INCOME TARGETING AND FARM LABOR SUPPLY

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There is considerable anecdotal evidence that farm workers who are paid by piece rate tend to "income target," or work only until they achieve a certain amount of daily income, and then stop work. We estimate reduced-form and structural models derived from the reference-dependent preference model of Koszegi and Rabin (2006) to test the income-targeting hypothesis using data from the National Agricultural Workers Survey (NAWS). We find evidence that supports the income-targeting hypothesis, in both the reduced-form and structural econometric models. Our findings suggest that even higher piece rates may not help the widely reported shortage of agricultural labor on the intensive margin as labor-supply curves can be backward bending.

Key words: Farmworkers, income-targeting, labor supply, minimum-wage policy, reference-dependent preferences.

JEL codes: J22, Q12, Q18.

Given the current environment of acute labor shortages in both agricultural and other industries, how workers respond to changes in pay is of critical importance. By now, we know a considerable amount about the productivity effects of paying agricultural workers by piece rates instead of hourly (Hill 2018; Stevens 2018) but less about the supply of labor for workers in piece-rate regimes. Many workers in piece-rate payment systems can vary the number of hours they work (Billikopf 2008), so labor-supply effects due to higher wages on the intensive margin, as opposed to the number of workers on the extensive margin, may be substantial. There is a large body of research in non-agricultural contexts that confirms the orthodox expectation that higher wages tied directly to effort (piece rates) can increase the quantity of labor supplied on the intensive margin (Oettinger 1999; Farber 2005, 2008, 2018; Stafford 2015). Yet, others find negative supply elasticities in piece-rate systems when workers have the ability to control the amount of time they spend working (Camerer et al. 1997; Chou 2002; Crawford and Meng 2011; Agarwal et al. 2015; Martin 2017). How can this happen? When workers have reference-dependent preferences (Kőszegi and Rabin 2006) and specific income goals, they may use higher wages in a piece-rate system to achieve their goal by working fewer hours and, ultimately, producing less. We test this hypothesis using a worker-level data set in the California farming industry and demonstrate its importance to the aggregate supply of farm labor through a series of counter-factual simulations.

In this paper, we present evidence from both reduced-form and structural models of labor supply to examine whether farm workers who are able to vary their hours tend to react to higher wages in a manner that is consistent with neoclassical or reference-dependent assumptions.[1] If the neoclassical model describes farm worker behavior better, then

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[1] Traditionally, labor-supply elasticities were estimated in annual data, but changes in annual wage changes are not plausibly negligible in terms of lifetime wealth. This observation gave rise to the daily-wage literature cited herein, as daily-wage changes are likely to be small relative to lifetime wealth.

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we can expect transitory increases in the wage to lead to greater supply on the intensive margin. In terms of labor-leisure choice, the substitution effect associated with higher wages dominates the income effect, and the amount of labor supplied rises. On the other hand, if workers' preferences are reference dependent, and they tend to income target, then it is possible that higher wages can reduce the supply of labor on the intensive margin. In a model of labor-leisure choice, the income effect dominates so the quantity of labor supplied actually falls if wages rise or rises if they fall. Only changes at high or low levels of income will induce the expected neo-classical response. We extend the theoretical model of Crawford and Meng (2011) and Martin (2017) to nest these two alternatives and provide a means of both deriving hypotheses regarding the effect of wage variation on labor supply and testing these competing hypotheses in a structural way. Our theoretical model predicts that increases in hourly wages when workers are either below their income and hour targets, or above both, will lead to a reduction in the quantity of labor supplied—a negative supply elasticity—whereas wage increases when workers are between their targets will lead to fully neoclassical responses.

Unlike empirical studies in the vein of Camerer et al. (1997) and subsequent reanalyses of the NYC taxi-driver case, in agriculture we do not have the luxury of data documenting every hour of every workers' day across a range of representative employers. Yet, our problem is critically important to understanding the behavior of agricultural labor markets. In this paper, therefore, we combine the insights from the theoretical and empirical literature on labor supply with a model that is appropriate for the best data available to understand labor-supply decisions in agriculture: the National Agricultural Workers Survey (NAWS). Because the NAWS data only reports broader aggregations than the shift-level taxi data available to others, we devise new empirical methods that are able to test the fundamental hypotheses from the neoclassical and behavioral labor-supply literatures but without the "narrow-bracketing" assumption typical in the literature.[2] We argue that the NAWS data are able to provide insights that are both important to the broader question of agricultural-labor supply and the ongoing debate between the two schools of thought on labor supply more generally. Our intent, therefore, is not to provide the definitive analysis of the neoclassical versus reference-dependent preference debate but rather to examine which is more likely in the best general data available for studying agricultural labor supply.

We assume workers form reference levels of income and hours by observing others in the same jobs, at the same time, and in the same crop. In the daily-labor-supply literature, how workers define reference points is a key point of departure. Farber (2015) assumes taxi drivers consider deviations from fixed worker, hour, day, week, and holiday averages as unexpected changes in hourly wages, concluding that targets, in general, are too unstable to represent viable reference-point measures. Crawford and Meng (2011), on the other hand, argue that targets are most logically formed from individual workers' rational expectations, based on their own experience on a comparative, historical basis. More recently, Thakrol and To (2017) reject both of these measures and argue instead for an adaptive measure that changes over time. However, when workers harvest in teams, interact frequently, and move from job to job, it is more likely that their targets are influenced by an exogenous reference point—the hours worked, and income earned, from other workers (Duesenberry 1949; Bandiera, Barankay, and Rasul 2005).[3] In this paper, therefore, we use the income earned, and hours worked, by other piece-rate workers in the same task, crop, and time as our targets.

