How Many Pears Would a Pear Packer Pack if a Pear Packer Could Pack Pears at Quasi-exogenously Varying Piece Rates?

An Empirical Investigation of Inter-temporal Labor Supply[1]

PRELIMINARY AND INCOMPLETE.
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Abstract

We examine the labor supply of fruit packers using a unique, panel dataset collected from a large California-based pear packing plant. The data consist of both worker-day level payroll data, along with data from a field collection effort that generated worker-minute level performance data. Workers face both expected and unexpected shocks to their wages, and we use this to evaluate different models of inter-temporal labor supply. In contrast to most previous work, the data allow us to examine worker response on the intensive margin with constrained hours. In response to unpredictable positive wage shocks, we find that workers decrease their effort. In response to predictable positive wage shocks, worker response depended on the shock frequency; inter-day shocks lead to increase in effort while high frequency intra-day shocks lead to a decrease in effort. Our results offer support for the Köszegi and Rabin (2006) model of reference-dependent preferences, but suggest that workers are failing to generate rational expectations targets for regular, high frequency changes.

Keywords: labor supply, reference dependent preferences.
JEL Classification: J22, D03

1 Introduction

Economists have long sought to understand how workers respond to changes in wages. The topic has implications for many areas of economics. In macroeconomics, it is a critical ingredient in models that predict how the business cycle will affect wages(Lucas and Rapping, 1969). In public finance, it determines in part how changes to the income tax will affect tax revenue (Feldstein, 1995). And in personnel economics, how workers respond to changes in incentives is a central part of any theory of optimal contracting (Lazear (2000) Prendergast (1999)).

Historically, studies of labor supply have faced several empirical challenges. Few data sets exists that contain accurate measures of both labor supply and wages. The available data typically contain wage changes that are not transitory, but rather correlated with lifetime income. Moreover, the available data typically describe workers who are not free to set their own hours. These challenges have made it difficult to interpret the generally low estimates of inter-temperal labor supply (Card, 1991; Blundell and MaCurdy, 1999).

To analyze how workers respond to changes in wage, we utilize a unique panel dataset in which workers are exposed to several different types of high frequency wage shocks. Unlike most previous studies, we study an environment in which worker hours are constrained but worker effort is not. Such an environment may be more representative of the general workforce, as most professions offer little flexibility in hours.

To the best of our knowledge, this paper is the first to examine the response of workers to changes in wage in an hours-constrained environment. Moreover, the findings are the first to demonstrate how the frequency of wage changes affect worker's response.

In particular, we study the behavior of workers at a firm that packages pears and ships them to retailers. The workers regularly face both expected and unexpected shocks to their wages. We examine the workers' response to both types of shocks, and this allows us to directly test several models of labor supply.

We study two types of wage shocks. The first of these are driven by state law 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 their compensation by 50%. This overtime pay leads to both predictable and unpredictable shocks to wage. Workers do not know the exact length of a shift on any given day, thus daily overtime represents a partially unexpected shock to wages. But workers also receive overtime pay once they have worked forty hours in any given week. Since most weeks last longer than forty hours, overtime at the end of a week represents a predictable increase in wage.

The second wage shock we examine is driven by the way that the work is organized on the factory floor. As workers package pears for shipping, they rotate across bins filled with pears of different sizes. The workers are paid a fixed piece rate for each box packed, regardless of the size of the pears packed. When assigned to pack large pears, their implicit wage rises, since fewer pears need to be packed per box. When assigned to small pears, their implicit wage lowers. The workers rotate across bins, spending fifteen minutes with each bin. As such, their piece rates vary in a predictable fashion throughout the day.

Our empirical analysis leads to three main findings. First, workers respond to daily overtime by exerting *less* effort. Second, workers respond to weekly overtime by exerting *more* effort. Third, when rotating across bins, workers work more *slowly* when packing larger pears and hence facing a higher implicit wage. These empirical findings suggest that workers set income targets based on rational expectations when facing overtime. But that workers are failing to use rational expectations based targets when rotating across bins

The paper is organized as follows. The subsequent section provides a brief review of the literature on labor supply and our contribution to this body of work. Section 3 describes the institutional details of the pear packing factory and the wage shocks experienced by the workers. Section 4 contains a brief overview of the different labor supply models and their implications for worker effort in our context. Section 5 describes our empirical framework and presents our estimates. Section 6 concludes.

2 Previous Research on Labor Supply

This paper contributes to a growing literature on the importance of reference-dependent preferences in determining labor supply. We focus on workers who do not control their schedules but only their effort. Previous studies have focused instead on workers in occupations with flexible hours. Camerer et al. (1997), for instance, study the behavior of New York City taxicab drivers. They use the average daily wage of other workers as an instrument for an individual driver's wage, and find that drivers work fewer hours on days with higher average wages; a result consistent with reference-dependent preferences, or "income targeting." Chou (2000) finds similar evidence among taxi drivers in Singapore.

Farber (2005, 2008), on the other hand, uses a different econometric strategy and finds mixed evidence that cab drivers use income targets. He concludes that although drivers may have income targets, such targets change each day. Such income targets, he argues, are too unstable and imprecisely estimated to be of much empirical use. Crawford and Meng (2008) use Farber's data to estimate a model based on recent theoretical work by Köszegi and Rabin (2006). They model drivers' income and hours-worked targets as rational expectations, and find "sensible" parameter estimates that are both "plausible and precisely estimated." Similarly, Giné et al. (2010) find support for a model of reference dependent preferences with rational expectations targets among South Indian fishermen.

