately a smaller factor in determining their packing effort.

We feel that such an explanation is unlikely to be the case. Difference in sizes between pears is not large, and the casual observer would find it difficult to distinguish pears taken from adjacent bins. Individual pears are also quite light (approximately 4 to 6 ounces); the effort lies in the act of hand-wrapping each pear in tissue paper, an act unaffected by pear size. More importantly, such an explanation would not account for the last box "hurry up" effect discussed above.

In summary, Table 1, Table 2, and Table 3 suggest that, on average, workers exert more effort as the incentive to do so diminishes. This effect, however, decreases with worker skill and reverses for high-skilled workers. In addition, worker effort is not constant *within* each bin rotation. The average worker exerts higher levels of effort in packing the final box in any given bin-rotation period. This effect also decreases with worker skill and disappears completely for high-skilled workers. In addition while skilled workers pack at a constant speed at each station, less skilled workers seem constantly surprised by the end of each 15 minute period, suddenly increasing their effort on the final box of each bin-rotation period.

Thus, the average worker exhibits behavior inconsistent with both neoclassical preferences and rational-expectations-based preferences. High-skilled workers, in contrast, exhibit behavior consistent with both. Furthermore, this difference between skilled and unskilled workers is consistent with the idea that worker skill is correlated with the ability to better generate or incorporate rational-targets into their packing behavior with respect to bin rotation. But we cannot distinguish this hypothesis from the alternative hypothesis that more skilled workers are simply more rational than their less-skilled peers.

One possible explanation for the behavior of the average response to bin rotation involves simple rate targets. Workers may try to pack a certain number of boxes per unit time (e.g. 12 boxes per hour, 1 box every 5 minutes). If workers follow such a heuristic, then they would increase effort when packing smaller pears in an attempt to maintain a constant box packing rate. The behavior we observe for the average worker is consistent with this hypothesis. Given the magnitude of the point estimates in Table 2, packers could earn substantially more money simply by providing effort at a constant rate. Specifically, the average worker would earn 7.3 percent more money each hour if they simply packed at a constant rate as compared to their observed behavior.

6 The Reaction of Workers to Overtime

Not only do workers' wages change as they rotate across bins, but their wage also changes when they shift from regular time to overtime work. This section exploits such transitions to test the models of labor supply presented above.

6.1 Overtime in the On-Site Data

Using the on-site data, we first examine how productivity varies throughout the work day. To do so, we regress the time it takes a worker to pack a single pear (measured in seconds per pear) on indicators for the time of day, worker fixed effects, and date fixed effects. All shifts in the on-site data started at the same time, thus time-of-day is equivalent to hours into shift.

Table 4 presents the results of this regression. Each column of Table 4 includes a different set of fixed effects. For all regressions, the first hour of work is the omitted category. The point estimates from column 4 of that regression are plotted in Figure 2. The figure and all four columns of Table 4 clearly show the same striking pattern: the coefficients are small and generally statistically insignificant until (or just before) 8 hours into the day, after which they become both positive and statistically significant.

The sudden change in productivity after 8 hours is particularly interesting as it relates to the effects of fatigue on packer behavior. One would not expect fatigue to have such a discontinuous effect after precisely 8 hours of work. Thus this suggests that the change in packer behavior during overtime is not driven by fatigue, but rather through some psychological channel. We discuss fatigue further, below.

The standard errors are much larger for the last quarter hour of each shift (7.75–8 hours) than any other time period we examine. Because the variance of packing speeds in that period is so large, we have little statistical power to test how packing speeds evolved immediately before and after the eight-hour mark. Regardless, the point estimates for the overtime periods are larger than any other regular-time periods. This difference is generally statistically significant across all four specifications, and always statistically significant in our preferred specification (column 4).

These results show that workers pack pears at a remarkably constant rate throughout the day until the last few minutes before the end of their shift. Then, once into overtime, workers take significantly more time to pack each pear. For instance, for the first 15 minutes of overtime, packers take an additional 0.298 to 0.588 seconds to pack each pear compared to during the first hour of a shift, 0.205 to 0.487 additional seconds compared to their daily average for regular time, and 0.321 to 0.601 seconds faster compared to their speed half an hour earlier.[21] Such a slowdown corresponds to a drop in effort of approximately 15–25 percent.

This basic pattern is the same across all our specifications. Packers, however, worked more than 8 hours on only 5 of the 18 weekday shifts in our on-site sample, with almost all overtime boxes packed on two days. As such, these results should be interpreted with some caution.[22] We, instead, focus on the effect of overtime in the payroll data.