There are a host of econometric issues in identifying whether labor-supply elasticities are driven by purely neoclassical considerations or if reference dependence is contextually important. Indeed, much of the debate in the literature revolves around controlling for sources of bias, rather than the form of the structural model brought to the data. For example, Stafford (2015) argues that failing to control for self-selection, wage-endogeneity, and wage-measurement errors is responsible

[2] Narrow bracketing is the implicit assumption from the reference-dependent labor supply literature that workers define targets over narrow periods of time, or "brackets," such as a day.

[3] Bandiera, Barankay, and Rasul (2005) do not define peer-based income targets as we do but show that farmworkers are aware of others' earnings, and this information affects their willingness to supply more labor. In fact, the authors argue that income-targeting is not likely a feature of their data but do not rigorously explore this assertion.

for enough downward bias in supply-elasticity estimates to produce spurious support for the income-targeting hypothesis.[4] Using a high-quality data set describing daily fishing trips for Florida lobster fishermen, she removes these sources of bias one by one to show how elasticity estimates change from negative to significantly positive. Therefore, in this study, we are careful to control for both endogeneity and wage-measurement errors in order to ensure that we test the income-targeting hypothesis consistently.

We find broad support for reference-dependent preferences among farm workers. Our reduced-form models show that simple labor-supply elasticities appear to be negative before we adjust for measurement errors and endogeneity in weekly wages. Once we correct for these issues, however, labor supply elasticities based on neo-classical assumptions, that is, that income and hours targets do not matter and are robustly positive. After introducing income and hours targets, we find that labor supply elasticities only remain positive if the worker is above either the hours or income target. If below either target, our findings strongly support the theoretical predictions of Crawford and Meng (2011), namely that the elasticity of labor supply turns negative, meaning that the labor-supply curve tends to be backward bending. These reduced-form results find further support in a structural model of labor supply in which we control for endogenous switching between regimes and parameterize the importance of gain-loss utility. Our findings have dramatic implications for agricultural labor markets as they imply that higher piece rates are not a simple solution to agricultural labor shortages on the intensive margin.

We contribute to both the substantive literature on farm labor shortages and to the more general literature on reference-dependent labor supply. Our empirical support of reference-dependent preferences among farm workers shows that the findings of Camerer et al. (1997), and many others since, are far more general than either the supply of taxi rides suggests. Further, we find that higher piece rates, productivity improvements with constant piece rates, or higher minimum wages that affect piece-workers' incomes will not necessarily help reduce the shortage of agricultural workers on the intensive margin. Rather, only wage improvements that move workers substantially above their target levels will have the expected, neo-classical effect on labor supply.

We begin with a brief description of the literature on income targeting and labor supply more generally. We then show how the conceptual model of reference-dependent preferences of Kőszegi and Rabin (2006) and Crawford and Meng (2011) applies to the agricultural-labor supply case and derive a set of empirically testable hypotheses. We explain the source of our data in the fourth section and provide some summary attributes of the data that support our empirical approach. A fifth section provides more detail on the empirical framework, including both the reduced-form and structural models, as well as how we account for endogenous switching among targeting regimes. In the sixth section, we present the results of a simple simulation exercise and follow with some implications for the agricultural labor market. The final section concludes and offers some guidance for future research in this area.

Background on Reference-Dependent Labor Supply

When employees are able to determine how many hours they work, anecdotal evidence suggests that income targeting is an important determinant of how much labor is actually supplied (Orde-Brown 1946; Berg 1961; Billikopf 2008). Income targeting is a manifestation of reference-dependent preferences (Kahneman and Tversky 1979; Kőszegi and Rabin 2006, 2007, 2009) in which workers form expectations of how much money they would like to make in a given day and either quit work or reduce effort after that point.

Although the underlying logic of the reference-dependent labor-supply model is intuitive, the empirical evidence is inconclusive. Camerer et al. (1997) find empirical support for this hypothesis using data from cab drivers in New York City as do Fehr and Goette (2007) in a field experiment using delivery people in Zurich, Crawford and Meng (2011) in a re-analysis of the Farber (2008) NYC taxi-driver data, Ashenfelter, Doran, and Schaller (2010)

[4] Most empirical studies calculate the implied daily wage by dividing daily income by the number of hours worked. In labor-supply regressions; therefore, the key variable on the right-side is calculated by dividing by the left-side variable, so any measurement error creates an inherent negative bias in the estimated relationship.

and Doran (2014) in similar NYC taxi data, Chang and Gross (2014) for workers at a pear-packing plant, Chou (2002) and Agarwal *et al.* (2015) in Singapore taxi drivers, Martin (2017) in a non-NYC sample of taxi drivers, MacDonald and Mellizo (2017) in 19th century farm workers, and Hammarlund (2018) in Swedish cod fishermen. On the other hand, Farber (2005, 2008, 2015) finds that a neo-classical model of labor supply is more appropriate in the same context as Camerer et al. (1997). His results were further supported by research among stadium vendors (Oettinger 1999), Uber drivers in the US (Chen and Sheldon 2016), and Florida lobster trappers (Stafford 2015). By now, there is a wealth of evidence on either side of the debate, so there is no firm conclusion from the empirical literature.