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 average wage while Paarsch and Shearer (1999) measure a positive relationship between piece rate and productivity among workers in a Cloumbia tree-planting firm. Similarly, Lazear (2000) finds that workers respond to a switch from fixed wages to piece-rates by increasing effort.

More recently, Fehr and Götte (2007) run a field experiment in which they randomly assign bicycle messengers to wages. They find that higher wages have a positive effect on the number of hours worked, but a negative effect on effort per hour. The authors conclude that workers have reference-dependent preferences, but find that the total amount of work provided is positively related to the wage.

A common characteristic of these studies is their focus on the extensive margin of labor (hours worked), and not on the intensive margin (effort). Dickinson (1999) attempts to directly address this shortcoming with a lab experiment. He finds that when hours are constrained, worker effort is positively correlated with wage. When his subjects are allowed to set their own hours, however, some respond to higher wages by working longer but exerting less effort.

In this paper, we focus on the intensive margin rather than the extensive margin, and we do so with data from the field. Moreover, our data allow us to measure worker response to both expected and unexpected shocks to wages. This allows us to test not only if workers have income targets, but whether those targets are set via rational expectations.

3 Institutional Background

We examine the behavior of workers who package pears to be shipped to market at one of the largest pear packing facilities in California. Because of their thin skin, pears do not respond well to bulk shipping. Instead, the workers wrap each pear individually in tissue paper and carefully arrange the pears in boxes for shipment. The procedure is labor-intensive and must be done by hand. But such packaging allows the firm to ship the pears directly to retail outlets and preserves the value of the fruit in transit.

Pears arrive at the factory each morning from farms throughout Northern California. Once washed, pears travel along a conveyor belt that sorts the pears into bins by size. Workers then individually wrap each pear and carefully arrange them into boxes. Following industry standards, the pears are sorted into one of eight sizes: 70, 80, 90, 100, 110, 120, 135, 150. Pear sizes indicate the number of such pears that will fit into a standard four-fifth bushel box. For example, 100 "size 100" pears must be packed into a standard box.

Workers are paid the same piece rate for each box, regardless of the number of pears it contains.[1] Both the firm and its workers recognize that workers who pack larger pears face a larger implicit wage. As a result, the firm requires workers to rotate across different packing stations, so that each worker spends the same amount of time with the different pear sizes. Typically, workers spend fifteen minutes at each station and then rotate to the next size. For instance, a worker would switch from packing size 120 pears to packing size 110 pears. When they reach the end of the line, the workers rotate back to the station with the smallest size pear. 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. Importantly bins are large enough that two workers can have simultaneous, unrestricted access to a single bin.

[1] Such a flat piece rate appears consistent with other pear packing facilities in the region.

While pear packing is neither mentally of physically difficult, it is very attention intensive. This, combined with the physical distance between each bin and the general noise level of the packing floor leads to little or no interaction among packers during working hours.

From the firm's founding in the early 1900's until 2003, workers were paid a single piece rate for each standard box packed. If a worker's piece rate earnings per day implied a wage lower than the California minimum wage, then the worker was paid minimum wage. This system was called "piece or hourly." In 2004, the firm implemented a more nuanced payment regime in which some workers were "piece or hourly" and some were paid "piece and hourly." Workers were so displeased with this change that management abandoned the scheme after one year, and returned to a flat piece rate regardless of pear size. In 2005, the firm switched from "piece or hourly" to "piece and hourly." Workers were paid an hourly wage and given a smaller piece rate for each box packed in addition to a fixed hourly wage.

For example, workers in 2005 were paid twenty cents for each standard box packed in addition to an hourly wage of \$6.25. This "piece and hourly" arrangement was meant to provide the worker with an incentive to be productive, but still compensate the worker if unexpected shocks reduced her output. Workers under the piece and hourly compensation scheme are occasionally asked to help with tasks other than packing boxes, such as restocking materials and cleaning the factory floor.

The firm provides overtime pay when it is legally required to do so. It pays workers overtime when they have been working for more than 8 hours in any given day or for more than 40 hours in any given week. Overtime wages are 50% higher than regular wages. For example in 2005, overtime increased a worker's hourly wage from \$6.25 an hour to \$9.37 an hour, and piece rates from 20 cents a box to 30 cents a box. Packers generally work 6 days a week (Monday thru Saturday) and are expected to stay for the entire shift regardless of duration.

This institutional framework subjects workers to several wage changes. First, workers experience predictable shocks to their wages as they rotate across packing stations. Secondly, workers face both predictable and unpredictable overtime. The firm faces a high variance in the total output needed; figure 6 describes this daily variation graphically.[2] That variation in output, combined with the state laws regarding overtime, leads to two types of shocks. Early in the week, packers face unexpected increases in their wage, when their shift lasts long than 8 hours. But by the end of a typical week, overtime is nearly automatic, provided that the work week has lasted longer than 40 hours. Thus overtime late in the week represents an expected increase in wage.

3.1 Data

Our analysis is based on two sources of data. First, we collected payroll and hours records from the firm's personnel department. The firm was able to provide us with payroll records for 2001, 2002, 2003. For each of those years, the payroll data contain the daily output for each worker in terms of total boxes packed, hours worked, and overtime hours worked. The payroll data do not, unfortunately, indicate the size of the pears packed in each box.

For that reason, we collected data on output for a small set of workers on the factory floor. A research assistant monitored workers along one line of the factory, recording the time at which each worker finished a box. The research assistant was able to capture the minute-by-minute output of workers on one line for 23 full days of work, which generated data on the time taken to pack 3,967 boxes by 70 packers.

4 Models of Labor Supply

This section reviews three different models of labor supply and concludes with the implications of each model for the workers in our sample.