6.2 Overtime in the Payroll Data

As described above, the firm's payroll records contain measures of the productivity of each worker each day. We analyze payroll records for all pear packers at the plant for the 2001, 2002, and 2003 seasons. We observe the regular time hours, overtime hours, boxes packed during regular hours, and boxes packed during overtime hours for each worker-day. These data consist of a total of 1,346,770 boxes packed by 191 unique workers over 275 shifts.

Table 5 presents sample statistics for these data. Overtime composes 10 percent of the sample. But Table 5 makes clear that this fraction varies across the days of the week. Approximately half of hours worked on Saturday are overtime, whereas roughly 8-9 percent of hours during the week are overtime.

[21] All such differences are statistically significant at conventional levels.

[22] Limiting the regression in Table 4 to the two dates for which we observe the vast majority of overtime, July 24 and August 6 (23 workers, 794 boxes), generates qualitatively similar results.

We measure how workers react to overtime with the following regression:

$$\left(\frac{\text{Total Boxes Regular Hours}}{\text{Regular Hours}}\right)_{id} - \left(\frac{\text{Total Boxes OT Hours}}{\text{OT Hours}}\right)_{id} = \alpha_0 + \beta \cdot \text{OT Hours}_d + \alpha_d + \nu_{id}. \quad (6)$$

The sample for this regression includes only days that involved both regular time and overtime. The left-hand side is the difference in regular time versus overtime packing rates for a given worker on a given day. We regress that outcome on a constant, a control for the day's total overtime hours, and worker fixed effects. If workers pack faster during overtime (when the incentive to do so is greater), then α_0, the constant, should be negative.[23] In that sense, the neoclassical model above predicts $\alpha_0 < 0$.[24]

Table 6 presents results from this regression for the 2,573 worker-days that included both regular and overtime hours. The first column presents estimates of equation (6) when only a constant is included on the right-hand side, while the second column controls for overtime hours. In both columns the constant is positive, suggesting that workers pack faster during regular working hours as compared to overtime.

Columns 3 through 6 stratify the sample into weekdays (Monday through Friday) versus Saturday shifts.[25] The weekday results are similar to the full sample results; the constant is positive and statistically significant. But the last two columns suggest that workers respond to overtime on Saturday very differently from overtime during the week. In contrast the constant is negative in columns 5 and 6 suggesting that workers respond in the opposite manner to overtime on Saturdays, packing faster during

[23]We discuss the effect of fatigue below.

[24]We repeat this same analysis but with the *ratio* of regular time to overtime packing rates as the dependent variable. Those results, presented in Appendix Table 3, are not materially different from the results reported here.

[25]Limiting the weekday sample to Monday through Thursday produces qualitatively and identical results.

overtime compared to regular working hours. This result is significantly different from zero for only column 6, though for both specifications the results are statistically different from the weekday point estimates. As such, we interpret these regression results as indicating that the response to overtime is markedly different on Saturday as compared to the rest of the week, and that the tendency to decrease effort during the overtime period for weekday shifts may reverse on Saturdays.

As described above, overtime on Saturdays is largely expected.[26] Thus we interpret these results as driven by the predictability of overtime. But the pattern of results could also be driven by an unobservable Saturday effect, or a non-linear impact of hours (i.e. fatigue) on production. That is, due to non-linear fatigue, which would not be captured by our linear control for hours, workers might respond differently for overtime that occurs 2 hours into a 9 hour shift as compared to 8 hours into a 9 hour shift.

To address this concern, we predict shift length based on day-of-week, week-of-year, and year fixed effects. We then create a binary variable that is equal to one if the predicted shift length is greater than 8 hours. This weekday "predicted overtime" variable is based solely on information observable to workers. Thus it is a proxy for the degree to which workers expect overtime.[27] Importantly, the predicted overtime indicator variable should not be interpreted as indicating that workers fully expect overtime. Rather, it is an indication that overtime is *more* expected on days when the proxy is one as compared to days when it is zero. We then include our predicted overtime indicator on the right-hand side of (6). This specification controls for the

[26] Over half of all Saturday shifts include some amount of overtime, with an average shift length of 6.1 hours with overtime starting 2.3 hours into the shift. Saturday overtime due to exceeding the 8 hours a day mark, as opposed to the 40-hours a week limit is also uncommon occurring at a rate of 0.054).

[27] This strategy is similar to that used by Crawford and Meng (2008) to separate predictable from unpredictable wage shocks for taxicab drivers. Cab drivers, however, can set their own hours, thus Crawford and Meng rely on driver-by-day-of-week and week-of-year fixed effects.

effect of shift length; it compares days with identical shift lengths that vary only in the degree to which workers anticipate overtime.