Which effect dominates is important for agricultural employers, because reference-dependent labor-supply tends to imply negative supply elasticities, with the quantity of labor supplied falling at higher hourly wages.[5] If there is a shortage of farm labor (Richards 2018), then efforts to address the problem through higher wages may be at least partially thwarted through lower labor supply from existing workers.[6] Whether paying workers more can solve the labor-supply problem depends, in part, on whether income targeting is an empirical regularity in the agriculture industry. Given the dangerous and tedious nature of farm work, the notion that workers are reluctant to spend more time at work each week has great intuitive appeal (Orde-Brown 1946; Berg 1961).

All of the previous empirical tests for reference-dependent preferences in labor supply, however, rely on rich data sets in which intra-day supply decisions are observed. There are a number of important contexts, however, in which income targeting may be important, but the data are not of the same quality. Failing to study labor supply in these contexts runs the risk of falling prey to the well-understood "streetlight effect," or searching for a solution only where it seems easiest to find. If we only test for reference-dependent preferences in contexts that provide daily data, we will only describe behavior in a limited set of markets, or for single, non-representative employers. For this reason, we use employee-level data from the NAWS data set.

Labor supply is clearly related to productivity when piece-rate payment is involved. In the general economics literature, Shearer (2004) and Paarsch and Shearer (2000, 2009) find that payment by piece rates can have substantial productivity effects relative to hourly payment. An emerging literature considers the productivity effects of paying on an hourly or piece rate in agricultural contexts. For instance, Stevens (2018) tests the hypothesis that piece-rate payment is associated with higher productivity using a quasi-experimental design from a single blueberry grower in California and finds an elasticity of productivity with respect to the wage rate of 0.70—much lower than comparable studies—and finds that temperature has a substantial effect on productivity.[7] Hill (2018) examines the interaction effect between minimum wages and productivity when workers are paid on piece rates. Both theoretically and empirically, she finds that productivity falls when the minimum wage is binding but considers assignment to hourly and piece-rate pay schemes as exogenous. Neither of these studies, however, address how piece rates affect labor supply. In this paper, we examine the labor-supply impact on the intensive margin of paying farm workers higher wages in piece-rate regimes.

In some contexts, workers select into piece-rate regimes, suggesting that the selection mechanism itself is important and endogenous. For example, Kandilov and Vukina (2016) use data from the National Agricultural Workers Survey (NAWS) to examine this issue and find little evidence that more productive workers sort into piece-rate jobs but stronger evidence that piece-rate payment attracts less risk averse workers. Although productivity is an important measure for the efficiency of labor employment, agricultural employers are often as interested in the effect of compensation on the amount of labor supplied, whether defined as the number of workers or the number of hours worked by an existing crew. In our analysis, we focus on piece-rate workers in order to abstract from selection bias. All of our results, therefore, are to be interpreted as applying only to workers that

[5] Fehr and Goette (2007) find that overall labor supply increases dramatically in the wage, but the number of hours supplied increases even more, suggesting a negative response in effort (amount of work per hour).

[6] Without data from a more general sample of employed and unemployed workers, we cannot examine this question on the extensive margin, so we consider only the intensive margin of currently employed workers here.

[7] The NAWS data does not contain enough location-date specificity to control for temperature effects on labor supply, so this is one limitation of using NAWS for this purpose.

endogenously match with suitable employers and payment schemes.

In the original model of loss aversion, Kahneman and Tversky (1979) left the notion of how reference points are formed open to speculation. Recently, however, Marzilli Ericson and Fuster (2011) and Abeler et al. (2011) provide lab evidence that reference points are largely determined by expectations—the higher the expectation, the higher the reference point. In a labor-market context, this suggests that if workers are able to vary their hours, raising income expectations in a piece-rate environment could have dramatic productivity effects. Thakral and Tô (2017) focus on the nature of the expectations-formation process and find that workers appear to form adaptive expectations, as opposed to the fixed expectations of Crawford and Meng (2011), for example. In each case, whether in the lab or with highly detailed hourly supply data, analysts are able to examine how workers form individual expectations from hour-to-hour decision processes. Intuitively, the notion that workers update expectations on a daily basis in agriculture is plausible but is simply not possible to model with our data. In this paper, we consider an expectations-formation mechanism that reflects the institutional realities of how workers in agriculture are likely to obtain information on potential earnings.

Workplaces are inherently social environments. Particularly in agricultural settings with piece-rate payment schemes, employers expect that workers will gauge their performance relative to others in the same field, packing plant, or orchard. Managing perceptions of relative performance is an important reason why piece-rate pay provides an incentive for greater performance (Paarsch and Shearer 2000, 2009; Shearer 2004). Therefore, based on the importance of peer observation in a farmworker setting noted by Bandiera, Barankay, and Rasul (2005), we assume that workers form income and hour targets through their expectations of other workers' performance. To keep the expectations process exogenous, simple, and tractable, we assume in the analysis below that a worker's income target is the mean of all other workers' weekly income, on a year, task, and crop basis, and that workers' hour target is the mean of all other workers' weekly hours worked, again controlling for the year, task, and crop.