4.1 Neoclassical Model

Under the neoclassical model, workers choose effort level e at each time t in order to maximize an additively separable lifetime utility function,

$$U = \sum_{t=0}^{T} \beta^t u(c_t, e_t, x_t), \tag{1}$$

[2] The variation in output is driven by the "just-in-time nature of pear packing. At one end, the firm must satisfy orders from retailers. But at the other end of the supply chain, the pears arrive from the fields at a stochastic rate.

subject to the budget constraint:

$$\sum_{t=0}^{T} \frac{p_t c_t}{(1+r)^t} = \sum_{t=0}^{T} \frac{w_t e_t}{(1+r)^t}. \tag{2}$$

Here we denote c_t as consumption, x_t as a variable that affects preferences at time t, $\beta < 1$ as the discount factor, r as the interest rate, p_t as the price of the consumption good, and w_t as the wage per unit of effort e_t. Additionally, within period utility, $u(\cdot)$, is increasing in c_t, decreasing in e_t, and strictly concave in both arguments. Within-period choice e_t of a packer can then be expressed in terms of the maximization of a static utility function

$$v(e_t, x_t) = \lambda w_t e_t - g(e_t, x_t), \tag{3}$$

where $g(\cdot)$ is strictly convex in effort.[3]

Given these assumptions, the workers' optimization problem is quite simple. Specifically, at each time t packers will exert effort e_t until the marginal cost of effort, $\frac{\partial g(e_t, x_t)}{\partial e}$, equals the returns from effort, λw_t. This implies that workers will exert more effort when they experience an increase in their wage.

4.2 Reference Dependent Preferences

The concept of income targeting is similar in spirit to prospect theory (Kahneman and Tversky, 1979). Income targeting implies that workers rely on a target income beyond which they become less responsive to changes in wage. Models of income targeting predict that workers may exhibit a negative wage elasticity, because a higher wage allows them to reach their income targets with less labor. Such models require individual preferences to "kink" at a reference point due to loss aversion. For example, the taxi drivers described by Camerer et al. (1997) may be more responsive to changes in wage if they are below their daily income target than above it.

More formally, income targeting can be expressed using equation (3) by adding a reference dependent component:

$$v(e_t, x_t, y_t; y_t^R) = \lambda w_t e_t - g(e_t, x_t) - 1_{(y_t^R - y_t < 0)} \gamma \lambda w_t e_t \tag{4}$$

[3]See Fehr and Götte (2007) or Browning et al. (1985) for a formal proof.

where y is the target variable, y^R is the target value for that variable, and $\gamma > 0$ is a measure of loss aversion.

The solution to the worker's optimization problem at time t is to exert effort e_t until the marginal cost of effort, $\frac{\partial g(e_t, x_t)}{\partial e}$, equals the returns from effort, $\lambda w_t(1 + 1_{(y^R - y_t < 0)}\gamma)$. The difference from the neoclassical model arises from the additional term, $1_{(y_t<0)}\gamma$, which reduces the marginal value of income (i.e. the returns from effort) when some variable y_t is above its reference value.

Since workers are much more likely to stop working when their target is reached, workers will work less when wages are high.[4] This theoretical result may explain the strong negative wage elasticities found in the study of certain professions, and could account for the "too small" estimates of wage elasticities in the general labor market.

4.3 Reference Dependent Model with Rational-Expectation Targets

One concern with most models of reference dependent preferences is that they fail to explain how such targets are determined. Partly in response, Köszegi and Rabin (2006) develop a theory of reference dependent preferences in which targets are set equal to the agents' rational expectations.

The preferences for a worker with rational-expectation based targets is identical to equation (4), but combined with a constraint that describes how targets are set:

$$y_t^R = E(y_t | E(w_t), x_t). \tag{5}$$

For example, a worker would set her daily income target higher on days when she expects to earn a higher wage, and lower on days when conditions make work more distasteful (e.g. when the worker is ill). This rational-expectations framework reproduces the standard predictions from the neoclassical model, so long as wage changes are perfectly anticipated. That is, if workers set targets via rational-expectations, deviations from neoclassical behavior are driven only by differences between actual and expected wages.

Using proxies for expected wage, recent studies by Crawford and Meng (2008) and Giné et al. (2010) provide strong evidence in support of this model for workers in highly

[4] That there will be a clustering of labor supply around the 'kink' in worker preferences.

flexible professions (New York City taxicab drivers and Indian fishermen respectively). To our knowledge, this paper is the first empirical test of rational expectation targets when workers are constrained in hours.

4.4 Predictions of the Labor Supply Models

Consider the response of a packer with neoclassical preferences. As she rotates from bin to bin, she is paid the same piece rate per box regardless of the number of pears required to pack each box. Thus her effective wage changes with pear size, and such changes are anticipated. If we assume that bin size is not systematically correlated with x_t (i.e. the cost of effort is not systematically affected by being at a particular bin), neoclassical packers will exert more effort when facing a higher effective wage. They will pack faster when stationed at bins that have larger pears.

Consider further how such a neoclassical packer would respond to overtime. Overtime represents an increase in the effective piece rate but has a negligible impact on lifetime wealth. As such, neoclassical workers should respond with an increase in effort.[5]

Workers with reference dependent preferences would react differently to wage shocks. Such workers would respond to both bin switching and overtime based on the difference between their target income and their realized income. If they are earning less than their target income, then they remain responsive to wage changes. But if workers are earning more than their target income, the marginal benefit of income drops and workers can exhibit a negative wage elasticity.[6]

In contrast, consider workers who hold reference dependent preferences and who set their income targets via rational expectations. Such workers will respond to bin rotation in a neoclassical manner. Since they set their income targets via rational expectations, their income targets account for bin rotation. Then, since $y_t^R - y_t \not< 0$, the extra term in equation (4) becomes irrelevant and the model reduces to the neoclassical case (equation 3).