Table 7 presents estimates of equation (6) that include an indicator variable for predicted weekday overtime. Saturdays are excluded from this sample as Saturday overtime is almost exclusively the result of the 40-hours-a-week overtime constraint, and hence largely predictable.[28] As in Table 6, Table 7 demonstrates that on weekdays workers pack at a slower rate during overtime than regular time; the regression constant is always positive and statistically significant. In contrast, the coefficient for predicted overtime is always negative and statistically significant. Worker effort is always lower during overtime, even after controlling for shift length. But on days in which overtime is predictable, this effect is substantially reduced.

This overall pattern of results is consistent with reference-dependent preferences with rational-expectations-based targets. Overtime is expected on weekends and on very busy weeks. And the last two columns of both Table 6 and Table 7 suggest that when overtime is unexpected, workers slow down during overtime. But when overtime is expected, this effect is greatly mitigated or even potentially reversed.

6.2.1 Fatigue

The theoretical framework in Section 4 makes clear that the negative effect of overtime we document is consistent with either reference-dependent preferences or neoclassical preferences that take into account fatigue. Under neoclassical preferences, when overtime is unexpected, workers may work too hard during regular hours, and thus not be able to increase their effort during overtime. That is, when overtime is unanticipated, workers fail to conserve enough energy to take advantage of the higher overtime piece

[28] During exceptionally busy weeks, the 40-hour overtime constraint can bind on Fridays. Thus, in regressions not shown, we have replicated Table 7 with a sample that excludes both Saturdays and Fridays. After doing so, the results are not materially different.

rates.

For this to be the case, however, effort during regular time should vary with the predictability of overtime. That is, when workers expect overtime, they should exert *less* effort during regular hours so as to reduce the effect of cumulative fatigue in the overtime period.

To test this prediction, we estimate equation (6) with solely regular-time packing rates as the dependent variable. Table 8 presents the results of that regression. Columns 1 and 2 estimate the impact of predictable overtime on workers' packing rate during regular hours. The effect of predicted overtime on packing rate during regular time is positive, small and statistically insignificant at conventional levels. This suggests that workers do not pack more slowly during regular time when they expect overtime.[29]

In contrast, columns 3 and 4 of Table 8 make clear that whether or not overtime is expected has a large effect on packing rates during overtime itself. Specifically, workers respond to expected overtime by exerting significantly more effort during overtime.

A further concern is that fatigue may accumulate over the week in a manner that correlates with the predictability of overtime. That is, working a long shift on one day may increase the dis-utility of effort on the following day. To test for such a pattern, we estimate the regressions above, but include variables that indicate whether the previous day's shift was longer than 8 hours. We also include a linear control for the day of week (equal to one through five). These results are presented in Table 9. The first three columns demonstrate the effect of having worked a long shift the previous day on the current day's productivity. All the coefficients for the "overtime on previous day" variable are small and statistically insignificant, suggesting that

[29]It is important to recognize that these regressions amount to a joint test of both the neoclassical model and a particular model of fatigue.

working a long shift the previous day does not affect worker productivity today. In contrast, the coefficients for predicted overtime are similar to those in the previous tables.

The last three columns of the table add a linear control for day of week. This also has little effect on the main point estimates. All the coefficients for day-of-week are small in magnitude, and the only statistically significant coefficient exists in column 5, regular shift packing rate, suggesting that workers actually work slightly faster during regular hours at the end of the week compared to the beginning. This result, though, is driven by a "Friday effect," and disappears when Fridays are removed from the sample.

6.2.2 Learning and Experience

We next address the question of whether all workers behave in a similar fashion. Unfortunately, we have little information on the workers' backgrounds. Nevertheless, we do observe whether workers return from one season to another. We can thus stratify workers by whether they are experienced, having been in the factory in a previous season. In addition, we observe the packing speed of each worker, which we can use as a proxy for their skill.

Table 10 presents estimates of equation (6) with additional controls for experience and overall packing speed. As with the on-site data, we construct an indicator variable that equals unity if a worker's average packing speed is in the top decile of the distribution. In addition, the experience variable is equal to unity if we are able to match the worker's name to one in the payroll records for the previous year. Because we do not possess payroll data for the year 2000, we run three different specifications: columns 1 and 2 treat workers who appear in at least 2 of our sample years as experienced in 2001, columns 3 and 4 drop 2001 from our sample entirely, and columns 5 and 6 treat all workers in 2001 as inexperienced.