Designing an empirical model that nests both the neoclassical and reference-dependent alternatives is a clear way of allowing the data to decide whether these income targets are important. Crawford and Meng (2011) attempt to reconcile the observations of Farber (2008) within a more tractable specification for reference-dependent preferences. Estimating both reduced-form and structural versions of an optimal-stopping model, they find support for reference-dependent preferences in the sense that workers appear to respond to both income and hours targets. By simulating the effect of wage changes in their model, parameterized to reflect both neoclassical and reference-dependent assumptions, they find negative labor-supply elasticities over a relatively large range of realized wages. However, they estimate a structural version of their optimal-stopping model to arrive at these conclusions, an option that is not available to us. In this paper, therefore, we estimate a continuous-choice version of their nested model and estimate in terms of hours per week and weekly income.

In the next section, we describe a simple theoretical model of income and hours targeting based on the reference-dependent model of Kőszegi and Rabin (2006) and Crawford and Meng (2011). We begin our empirical analysis by deriving a simple analytical model of income targeting and labor supply, then we follow by describing our data, then provide some reduced-form evidence, followed by estimates of structural labor-supply elasticities that account for the possibility that workers target both income and hours.

Theoretical Model of Income Targeting

In this section, we derive a model of reference-dependent preference that builds on the core insights of Kőszegi and Rabin (2006, 2007, 2009) as applied to the labor-supply problem by Farber (2008, 2015) and Crawford and Meng (2011). In our model, however, the objective is not to explain the probability of stopping work during the day if either income or hours targets are reached but rather to estimate the elasticity of labor supply in a setting where farmworkers may or may not goal target in determining their weekly labor-supply decisions. We first provide some simple analytics to demonstrate the likely implications of income and hours targeting, then bring the model to our NAWS data set and estimate labor-supply elasticities in a multi-regime endogenous-switching framework.

We follow Kőszegi and Rabin (2006) and Crawford and Meng (2011) and assume workers derive both "consumption utility" and "gain-loss utility" from their work activity. Consumption utility reflects a standard, neoclassical approach to studying labor supply as workers trade-off the greater consumption potential from working more today, through income, with the loss of leisure time. Work hours are the complement of leisure given a 24-hour time constraint on workers' day. Gain–loss utility, on the other hand, represents the loss in utility workers experience if they deviate from either income targets or hours targets.[8] In our model, we assume consumption and gain–loss utility are additively separable, and the components of gain–loss utility (income or hours) are also additively separable. We also assume, for tractability, a constant parameter for gains and losses, so we do not allow for the diminishing sensitivity to either inherent in prospect theory (Kahneman and Tversky 1979; Martin 2017).

In general notation, our utility model is written as:

$$(1) \quad v(m,h \mid m^T,h^T) = (1-\eta)(u_1(m) - u_2(h)) + \eta g(m,h \mid m^T,h^T),$$

where $m = wh$ is the amount of weekly income earned by working h hours per week for an hourly wage of w, $l = 168 - h$ is the implied amount of weekly leisure consumed, u_1 is the utility from income, u_2 is the disutility from work hours, g is the gain-loss utility function (to be specified more explicitly below), m^T is the weekly income target, h^T is the weekly hours target, and η is the relative weight placed on gain–loss utility compared to consumption utility. Utility rises in income but declines in the number of hours worked and is concave in each. Clearly, if $\eta = 0$ this utility function becomes a standard, neo-classical utility function, with all the implications that entails.

Gain–loss utility assumes a particularly simple form but is complicated by the fact that a worker can be in any one of four regimes: (1) below her income and hours target, (2) below her income target but above her hours target, (3) above her income target but below her hours target, and (4) above both her income and hours targets. Because of this inherent complexity, we assume gain–loss utility is linear and separable in each regime as in:

$$(2) \quad g(m,h \mid m^T,h^T) = d\lambda(u_1(m) - u_1(m^T)) + (1-d)(u_1(m) - u_1(m^T)) + e\lambda(u_2(h) - u_2(h^T)) + (1-e)(u_2(h) - u_2(h^T)),$$

where $d = 1$ if the worker is below her income target ($m < m^T$), $e = 1$ if the worker is above her hours target ($h > h^T$), λ is the utility loss suffered if the worker misses a target (or the coefficient of loss aversion) and is assumed to be ≥0. As in Crawford and Meng (2011), we assume λ is the same for missing both income and hours targets in this model but relax this assumption in the empirical application below.

In this framework, we assume the income and hours targets are determined relative to external reference points, namely the social-work environment in which each worker finds themselves. Because each worker is assumed to make the best use of all information available to them, consistent with the rational expectations assumption of Kőszegi and Rabin (2006) and Crawford and Meng (2011), and yet has limited own experience in each crop and task, we assume that the dominant source of information comes from others' experiences. Bandiera, Barankay, and Rasul (2005) show that agricultural harvesters are indeed aware of others' earnings, and comparing their earnings to others' impacts their own effort, so this assumption is reasonable. Each target is calculated as the average of all other workers in the same task, crop, and year, so is very specific to each workers' experience, and yet the specific value of the target is exogenous to their own decisions. Our assumption also avoids the criticism of Farber (2008) that worker-specific, time-varying targets are too unstable to be useful for empirical purposes.