[5] On the other hand, packers are exposed to overtime only on work days that last longer than 8 hours or work weeks that last longer than 40 hours. Overtime hours then may be systematically correlated with changes in x_t. This becomes critical in our empirical strategy and is described below.

[6] Note also that the workers will exhibit a negative effort elasticity if the actual wage is so low that they *never* exceed their target income.

5 Results

Below we present our analysis of workers' responses to changes in the implicit wage. We first examine worker response to the high frequency wage shocks generated by differences in pear size and next examine how workers respond to overtime.

The wage shocks driven by differences in pear size, occur roughly every 15 minutes and consist of a 12.5% increase in the base piece rate as workers move down the line and to a 50% decrease when they rotate to the head of the line. The unexpected wage shocks are driven by overtime, and consist of a 50% increase in wage when either the 8-hour-a-day or 40-hour-a-week limits are reached.

5.1 The Reaction of Workers to Expected Shocks in Implicit Wages

We begin by comparing the effort of workers when assigned to pack small pears versus larger pears. Such a comparison isolates how workers react to an expected shock to wages. The standard life-cycle labor supply model suggests that workers ought to exert more effort when packing larger pears than small pears, as the constant piece rate per box implies a larger implicit wage for smaller pears. In contrast, if workers have reference-dependent preferences, we might decrease in effort when packing larger pears. And finally, since these wage shocks are completely predictable, according to Köszegi and Rabin (2006), worker behavior would be consistent with the standard life-cycle model.

Table 1 presents sample statistics for the on-site datadescribed above. Overall, we observe 3,967 boxes being packed by 70 workers. Across all pear sizes, it takes a worker approximately 2.4 seconds to pack a single pear, with a standard deviation of 0.86 seconds.

To account for worker and day-specific variation, we regress the time in seconds in which packer i packs a single pear on day t and the size of the pear. Specifically, we estimate the equation

$$\text{Seconds Per Pear}_{it} = \alpha_0 + D_{90} + D_{100} + D_{110} + D_{120} + \alpha_i + \alpha_t + \epsilon_{id}, \qquad (6)$$

where D_n are indicator variables for pears of size n, α_i is a worker fixed effect, and α_t are date fixed effects.

Columns 1 through 4 of Table 2 present the results of this regression. For each box observed we calculate the speed of the worker in producing that box, measured in seconds per pear. Size 80 pears are the omitted category.[7] The point estimates for pear size decrease monotonically; workers spend 0.534 seconds less on each of the smallest pears as compared to the largest pears. For the smallest pears, such a difference is statistically significant at conventional levels. The worker and date fixed effects increase precision but do not qualitatively change the basic pattern formed by the point estimates.

The second panel of table 2 substitute the four pear indicator variables for one variable measuring the size of each box. That specification leads to the same conclusion: workers pack the smaller pears faster. The effect of pear size on speed is statistically significant in all specifications and robust to worker fixed effects and date fixed effects. In general, as the implicit wage increases, workers pack more slowly.

One concern with these results is that smaller pears may simply require less effort to pack. But the size difference between different count pears is not large, and the casual observer would be hard pressed to tell the difference between pears taken from adjacent bins. In addition, when asked, the packers stated that there was very little difference in perceived effort between the different sized pears.

A second concern is that workers may simply be unable to "solve" the effort optimization problem. This also seems an unlikely issue. The pear packer's optimization problem is exceedingly simple. The workers experience the wage changes every fifteen minutes, and their earnings are made clear to them every day. Moreover, table 2 suggests that the workers not only fail to optimize (i.e. work harder when their wage is higher), but instead exert effort in a way that lowers their total earnings. The magnitude of the point estimates in table 2 suggest that packers could earn substantially more money if the packed at a more efficient rate. They would earn 7.3% more money each hour if they packed at a constant rate. This amounts to almost one additional box an hour.

A final concern is that the workers' effort may be determined, in part, by peer pressure. A growing literature has emerged showing the importance of social networks in determining how workers respond to incentives(Mas and Moretti, 2009; Bandiera et al., 2010). In this

[7] We exclude size 70, 135, and 140 pears as they are not commonly observed in the data.

setting, packers may pressure each other to exert less effort when packing the larger, more profitable pears. But the nature of pear packing, and the monotonic nature of the results makes such an explanation unlikely.

There are at least two reasons why peer pressure is an unlikely explanation for table 2. First, in most settings in which network effects are discussed, the workers work together on activities that require collaboration. In contrast, pear packers work alone at each station, and are forced to rotate, so that each worker gets equal time to pack the largest pears. The circumstances do not present the workers with a free-rider problem that requires a joint solution.

Second, the task of pear packing, while simple, requires the workers' undivided attention. The job requires the workers to constantly pick, wrap, and place pears into a box. As such, workers would have to stop working in order to observe the productivity of other workers. The workers do not speak to each other while packing. As such, it is difficult for the workers to monitor the output of their peers.

A more plausible explanation for table 2 comes from the workers themselves: target rates. When asked, workers say that they try to pack a certain number of boxes per hour. That is, that workers are target earners. If workers follow such a simple heuristic, then they will have to increase effort when packing smaller pears in order to maintain a constant rate. Worker effort would then be negatively correlated with the implicit piece rate, the result suggested by table 2.