The first implication of these regression results is that packing speed has very little predictive power in terms of either the base difference in rate or the impact of overtime predictability. In contrast, experience generally predicts differential behavior in both the overall difference in packing speed between overtime and regular time and in response to the predictability of overtime. This suggests that while packing speed in and of itself is not correlated with one's ability to predict overtime, experience is. Experienced workers respond much more strongly to predictable overtime than their less-experienced peers. To the extent that one believes experience, and not packing speed, determines the ability of workers to predict overtime, these regressions provide additional support to the idea that workers behave in a manner consistent with reference-dependent preferences with rational-expectations-based targets.

6.3 Alternative Specifications

The regressions above all involve packing rates as the outcome of interest. As a robustness test, this section considers alternative specifications that involve the raw variables from the payroll data, rather than calculated rates. Such specifications address the possibility of division bias (Borjas, 1980).

In particular, we estimate the following regression:

$$\begin{aligned}\text{Total Boxes}_{ids} \;=\; & \alpha_0 + \\ & \gamma_1 \cdot I\{\text{RT}\}_{ds} \cdot \text{Hours}_{ds} + \\ & \gamma_2 \cdot I\{\text{OT}\}_{ds} \cdot \text{Hours}_{ds} + \\ & \gamma_3 \cdot I\{\text{RT}\}_{ds} \cdot \text{Predicted Overtime}_d \cdot \text{Hours}_{ds} + \\ & \gamma_4 \cdot I\{\text{OT}\}_{ds} \cdot \text{Predicted Overtime}_d \cdot \text{Hours}_{ds} + \\ & \beta \cdot \text{Predicted Overtime}_d + \alpha_i + \nu_{ids}. \end{aligned} \tag{7}$$

The outcome in equation (7) is the total number of boxes packed for worker i on day d and shift s (regular time or overtime). The samples consist of two observations for each day, one for regular time and one for overtime. We then regress the total boxes packed during each shift on the number of hours worked that shift. The coefficients γ_1 and γ_2 capture the average rate (number of boxes packed per hour) during regular and overtime hours respectively. And the coefficients γ_3 and γ_4 capture the differential rate during regular and overtime hours for a shift when overtime is anticipated.

Appendix Table 4 presents estimates of equation (7). Columns 1–3 show worker packing rates during regular time and overtime in the full sample, weekdays, and Saturdays respectively. The pattern exhibited here is similar to that found in Table 5, with an even starker difference between overtime and regular time packing rates on Saturdays. During weekdays, workers pack faster during regular time hours compared to overtime hours, but the pattern is reversed on Saturdays.

The remaining columns present specifications with predicted overtime as an independent variable. Column 4 presents regressions based solely on weekdays, and column 5 presents the same regression when the sample is restricted to weekdays in which an overtime shift occurred. The latter sample is identical to that used in our main specification.

These regressions suggest that worker effort during regular hours seems unaffected by whether or not overtime is anticipated that day. That is, the interaction between predicted overtime and regular time hours, γ_3, is small and statistically insignificant. This result is consistent with columns 1 and 2 in Table 7. In contrast, the effect of predicted overtime on packing rates during overtime, γ_4, is large and statistically significant at conventional levels. Workers pack faster during overtime when overtime is anticipated. This result confirms those found in Table 7.

7 Conclusion

The payroll and on-site data suggest two general patterns in how packers respond to changing wages. First, packers respond to overtime pay differently depending on the predictability of overtime. Overall, packers respond to overtime by decreasing their effort and thus exhibiting a negative wage elasticity. However, the predictability of overtime is associated with an increase in worker effort, with more experienced workers exhibiting a larger response than their less-experienced peers. We also explicitly test for and reject cumulative fatigue as the source of the observed negative wage elasticities in response to overtime pay. These results are consistent with reference-dependent preferences with rational-expectations-based targeting. Since overtime corresponds to a 50-percent increase in piece rates, the results indicate that the targeting effect (λ) is quite powerful.

Second, while the average packers monotonically *decrease* their effort as their piece rate *increases*, this result is reversed for the most skilled workers. Similarly while skilled workers supply effort at a constant rate within each bin, their less skilled peers seem to be constantly surprised by the end of each 15 minute bin cycle, markedly increasing their effort for the last box of each bin rotation period.

This finding, for the average worker at least, is inconsistent with the neoclassical model. And since rotation across bins is both routine and predictable, it is also inconsistent with rational-expectations-based targets. While the results for skilled workers are consistent with rational-expectations-based targets, we are unable to distinguish between the possibility that more skilled workers are better at setting rational expectations or that they are simply more rational than their less-skilled counterparts.

Our results suggest that reference dependence extends to settings in which hours are constrained and supports the model of Köszegi and Rabin (2006). In addition they suggest a potential mechanism by which experience reduces behavioral bias: more experienced workers are less likely to be surprised by events and thus behave in a manner more consistent with the neoclassical model.