In order to demonstrate the implications of this utility structure for labor supply, relative to a typical neo-classical specification, we follow Farber (2008, 2015) and Crawford and Meng (2011) and assume a particular functional form for consumption utility in order to derive a tractable model of labor supply. We define $u_1(m) = wh$ and $u_2(h) = \left(\frac{\theta}{1+\rho}\right)h^{1+\rho}$ where θ is defined as the marginal disutility of hours worked ($\theta > 0$), and ρ is the elasticity of the marginal rate of substitution between

[8] Farber (2008, 2015) assumes that workers (cab drivers) target only income and not hours, substantially simplifying the problem but ignoring the observation that many workers appear to stop work prior to earning their target income level.

hours worked and income (also assumed to be >0). We then substitute these sub-utility functions into the general framework of equation (1) to arrive at an expression for utility across each of the four possible regimes:

$$(3)\quad v(m,h \mid m^T,h^T)$$

$$= (1-\eta)\left(wh - \left(\frac{\theta}{1+\rho}\right)h^{1+\rho}\right)$$

$$+\eta\left(d\lambda(wh-m^T) + (1-d)(wh-m^T)\right)$$

$$-\eta\left(e\lambda\left(\frac{\theta}{1+\rho}h^{1+\rho} - \frac{\theta}{1+\rho}(h^T)^{1+\rho}\right)\right)$$

$$-\eta\left((1-e)\left(\frac{\theta}{1+\rho}h^{1+\rho} - \frac{\theta}{1+\rho}(h^T)^{1+\rho}\right)\right),$$

where the worker endogenously selects into the relevant regime, based on their behavior relative to either the perceived income or hours target. In the daily-labor supply literature, a gain–loss utility model such as (3) is commonly used to motivate an optimal stopping model, so forms the utility function that underlies a discrete-choice model of stopping times. However, in our application, we are more interested in how the hours of work supplied per week vary with changes in the implicit hourly wage.

Solving for the optimal supply of labor from the utility function in (3) on a regime-by-regime basis gives the following expression, as a function of only the wage and parameters of the model:

$$h^*(w \mid m^T,h^T,\Omega)$$

$$(4)\quad = \left\{\begin{array}{ll} \left(\frac{w(1-\eta+\eta\lambda)}{\theta}\right)^{1/\rho} & if\ d=1,e=0 \\ \left(\frac{w}{\theta}\right)^{1/\rho} & if\ d=1,e=1 \\ \left(\frac{w}{\theta}\right)^{1/\rho} & if\ d=0,e=0 \\ \left(\frac{w}{\theta(1-\eta+\eta\lambda)}\right)^{1/\rho} & if\ d=0,e=1, \end{array}\right\}$$

where Ω is a vector of parameters, and recall that λ measures the marginal loss in utility from missing a target, and η the relative importance of gain–loss utility relative to consumption utility. This distinction is important, because it is clear that these two parameters are not separately identified in the structural model. As in the discrete-stopping model of Crawford and Meng (2011), however, we know that this model collapses to the neo-classical labor-supply model if either $\eta = 0$ or $\lambda = 1$. Equivalently, this implies a test of $\eta(\lambda - 1) = 0$. Therefore, in the empirical model below we re-parameterize the model in (4) and estimate the model with $\delta = \eta(\lambda - 1)$ as a composite parameter, and test the reference-dependent model against the neo-classical alternative using a simple Wald test of the null hypothesis that $\delta = 0$.

The implications for behavior in each regime of equation (4) are straightforward. If a worker is in the fourth regime, that is, above both her income and hours targets ($d = 0$ and $e = 1$), then whether her response to a change in the wage is positive or negative is determined entirely by the sign of δ. If $\delta < 0$, or the importance of gain–loss utility is large relative to the degree of loss aversion, then hours worked will indeed fall if wages rise. Having achieved both of her objectives for the week, there is simply no need to work longer, and a higher wage will not induce her to supply more hours. This same outcome will occur in the first regime, when the worker is below both her hours and income targets. In this case, an increase in the wage causes the income-target to bind first, and she reduces the amount of labor supplied, even though the hours target has not been met. In the intermediate regimes, however, if the worker is below her income target and above the hours target, or above her income target and below her hours target, the model suggests a neo-classical supply response as gain–loss utility does not enter the decision, so it does not outweigh the positive utility associated with more income.

Prior to evaluating the empirical implications of the structural labor-supply model, however, it is necessary to establish whether these regimes are likely to be empirically important. That is, do we observe workers somewhat equally distributed among the regimes in (4) so that we can expect to observe some variation in behavior? Based on our sample of California farm workers in the NAWS, we find that 35.07% of all workers are in the first regime above, 18.22% are in the second, 10.95% in the third, and 33.42% in the fourth regime. Therefore, if workers do indeed respond to wage changes in different ways depending on their relative income and hours, compared to others, our sample should capture this behavior. In the next section, we provide more detail on the NAWS sample and then explore some empirical regularities it reveals.

Data and Summary Evidence

Our data are from the National Agricultural Workers Survey (NAWS). NAWS is a retrospective, cross-sectional survey in the sense that survey respondents report their most recent weekly-income and weekly-hours experience, in addition to their current labor-force status and a range of demographic and socioeconomic variables. Some questions require workers to report their experience over the past 52 weeks, such as the number of employers they have had, the total number of work weeks, and any non-farm employment they may have had.