Such targeting behavior stands in contrast to the predictions of both the neoclassical model and a rational-expectations targeting model. Since there is no uncertainty as to the implicit wage across bins, the expected income will equal the actual income, a condition under which the simple adaptation of Köszegi and Rabin (2006) above is fully equivalent to the neoclassical model.

5.2 The Reaction of Workers to Overtime

We turn next to payroll data, which describe workers' daily output and daily hours. We focus on the way in which wages are increased during overtime. Table 3 presents sample statistics for the payroll data. Workers spend 18 percent of their time earning overtime pay. They spend 61 percent of Saturdays earning overtime, and roughly 10 percent during the week on overtime. This section explores how workers react to that overtime pay.

In particular, we rely on the following two specifications to capture the effect of overtime on effort:

$$\text{Total Boxes}_{id} = \alpha_0 + \gamma_1 \text{OT Hours}_{id} + \gamma_2 \text{RT Hours}_{id} + \alpha_i + \alpha_d + \nu_{id} \tag{7}$$

and

$$\frac{\text{Total Boxes}_{id}}{\text{Total Hours}_{id}} = \alpha_0 + \beta_1 \frac{\text{OT Hours}_{id}}{\text{Total Hours}_{id}} + \beta_2 \text{Total Hours}_{id} + \alpha_i + \alpha_d + \epsilon_{id}, \tag{8}$$

where α_i and α_t are individual and date fixed effects respectively. In equation (7), we regress total boxes produced by a worker in a given day on the number of overtime hours and regular time hours. For that specification, the test of an effort response to wage is simply a test of whether overtime hours lead to the same total boxes as regular hours, $\gamma_1 = \gamma_2$. In equation (8), we also regress each worker's daily rate (total boxes divided by total hours) on the worker's total hours and the share of total hours that are overtime. A test of an effort response to wage is simply a test of whether $\beta_1 = 0$.

Table 4 presents ordinary least squares estimates of these two equations. The first three columns report the estimates of equation (7), estimated separately for different days of the week. The first column demonstrates that overtime hours lead to more production than regular time hours (3.00 boxes per hour for overtime versus 2.66 for regular time). But this difference in productivity is not statistically significant at conventional levels (a p-value of 0.77). Restricting the sample to either the beginning of the week or the end of the week drastically changes this basic pattern.

The second column of table 4 suggests that during the week, overtime leads to *less* production. Workers produce 4.91 boxes per hour during regular time, but only 1.85 extra boxes during overtime. On Saturdays, however, the pattern is reversed; workers produce more boxes during overtime than regular time. On Saturdays workers produce 3.73 boxes per hour during overtime, but only 1.20 boxes during regular time. The remaining columns of table 4 present estimates of equation (8). The estimates are much less precisely estimated and are inconclusive.

Nevertheless, the ordinary least squares results in table 4 may be biased. In particular, hours are set by the firm, and the firm may be forced to offer overtime due to omitted variables that also reduce effort. With neither total hours nor overtime being assigned at random, we cannot interpret the results of table 4 as consistent estimates.

Instead, we pursue an instrumental variables (IV) strategy. Analogous to the strategy pursued in Angrist (1991), we use time fixed effects—indicator variables for day of week and for week—as instruments for overtime hours. The results of the first stage regressions are shown in table 5.

The validity of this IV strategy requires that the fixed effects are not correlated with the cost of effort on a particular day of week or week of the year. Note that this requirement is much less onerous than the equivalent condition for workers who can set their own hours. That is, when workers can choose their own hours, our IV strategy would require that the opportunity cost of working for an hour on Saturday is the same as working an hour on Wednesday. In contrast, workers here are required to come to work, and so can only adjust their effort level. Therefore our IV strategy requires only that packing a pear entails the same degree of effort on Monday as on Wednesday.

An additional concern regarding this IV strategy is that overtime may be correlated with fatigue. At the end of a work day, when overtime binds, workers may be fatigued. Similarly, workers may be especially fatigued during weeks in which they work more than forty hours. But these daily and weekly effects of fatigue are likely not a source for bias. Equation (8) controls for total hours in a given day, alleviating the first concern. Further, we examined worker performance for weeks during which workers did not receive any overtime. For those weeks, we did not find any relationship between cumulative hours worked and worker packing rates.

Table 6 presents two stage least squares estimates of equations (7) and (8). The table demonstrates that, during the week, workers pack more slowly during overtime than during regular time. For instance, column four of table 6 demonstrates that workers pack over twice as many boxes during regular time as overtime, once Saturdays are excluded from the sample.[8]

[8]Roughly a third of workers from one season work at the firm the next season. The results of table 6 do

Table 6 also demonstrates that Saturdays follow a different pattern from weekdays. Columns 5 and 6 suggest that on Saturdays workers do indeed exert more effort during overtime, the opposite of what occurs during the week. This pattern is consistent with rational expectations preferences. Overtime is rare during the week but common on Saturdays. Thus workers exert more effort in response to expected (Saturday) overtime, but exert substantially less effort in response to unexpected (weekday) overtime.

Neither the OLS nor IV results in tables 4 and 6 are without problems. In particular, the IV strategy may be invalid if unobserved productivity shocks are correlated with the instruments. For instance, the IV estimates would be biased if on certain weeks the factory receives a distribution of pears that affects both overtime hours and the packing rate of workers. We cannot rule out that possibility. Nevertheless, we interpret both sets of results as broadly inconsistent with the neoclassical model. Neither table 4 nor 6 suggests that workers exert more effort when their piece rate increases.