Our results have normative implications for the incentives given to workers at other firms. Most obviously, they suggest that worker response to overtime is determined in part by their expectations regarding the probability of overtime. Thus, when overtime is necessary, managers should handle workers' expectations with care. If workers are surprised by overtime, they may exert less effort when it arrives.

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Figure I. Hours and Boxes Packed over the 2002 Season

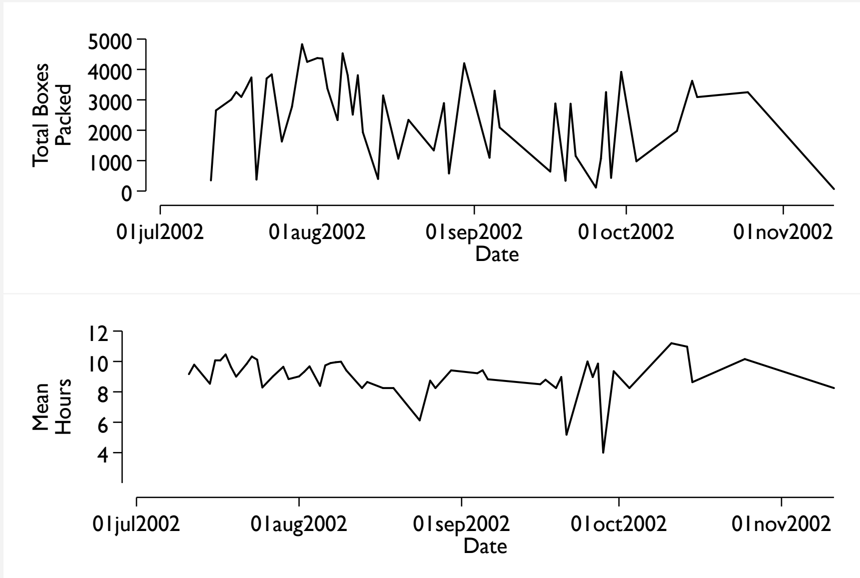

Figure II. Average Packing Speed by Hours Into Shift

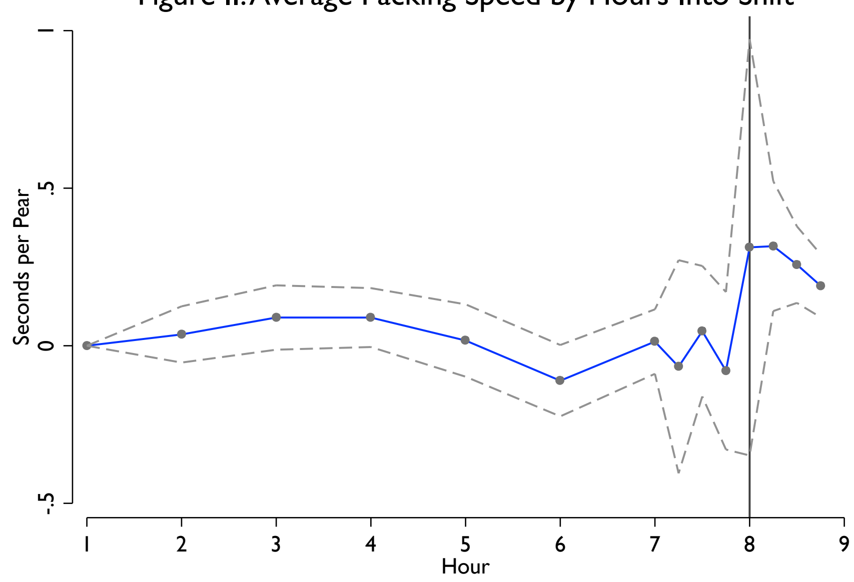

Table 1. Sample Statistics for the On-Site Data

Pear Size (Pears per Box)	Observations	Minutes per Box	Seconds per Pear (SPP)	Std. Dev. of SPP
All	3,960	3.94	2.41	0.86
80	586	3.57	2.64	1.01
90	943	3.76	2.49	0.92
100	1,391	3.91	2.33	0.81
110	843	4.40	2.36	0.73
120	197	4.21	2.08	0.62

Note: Packing speed is measured in seconds per pear. The data set contains a record for every box packed by a sample of workers, and the time it took them to pack each box.