We focus on a subsample of the broader NAWS data set that draws workers from California's farming industry over the 1989–2014 time period. As a retrospective cross-section, the NAWS data represents a variation on a panel data set as respondents report work history that may vary over time, albeit each time-series is limited to a relatively short period. We use the NAWS data to first draw some reduced-form evidence on the nature of labor supply among our sample of farm workers and then to estimate a structural model of agricultural labor supply and target formation. With this data, we are able to identify key elements of the reference-dependent model, test structural hypotheses that shed light on the elasticity of labor supply, and calculate the effect of changing implicit hourly wage rates on the agricultural labor market in California.

Workers in the California farming industry form a natural target sample as they are the most likely to have some measure of flexibility in determining their weekly hours of work. Moreover, piece rates vary widely both between crops for the same tasks and between tasks in the same crop. Because piece rates are highly variable, the implied hourly wage, and resulting supply of weekly hours, is also highly variable (table 1). Variability in our key outcome variables is not only necessary for econometric identification but suggests that the issue of heterogeneity in labor supply is more than a curiosity.

There are a number of other institutional features of the agricultural labor market that are important to our analysis. First, the share of workers in piece-rate jobs in our NAWS sample is 17% (3,552 / 20,875) over the entire sample period. In the most recent year of our data (2014), the proportion of piece-rate workers was 13.2% (141 / 1,064), so this suggests that the use of piece-rate contracts appears to be of continuing importance but is declining over time. Only 1.7% of workers in the data are on annual salary, and 3.3% are paid in some combination of wages, piece rate, bonus, and salary. In this analysis, we focus exclusively on workers paid by piece rate in order to remain consistent with the literature on this topic, so all of our findings are conditional on workers who are paid by piece rate, whether this is by choice or by assignment.

How a worker's time is allocated to crops and tasks is a matter of considerable heterogeneit, and depends on farm size, farm-labor contractor (FLC) status, and worker experience. With the increasing trend toward year-round employment of experienced workers, growers tend to "find jobs" for valuable workers, even sharing them with other growers (Strochlic and Hamerschlag 2005; CFBF 2019). But workers employed by large farms with critical harvest needs, and FLCs that respond to specific requests from growers, tend to focus on single tasks and crops.

There is also considerable heterogeneity in how workers and employers agree on the specific piece rate. Ideally, growers should set a rate that is consistent with a target level of labor cost per unit of production (between 30% and 60% of production costs for California commodities) rather than trying to estimate productivity by targeting an implicit hourly rate (Billikopf 2014).[9] In reality, our conversations with a large strawberry grower suggested that they tend to set rates consistent with their perceptions of the "market rate" that will both attract workers and increase productivity relative to an hourly rate, but costly mistakes are often made as there is no universal approach to piece-rate design (Billikopf 1996; Mar Vista Berries, personal communication, May 2019). In fact, growers tend to adjust the rate as the season progresses if they feel the rate is being set too high or too low, but they are averse to adjusting rates too often in response to transitory changes for fear of providing workers the wrong incentives. For example, if growers raise piece rates in response to a short crop, worker goodwill is dramatically reduced if they are subsequently reduced. Piece-rate payment schemes can involve either a flat rate per piece or a

[9] Further, Moretti and Perloff (2002) argue that "Piece rates and other incentive payments may be used to ensure productivity in lieu of efficiency wages or monitoring" (p. 1144). But, we are unable to formally test this hypothesis in our piece-rate-only sample.

Table 1. Summary of Wage and Income Data

	Hourly wage		Piece rate		Income		
	Mean	SD	Mean	SD	Mean	D	N
Crop 1	9.943	4.278	8.419	2.747	367.320	151.453	21
Crop 2	8.185	3.336	6.849	3.905	316.741	151.918	2,944
Crop 3	6.701	2.715	6.701	2.715	292.825	140.487	27
Crop 4	9.821	4.225	9.482	3.991	399.436	226.722	525
Crop 5	9.401	4.168	8.580	2.878	368.650	255.407	35
Task 1	7.481	3.119	7.338	2.924	299.314	146.665	157
Task 2	8.407	3.850	7.246	2.831	333.637	228.517	2,266
Task 3	8.675	3.532	7.095	4.319	333.640	168.666	202
Task 4	10.188	4.350	8.622	4.913	405.791	196.873	889
Task 5	8.161	3.389	7.496	3.091	343.549	197.797	6
Task 6	9.341	3.858	8.258	5.381	335.239	147.270	32

Note: N = 3,552. Data from NAWS (California, piece-rate workers). Data averaged over all years 1989–2014.

minimum hourly rate plus a bonus tied to piece-rate performance (Billikopf 2008). In our analysis, however, we impute an average hourly wage from reported weekly income and divide by the number of hours worked. We describe how we account for the resulting "division bias" in the next section.