Finally, table 7 confirms this basic overtime result with the on site data. It presents the average packing speed of workers throughout the day. The table suggests that workers pack more slowly once overtime is in effect. For instance, at 8 hours and 15 minutes into the day (and hence well into overtime) the packers take 0.15 seconds more per pear. This finding from the on site data corresponds to the results of tables 4 and 6, which are based on the payroll records.[9]

6 Conclusions

This paper presents evidence that workers in an hours-constrained environment exhibit behavior consistent with daily income targeting and rational expectations based targets. Workers respond to unexpected increases in wages due to overtime by decreasing effort, but exert higher effort when the overtime is predictable.

Furthermore, the paper demonstrates that the way in which shocks are distributed over time—their frequency—can determine worker response. We find that workers rely on rational targets in relation to overtime, but use simple heuristics when faced with the

not change substantially when we interact the effect of overtime with a control for experience.

[9]The basic results of table 7 remain unchanged when the sample is restricted to Monday through Thursday, or when the sample is restricted to days with more than 8 hours of work.

predictable, but high frequency, shocks caused by bin rotation. This suggests that different theoretical models may be required to model labor supply in different contexts, even for the same worker.

This paper is part of a growing literature that presents a more nuanced picture of how workers supply their labor. Though the literature is certainly not monolithic, many studies suggest that the neoclassical labor supply model alone does not adequately describe how workers choose how much labor to supply. The results here confirm that finding.

References

Angrist, J. D. (1991). Grouped-data estimation and testing in simple labor-supply models. *Journal of Econometrics 47*(2-3), 243–266.

Bandiera, O., I. Barankay, and I. Rasul (2010, April). Social incentives in the workplace. *Review of Economic Studies 77*(2), 417–458.

Blundell, R. and T. MaCurdy (1999). Labor supply: A review of alternative approaches. *Handbooks In Economics 5*(3), 1559–1696.

Browning, M., A. Deaton, and M. Irish (1985). A profitable approach to labor supply and commodity demands over the life-cycle. *Econometrica 53*(3), 503–543.

Camerer, C., L. Babcock, G. Loewenstein, and R. Thaler (1997, May). Labor supply of New York City cabdrivers: One day at a time. *The Quarterly Journal of Economics 112*(2), 407–441.

Card, D. (1991). Intertemporal labor supply: An assessment. Working Paper 3602, National Bureau of Economic Research.

Chou, Y. K. (2000). Testing alternative models of labor supply. evidence from taxi-drivers in singapore. Working Paper.

Crawford, V. P. and J. Meng (2008). New York City cabdrivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. Working Paper.

Dickinson, D. L. (1999). An experimental examination of labor supply and work intensities. *Journal of Labor Economics 17*(4), 638–670.

Farber, H. S. (2005). Is tomorrow another day? The labor supply of New York City cabdrivers. *Journal of Political Economy 113*(1), 46–82.

Farber, H. S. (2008). Reference-dependent preferences and labor supply: The case of New York City taxi drivers. *American Economic Review 98*(3), 1069–82.

Fehr, E. and L. Götte (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *American Economic Review 97*(1), 298–317.

Feldstein, M. (1995). The effect of marginal tax rates on taxable income: A panel study of the 1986 Tax Reform Act. *The Journal of Political Economy 103*(3), 551–572.

Giné, X., M. Martinez-Bravo, and M. Vidal-Fernandez (2010). Intertemporal substitution, weekly target earnings or both? Evidence from daily labor supply of southern indian fishermen. Working Paper.

Kahneman, D. and A. Tversky (1979, March). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–291.

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics 121*(4), 11331165.

Lazear, E. (2000). Performance pay and productivity. *The American Economic Review 90*(5), 1346–1361.

Lucas, R. E. and L. A. Rapping (1969). Real wages, employment, and inflation. *The Journal of Political Economy 77*(5), 721–754.

Mas, A. and E. Moretti (2009, March). Peers at work. *American Economic Review 99*(1), 112–145.

Oettinger, G. S. (1999, April). An empirical analysis of the daily labor supply of stadium vendors. *The Journal of Political Economy 107*(2), 360–392.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of Economic Literature 37*(1), 7–63.

Figure 1. Total Daily Boxes and Hours.