Table 2. The Effect of Expected Shocks on Effort, On-Site Data
Dependent Variable: Seconds per pear packed

	(1)	(2)	(3)	(4)
90 pears per box	0.002	- 0.083		
	(0.082)	(0.063)		
100 pears per box	- 0.125	- 0.204		
	(0.099)	(0.074)		
110 pears per box	- 0.302	- 0.387		
	(0.095)	(0.064)		
120 pears per box	- 0.533	- 0.434		
(smallest pears)	(0.113)	(0.090)		
Pears per box			- 0.012	- 0.012
			(0.003)	(0.002)
Constant	2.745	2.991	3.754	3.986
	(0.098)	(0.175)	(0.325)	(0.260)
Worker Fixed Effect		✓		✓
Date Fixed Effect		✓		✓
R^2	0.039	0.249	0.036	0.249

Note: N = 3,908. The pears-per-box variables equal unity when the box packed has the given number of pears. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker. All specifications include an indicator variable for whether the box packed is a standard, four-fifth-bushel box. The data set contains a record for every box packed by a sample of workers and the time it took them to pack each box.

Table 3: The Reaction of Workers to Expected Shocks by Skill Level, On-Site Data

Dependent Variable: Seconds per pear packed

	(1)	(2)
Pears per box	- 0.063	- 0.011
	(0.023)	(0.002)
Packing speed × pears per box	0.073	
	(0.032)	
Packing speed	- 10.300	
	(3.591)	
Fastest workers × pears per box		0.023
		(0.006)
Fastest workers		- 2.985
		(0.590)
R^2	0.207	0.136

Note: N = 3,908. Standard errors in parentheses allow for auto-correlation between observations based on the same worker. All specifications include an indicator variable for whether the box packed is a standard, four-fifth-bushel box. Packing speed is a continuous variable, scaled to vary between 0 and 1. The "fastest workers" indicator variable is equal to unity if the given worker is in the top decile of packing speeds.

Table 4. Packing Speeds by Hours into Shift, On-Site Data
Dependent Variable: Seconds per pear packed

	(1)	(2)	(3)	(4)
1-2 hours	0.047	0.037	0.089	0.036
	(0.054)	(0.049)	(0.051)	(0.045)
2-3	0.135	0.098	0.161	0.090
	(0.059)	(0.056)	(0.052)	(0.052)
3-4	0.143	0.110	0.171	0.089
	(0.064)	(0.050)	(0.059)	(0.047)
4-5	0.130	0.070	0.091	0.017
	(0.078)	(0.065)	(0.066)	(0.058)
5-6	0.052	- 0.058	0.000	- 0.111
	(0.069)	(0.061)	(0.065)	(0.057)
6-7	0.095	0.048	0.071	0.013
	(0.069)	(0.058)	(0.056)	(0.052)
7-7.25	- 0.030	- 0.135	0.048	- 0.067
	(0.204)	(0.176)	(0.179)	(0.171)
7.25-7.5	0.145	0.041	0.152	0.046
	(0.124)	(0.116)	(0.105)	(0.105)
7.5-7.75	- 0.023	- 0.112	0.013	- 0.079
	(0.142)	(0.125)	(0.138)	(0.126)
7.75-8	0.480	0.299	0.713	0.312
	(0.438)	(0.330)	(0.428)	(0.334)
8-8.25	0.298	0.324	0.588	0.316
	(0.194)	(0.099)	(0.215)	(0.104)
8.25-8.5	0.186	0.241	0.520	0.257
	(0.191)	(0.042)	(0.218)	(0.061)
8.5-8.75	0.017	0.198	0.279	0.190
	(0.175)	(0.081)	(0.205)	(0.051)
Worker FE		✓		✓
Date FE			✓	✓
R^2	0.043	0.212	0.117	0.255

Note: N = 3,908. The omitted category indicates the first hour of the day. Standard errors in parentheses allow for auto-correlation between observations based on the same worker. All specifications include an indicator variable for whether the box packed is a standard, four-fifth-bushel box. The data set contains a record for every box packed by a sample of workers, and the time it took them to pack each box. A research assistant collected the data over the course of one month.

Table 5. Sample Statistics for Payroll Data

	Percent Overtime	Std. Dev. Of % Overtime	Boxes per hour	Hours Overtime	Total Hours
Monday	6.91	8.00	13.23	0.66	8.31
Tuesday	7.02	7.72	13.42	0.67	8.30
Wednesday	7.25	8.12	13.21	0.69	8.19
Thursday	6.09	7.61	13.50	0.58	8.19
Friday	7.64	9.19	14.90	0.73	8.43
Saturday	45.00	41.05	20.49	3.04	5.96
All	10.42	18.18	14.30	0.88	8.08

Note: The data set is based on payroll records covering the 2001 through 2003 packing seasons.