We focus only on workers who receive piece-rate pay. When workers are paid by the box, if harvesting is their primary task, or by the tree if trimming, to name two examples, then their weekly income depends not only on the piece-rate wage but the number of hours they work and the rate at which they work. Importantly, workers receiving piece-rate pay are also more likely to be able to vary their weekly hours and stop work when an income or hourly target is achieved. In fact, we calculated the coefficient of variation of weekly hours for workers receiving piece-rate pay and hourly pay in the NAWS data set and found that the average weekly hours worked is 3% more variable for workers receiving piece-rate pay than for those on fixed hourly wages (see table 2). By the same measure, income is 13.3% more variable for piece-rate workers than for hourly workers. Conversations with a large apple grower in Washington state suggested that his attempt to increase harvesting productivity by adopting semi-dwarf trees was at least partially thwarted through exactly the mechanism we describe here: rather than harvesting more apples per day, workers simply harvested for fewer hours and went home (Stemilt Growers, personal communication, May 16, 2001).

How we define workers' targets is a critical assumption that underlies our analysis. In California, however, there are three institutional features that would make our targets much more plausible. First, many workers (28.8% over the whole sample of California workers, 47.4% in our subsample) work for FLCs, so they move from farm to farm working in the same crew-type environment.[10] In this case, it is very likely that workers interact and share information on both work schedules and incomes. Second, although it is small relative to the total number of farm workers in the state (likely due to the number of undocumented workers), the United Farm Workers of America (UFW, now affiliated with Change to Win Federation) actively supports farm laborers' rights in California, including providing information on wages and hours. Further, the average worker has 1.6 employers each year and so is quite likely to move, but the NAWS data does not reveal whether he or she stayed with the same crop and task. Third, the Employment Development Department (EDD) of the California government provides a Labor Market Information (LMI) site that links to the Quarterly Census of Employment and Wages (QCEW), which is a key source of wage and income data by geography and occupation. Although we are under no illusion that all farm workers are online, some surely are, so this information is easily accessible and shareable.[11]

[10] Workers employed by a FLC report the wages paid by and hours worked for the FLC. In our piece-rate sample, hours-worked per week is slightly less variable than for non-FLC workers (coefficient of variation is 24.9% for FLC workers versus 26.9% for non-FLC workers).

[11] We estimated kernel densities of the hours and income targets, and they show no evidence of external constraints from minimum wage laws, 40-hour work weeks, or overtime policies. These densities are available in the online appendix.

Table 2. Summary Evidence on Piece-Rate and Labor Supply

		Mean	SD	CV	N
Piece	Hours	38.9837	10.1523	0.2604	3,552
	Income	329.5927	168.8281	0.5122	3,552
Hourly	Hours	44.7794	11.3125	0.2526	17,323
	Income	326.9323	147.6888	0.4517	17,323

Note: N = 20,875 from NAWS California farm-worker sample.

Others document evidence that workers tend to look to peer networks for expectations regarding work performance and compensation. Mas and Moretti (2009) find that, in a sample of retail grocery checkout workers, replacing a below average productivity coworker with an above-average coworker increases productivity by 1.0%, and they interpret their finding as a manifestation of positive social externalities. Their findings are similar to Bandiera, Barankay, and Rasul (2010) who use the same data as their earlier paper (UK fruit harvesters) to show that workers assigned to harvest with members of their social network will either increase their productivity in the presence of a more-productive friend or reduce productivity when assigned with a less-productive one. In a more recent study most closely related to this one, Cornelissen, Dustmann, and Schönberg (2017) investigate whether there are more general *wage* spillovers among peers within the same firm, doing similar jobs, but using data across a large panel data set of firms in a local labor market. They find that there are and attribute their finding to knowledge spillovers or learning from others. Importantly, they find that this wage effect is most pronounced in lower skilled jobs such as those we consider here. Although these studies do not address targeting *per se*, and we cannot investigate these peer mechanisms in our data, they do show that workers clearly form expectations of their own income and performance, based on the observed experiences of others. In the next section, we show how these targets are implemented in our empirical model.

Empirical Test of Reference-Dependent Preferences

Our empirical model builds on the theoretical framework with reference-dependent preferences of Kőszegi and Rabin (2006, 2007, 2009) and Crawford and Meng (2011). In this section, we first describe how we identify supply elasticities using the NAWS data. Next, we present estimates from a set of reduced-form labor-supply equations analogous to those presented in Camerer et al. (1997), Stafford (2015), and others, in order to compare the implied labor-supply elasticities in a framework that is consistent with the existing literature. We then estimate a structural version of (4) that accounts for the nonlinearity of hours disutility and the relative weight of consumption and gain-loss utility.

Identification

In order to identify labor-supply elasticities in the NAWS data, we first need to correct for three clear confounding problems: division bias, wage endogeneity, and endogenous switching among regimes. In this subsection, we explain each of these issues and how we design our empirical approach in response.

Hourly wages are likely to suffer from division bias when an explanatory variable is created by dividing weekly income by the dependent variable: weekly hours (Farber 2015; Stafford 2015). Farber (2015) and Stafford (2015) use instrumental-variables procedures similar to ours to correct for division bias and demonstrate that the bias can be sufficiently large to cause qualitatively different conclusions regarding the labor-supply elasticity (i.e. negative elasticities become positive).