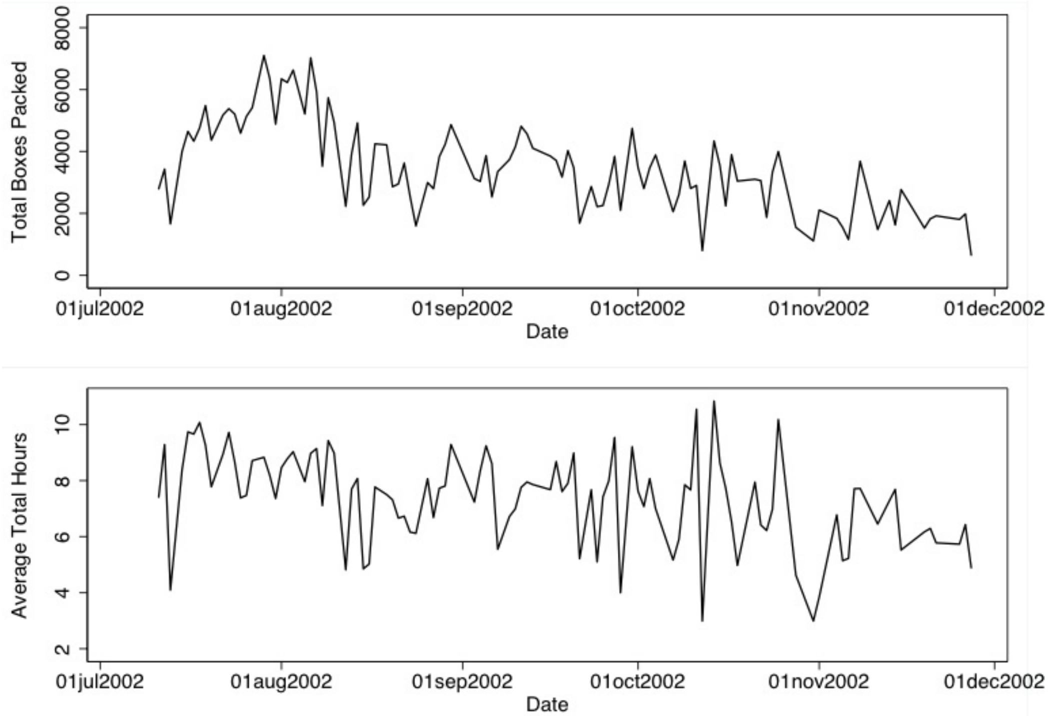

Figure 2. Total Daily Boxes by Length of Shift.

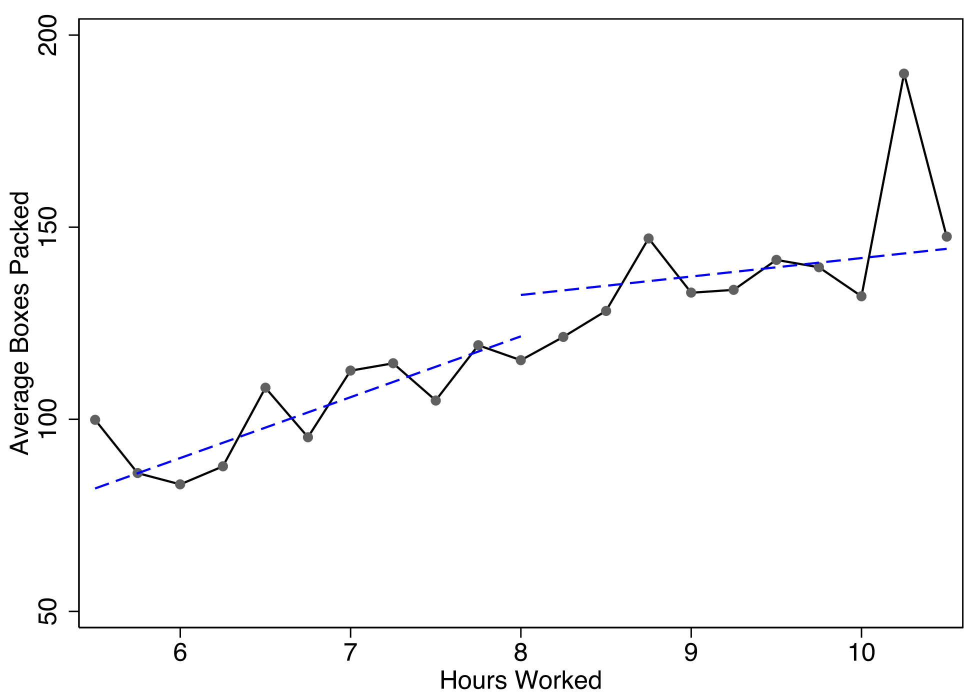

Table 1
Sample Statistics of On-Site Data [a]

Pear Size	*Obs.*	*Minutes per Box*	*Packing Speed*	*Std. Dev. Packing Speed*
All	3,967	3.94	2.406	0.856
80	588	3.57	2.635	1.006
90	944	3.76	2.487	0.924
100	1,394	3.91	2.330	0.810
110	844	4.40	2.358	0.727
120	197	4.21	2.075	0.616

[a]Note: Packing speed is measured in seconds per pear.

Table 2
The Effect of Expected Shocks on Effort [a]

Panel A

	(1)	(2)	(3)	(4)
Dep. Var.	*Seconds per Pear (SPP)*			
90 pears per box	-0.003	0.001	-0.096	-0.090
	(0.008)	(0.064)	(0.071)	(0.062)
100 pears per box	-0.131	-0.099	-0.241	-0.213
	(0.099)	(0.075)	(0.080)	(0.074)
110 pears per box	-0.299	-0.375	-0.237	-0.383
	(0.095)	(0.069)	(0.079)	(0.064)
120 pears per box	-0.534	-0.543	-0.389	-0.433
	(0.113)	(0.103)	(0.110)	(0.090)
Constant	2.743	2.773	3.043	2.992
	(0.098)	(0.059)	(0.208)	(0.175)
Worker FE	N	Y	N	Y
Date FE	N	N	Y	Y
R-squared	0.039	0.207	0.108	0.249
Observations	3,908	3,908	3,908	3,908

Panel B

	(5)	(6)	(7)	(8)
100 X pears per box	-0.012	-0.013	-0.009	-0.012
	(0.003)	(0.002)	(0.002)	(0.002)
Constant	3.745	3.861	3.772	3.977
	(0.326)	(0.257)	(0.301)	(0.260)
Worker FE	N	Y	N	Y
Date FE	N	N	Y	Y
R-squared	0.036	0.204	0.107	0.249
Observations	3,908	3,908	3,908	3,908

[a]Note:

1. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker.
2. All specifications include a fixed effect for the type of box packed.
3. The omitted box size is 80 pears per box.