Table 6. The Effect of Overtime on Packing Speed, Payroll Data
Dependent Variable: Difference between regular time and overtime packing speeds

	(1)	(2)	(3)	(4)	(5)	(6)
Days in Sample	All		Weekday		Saturday	
Hours Overtime		0.278		- 0.928		0.633
		(0.271)		(0.822)		(0.226)
Constant	2.485	2.056	2.795	3.993	- 0.483	- 3.019
	(0.131)	(0.482)	(0.142)	(1.149)	(0.339)	(0.998)
R^2	0.571	0.571	0.569	0.570	0.492	0.522
N	2,498	2,498	2,262	2,262	236	236

Note: Standard errors in parentheses allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2000 through 2003 packing seasons. The sample covers only shifts which included both overtime and regular hours. All regressions include date fixed effects.

Table 7. The Effect of the Predictability of Overtime on Packing Speed, Payroll Data
Dependent Variable: Difference in regular time and overtime packing speeds

	(1)	(2)	(3)	(4)
Predicted Overtime	- 5.877	- 3.599	- 6.772	- 4.096
	(0.913)	(0.928)	(1.008)	(1.065)
Overtime Hours		- 3.930		- 4.283
		(0.347)		(0.331)
Constant	8.446	11.326	9.307	12.258
	(0.884)	(0.933)	(0.969)	(0.996)
Worker Fixed Effects			✓	✓
R^2	0.018	0.118	0.067	0.176

Note: N = 2,262. The sample consists only of weekdays. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2001 through 2003 packing seasons. Predicted Overtime is an indicator function for whether the predicted shift length was greater than 8 hours.

Table 8. The Effect of Overtime on Packing Speed, Payroll Data

	(1)	(2)	(3)	(4)
Dependent Variable	Regular time packing rate		Overtime packing rate	
Predicted Overtime	1.019	0.507	7.275	7.742
	(0.483)	(0.359)	(0.792)	(1.120)
Constant	13.853	14.346	5.378	4.929
	(0.547)	(0.345)	(0.694)	(1.077)
Worker Fixed Effects		✓		✓
R^2	0.002	0.315	0.018	0.128

Note: N = 2,262. The sample consists only of weekdays. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2001 through 2003 packing seasons.

Table 9. The Effect of Cumulative Fatigue on Packing Speed, Payroll Data

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Rate Δ	Rate RT	Rate OT	Rate Δ	Rate RT	Rate OT
Predicted Overtime	- 6.665	0.554	7.652	- 6.978	0.160	7.570
	(1.016)	(0.361)	(1.122)	(1.032)	(0.364)	(1.136)
Overtime on Previous Day	- 0.464	- 0.205	0.387			
	(0.359)	(0.221)	(0.411)			
Day of Week				0.156	0.264	0.130
				(0.108)	(0.066)	(0.131)
Constant	9.567	14.461	4.712	9.036	13.888	4.703
	(0.960)	(0.364)	(1.098)	(0.983)	(0.375)	(1.090)
R^2	0.067	0.315	0.129	0.067	0.320	0.129

Note: N = 2,262. The sample consists only of weekdays. The dependent variable "Rate Δ" is the difference between regular time and overtime packing speeds. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2001 through 2003 packing seasons. All regressions include worker fixed effects.

Table 10: The Effect of Overtime on Packing Speed by Skill, Payroll Data
Dependent Variable: Difference between regular time and overtime packing speeds

	(1)	(2)	(3)	(4)	(5)	(6)
	All 2001 workers classified as experienced		Excluding 2001		All 2001 workers classified as inexperienced	
Predicted overtime	- 5.143	- 3.027	- 7.057	- 4.385	- 5.144	- 3.128
	(1.090)	(1.125)	(0.765)	(0.932)	(1.081)	(1.112)
Experienced packer	4.874	4.006	3.251	2.384	4.874	3.985
	(1.411)	(1.396)	(1.143)	(1.143)	(1.411)	(1.397)
Fastest worker	- 0.081	- 0.879	- 0.869	- 1.669	- 0.081	- 0.898
	(4.038)	(3.681)	(3.524)	(3.168)	(4.038)	(3.675)
Hours overtime		- 3.901		- 3.932		- 3.996
		(0.350)		(0.498)		(0.355)
Predicted overtime × experience	- 4.656	- 3.782	- 2.774	- 1.766	- 4.450	- 2.619
	(1.414)	(1.422)	(1.200)	(1.278)	(1.453)	(1.502)
Predicted overtime × fastest worker	1.056	1.352	2.487	3.454	1.078	1.369
	(3.991)	(3.622)	(3.571)	(3.203)	(3.988)	(3.569)
Constant	7.498	10.572	9.260	12.350	7.498	10.647
	(1.033)	(1.072)	(0.664)	(0.771)	(1.033)	(1.074)
R^2	0.022	0.120	0.057	0.176	0.022	0.123
N	2,262	2,262	1,333	1,333	2,262	2,262

Note: Standard errors in parentheses allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2000 through 2003 packing seasons. The sample covers only shifts which included both overtime and regular hours.