Table 3
Sample Statistics of for Payroll Data

	Percent	*Overtime* *Std. Dev.*	*Hours*	*Hourly* *Rate*	*Total* *Hours*
Monday	7.31	9.03	0.73	13.17	8.39
Tuesday	7.48	8.87	0.75	13.33	8.39
Wednesday	7.78	9.34	0.79	13.12	8.30
Thursday	6.60	9.01	0.67	13.39	8.29
Friday	8.15	10.40	0.83	14.74	8.54
Saturday	31.90	39.15	2.23	16.96	6.80
All	10.58	18.37	0.94	14.02	8.19

Table 4
OLS Regressions of Payroll Data [a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.		*Boxes*					*Rate*		
	All	*Mon-Fri*	*Sat*	*All*	*Mon-Fri*	*Sat*	*All*	*Mon-Fri*	*Sat*
OT Hours	3.00	1.85	3.73						
	(1.35)	(1.37)	(1.61)						
RT Hours	2.66	4.91	1.20						
	(0.93)	(1.00)	(1.55)						
Share OT				-4.37	-11.48	-0.14	1.75	2.21	1.89
				(1.93)	(2.56)	(1.19)	(0.85)	(2.04)	(1.21)
Total Hours							-0.94	-0.91	-1.09
							(0.09)	(0.12)	(0.23)
Constant	107.87	79.83	38.74	15.45	15.74	8.50	23.04	21.85	14.33
	(9.71)	(10.08)	(15.85)	(0.44)	(0.68)	(0.81)	(0.90)	(1.07)	(1.91)
p(OT = RT)	0.77	0.04	0.01						
R-squared	0.68	0.67	0.75	0.56	0.57	0.63	0.58	0.58	0.68
Observations	5,002	4,375	627	5,002	4,375	627	5,002	4,375	627

[a]Note:

1. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker.
2. All regressions have worker and date fixed effects.

Table 5
First Stage Regressions of Payroll Data [a]

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dep. Var.	*Share OT*	*Share OT*	*Total Hours*	*Hours OT*	*Hours RT*
Tuesday		0.001	0.028	0.026	0.002
		(0.002)	(0.037)	(0.024)	(0.027)
Wednesday		0.025	-0.044	0.200	-0.244
		(0.003)	(0.057)	(0.032)	(0.053)
Thursday		0.006	-0.015	0.040	-0.055
		(0.002)	(0.044)	(0.024)	(0.043)
Friday		0.007	0.201	0.111	0.090
		(0.003)	(0.043)	(0.040)	(0.032)
Saturday		0.245	-1.333	1.583	-2.916
		(0.026)	(0.090)	(0.170)	(0.203)
Week F-Stat	1.9e+05	930.65	21138.03	556.85	30727.63
Day F-Stat		38.61	68.36	33.00	97.03
R-squared	0.291	0.464	0.455	0.434	0.454
Observations	5,002	5,002	5,002	5,002	5,002

[a]Note: Standard errors in parenthesis allow for auto-correlation between observations based on the same worker.

Table 6
IV Regressions of Payroll Data [a]

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*Rate*	*Boxes*	*Rate*	*Boxes*	*Rate*	*Boxes*
	All		*Mon-Fri*		*Sat*	
Share OT	1.93		-13.96		2.82	
	(0.82)		(5.01)		(1.16)	
Total Hours	0.81		1.62		0.25	
	(0.14)		(0.37)		(0.16)	
OT Hours		19.42		13.25		16.93
		(1.50)		(1.98)		(1.17)
RT Hours		19.34		27.50		13.70
		(1.28)		(2.95)		(1.75)
p(OT = RT)		0.93		0.00		0.02
R-squared	0.26	0.40	0.24	0.38	0.47	0.57
Observations	5,002	5,002	4,375	4,375	627	627

[a]Note:

1. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker.
2. All regressions have worker fixed effects.

Table 7
Packing Rate by Hours into Shift [a]

	(1)	(2)	(3)	(4)
2	-0.031	0.005	0.043	0.021
	(0.067)	(0.047)	(0.062)	(0.058)
3	0.092	0.086	0.136	0.119
	(0.081)	(0.048)	(0.079)	(0.075)
4	0.006	0.057	0.023	0.102
	(0.114)	(0.073)	(0.094)	(0.113)
5	-0.124	-0.109	-0.087	-0.057
	(0.083)	(0.060)	(0.083)	(0.088)
6	-0.007	-0.008	-0.011	0.004
	(0.089)	(0.058)	(0.088)	(0.088)
7	-0.002	-0.062	0.023	-0.024
	(0.091)	(0.086)	(0.122)	(0.131)
7:15	-0.049	-0.093	0.002	-0.007
	(0.108)	(0.102)	(0.095)	(0.090)
7:30	-0.021	-0.015	0.126	0.086
	(0.287)	(0.193)	(0.374)	(0.326)
7:45	0.136	0.137	0.412	0.221
	(0.236)	(0.177)	(0.071)	(0.086)
8:00	0.079	0.100	0.223	0.082
	(0.131)	(0.106)	(0.128)	(0.066)
8:15	0.157	0.164	0.258	0.151
	(0.072)	(0.163)	(0.138)	(0.070)
8:30	0.232	0.340	0.431	0.509
	(0.085)	(0.117)	(0.076)	(0.067)
8:45	0.262	0.349	0.291	0.369
	(0.079)	(0.346)	(0.076)	(0.067)
Worker FE	N	Y	N	Y
Date FE	N	N	Y	Y
R-squared	0.26	0.22	0.12	0.04
Observations	3,149	3,149	3,149	3,149

[a]Note:

1. Standard errors in parenthesis allow for auto-correlation between observations based on the same worker.
2. The omitted time period is hour 1.
3. A half hour lunch break is taken in hour 5.