Appendix Table 1: The Effect of Box Order on Packing Speed, On-Site Data
Dependent Variable: Seconds per pear packed

	(1)	(2)	(3)	(4)
Order of box packed at bin	0.000 (0.003)	0.000 (0.003)		
90 pears per box	- 0.083 (0.064)	- 0.083 (0.064)		
100 pears per box	- 0.204 (0.074)	- 0.204 (0.074)		
110 pears per box	- 0.387 (0.064)	- 0.387 (0.064)		
120 pears per box	- 0.433 (0.090)	- 0.433 (0.090)		
Last box at bin			- 0.119 (0.031)	- 0.119 (0.031)
Pears per box			- 0.012 (0.002)	- 0.012 (0.002)
Constant	2.991 (0.177)	2.991 (0.177)	4.048 (0.257)	4.048 (0.257)
R^2	0.249	0.249	0.253	0.253

Note: N = 3,908. The pears-per-box variables equal unity when the box packed has the given number of pears. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker. All specifications include a fixed effect for the type of box packed, the worker, and the date. The data set contains a record for every box packed by a sample of workers and the time it took them to pack each box.

Appendix Table 2. The Reaction of Workers to Box Order by Skill Level, On-Site Data

Dependent Variable: Seconds per pear

	(1)	(2)
Last box	- 0.169	- 0.170
	(0.033)	(0.033)
Box order × fastest workers	0.206	0.203
	(0.092)	(0.092)
Fastest workers	- 0.839	- 0.841
	(0.126)	(0.127)
90 pears per box	- 0.091	
	(0.069)	
100 pears per box	- 0.205	
	(0.074)	
110 pears per box	- 0.272	
	(0.074)	
120 pears per box	- 0.413	
	(0.112)	
Pears per box		- 0.010
		(0.002)
Constant	3.131	3.919
	(0.200)	(0.295)
R^2	0.141	0.141

Note: N = 3,908. The pears-per-box variables equal unity when the box packed has the given number of pears. Standard errors in parentheses allow for auto-correlation between observations based on the same worker. All specifications include a fixed effect for the type of box packed and the date. The data set contains a record for every box packed by a sample of workers and the time it took them to pack each box.

Appendix Table 3. The Effect of Overtime on Packing Speed, Payroll Data

Dependent Variable: Ratio of overtime packing to regular time packing speeds

	(1)	(2)	(3)	(4)	(5)	(6)
Days in Sample:	All		Weekday		Saturday	
Hours Overtime		- 0.034		- 0.021		- 0.038
		(0.019)		(0.058)		(0.017)
Constant	0.918	0.971	0.899	0.926	1.101	1.254
	(0.009)	(0.035)	(0.010)	(0.081)	(0.022)	(0.074)
R^2	0.481	0.483	0.471	0.471	0.515	0.537
N	2,498	2,498	2,262	2,262	236	236

Note: Standard errors in parentheses allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 200 through 2003 packing seasons. Regressions include only shifts which included both overtime and regular hours. All regressions include date fixed effects.

Appendix Table 4. Box Count Regressions

Dependent Variable: Number of boxes packed

	(1)	(2)	(3)	(4)	(5)
Days in Sample	All	Weekday	Saturday	Weekday	OT Weekday
Hours RT	12.966	13.398	5.855	12.915	14.929
	(0.327)	(0.324)	(0.469)	(0.324)	(0.434)
Hours OT	12.652	11.058	12.480	5.525	10.002
	(0.492)	(0.794)	(0.540)	(1.353)	(2.327)
PO × Hours RT				0.719	0.577
				(0.273)	(0.429)
PO × Hours OT				5.815	8.417
				(1.314)	(2.427)
Predicted Overtime (PO)				1.234	- 4.640
				(1.439)	(2.338)
Constant	2.976	2.501	15.165	2.156	- 1.270
	(1.373)	(1.455)	(1.421)	(1.445)	(2.502)
R^2	0.726	0.778	0.427	0.780	0.802
N	10,004	8,750	1,254	8,750	4,524

Note: Standard errors in parentheses allow for auto-correlation between observations based on the same worker. The data set is based on payroll records covering the 2001 through 2003 packing seasons. All regressions include worker fixed effects and date fixed effects.