Hourly wages are also likely to be endogenous for reasons beyond the division-bias issue described above.[12] If weekly hours are indeed flexible, as our data shows to be the case, and hourly wages are only implicit in our measure of weekly income and hours worked, then there are likely to be unobservable factors in the labor-supply model that are correlated

[12] We formally test for wage-endogeneity using a Wu–Hausman test, with our maintained instrument. Using OLS as the efficient, and 2SLS as the consistent estimator, we find a chi-square statistic of 48.161, so we easily reject the null hypothesis of exogeneity.

with the implied hourly wage rate. Endogeneity such as this is also likely to remain when conditioned on a set of covariates that may help explain any observed variation in productivity. For example, suppose a worker is assigned to pick apples in trees that are highly productive but only half the height of regular apple trees. Holding the piece rate constant, this worker is likely to generate a relatively high weekly income and a correspondingly high hourly wage. Because we do not observe the height of the tree in our data, this high hourly wage is endogenous as the likelihood of working with shorter trees is correlated with the hourly wage and is likely important to labor supply. We address the issues of wage endogeneity and measurement error (division bias) using a control-function approach (Petrin and Train 2010).

Our instrument consists of all other workers' wages in the same year, crop, and occupation as the focal worker. Our instrument is likely to be valid, because, in a labor-supply context, the unobservables in each individual's labor-supply decision are likely to be unrelated to the wages paid to others in similar occupations, controlling for the inherent similarity of wages among people who do the same jobs or work in similar crops (where wages would be influenced by changes in market-prices for the crop in question). From first principles, if growers pay their workers their marginal value product, that is, the product of their marginal productivity and the output price, and we control for the former by averaging by crop and task, then the remaining source of variation is the output price, which is clearly exogenous to a worker's labor-supply decision. There will be some part of the output price that represents a common shock across workers in the same crop, but heterogeneity inherent in fruit and vegetable production in California means that most of the local variation in yields, contract prices, and growing conditions mean that the common shocks are likely swamped by more local concerns. Moreover, each worker represents only a very small part of the sample wage, so conditions specific to each worker's wage are unlikely to be related to those at other farms. In this regard, our instrument is very much like those used by Hausman, Leonard, and Zona (1994) in an empirical industrial organization setting.

Estimates from a first-stage instrumental variables regression, in which we regress the observed hourly wage on our measure of year–crop–task worker average wages, shows an F-statistic of 2, 555.5, so our instrument is not weak in the sense of Staiger and Stock (1997). From first principles, this instrument is likely to be valid because any individual workers' hourly wages are likely to be highly correlated with wages earned by others in the same industry-task pair due to the simple fact that wages are determined by the marginal product of the worker and the output price. For any given technology, the difference in marginal products among workers in the same industry or task are likely to be far smaller than the wage differences across industries and tasks. Further, defining the instrument on a year–task–industry (crop) basis is likely to capture intra-industry wage correlation driven by variation in output prices or the willingness of producers to compete against each other for the best workers.

The fact that our instrument is related to workers' income and hours targets represents a potential problem. The question here is whether the hours-and-income target effects are separately identifiable from the wage effect? In fact, our approach is a simple application of the endogenous peer-effect econometric approach of Bramoullé, Djebbari, and Fortin (2009). In our model, the hours chosen by peers exert an influence on own hours through an "endogenous peer effect," studied extensively since Manski (1993) questioned whether the "reflection problem" meant that peer effects were ever likely to be identified. Bramoullé, Djebbari, and Fortin (2009) investigate this question formally and prove that there are three conditions under which our endogenous peer effects (hours and income targets) are identified: (1) groups (crop and occupations) differ in size (Lee 2007), (2) the data reflect individual choices as influenced by group-wise mean effects, and (3) non-linearities in the peer-response function break the perfect collinearity between individual responses to peer-group measures (Brock and Durlauf 2001). Our data satisfy all three of these conditions, as our crop-occupation groups do indeed differ in size, our data capture individual responses to group-mean hours and income variables, and our hours and income thresholds create a similar non-linearity to the discrete choices of Brock and Durlauf (2001). Therefore, we are confident that our target effects are well-identified for reasons that follow from both our data and our model.[13]

[13] Note, however, that we do not know enough about the group-assignment process to control for any endogeneity that may be involved in group membership.

Even if the target effects are well-identified, membership in each regime is not randomly assigned. Although the targets are exogenous to each worker's behavior, how they adjust their behavior, and hence determine membership, is not. Therefore, the empirical model is a multinomial endogenous switching regression (Dahl 2002; Bourguignon, Fournier, and Gurgand 2007). Intuitively, this approach consists of two stages. In the first stage, workers are endogenously sorted into one of the four regimes, with the probability of assignment determined by a multinomial process, driven by attributes of the worker and his or her job. In the second stage, we estimate non-linear parametric forms of the model in (4), controlling for the probability of regime membership using the multinomial selection mechanism of Dahl (2002).[14] In the next section, we demonstrate the importance of using this method in estimating labor-supply elasticities.

Reduced-Form Evidence

In this section, we estimate a number of reduced-form models in order to compare our evidence for neo-classical or reference-dependent labor-supply behavior to similar models in the literature. We consider many variations on how workers may respond to wage changes, from a model that reflects purely neo-classical considerations to one that includes the full range of income- and hours-targeting behavioral possibilities described by Crawford and Meng (2011). Each successive model provides a better fit to the California NAWS data and ultimately provides a good description of behavior observed in the field. In general, the number of hours worked is a function of the wage paid and other attributes of the job itself, such as the task, yearly fixed effects, and of course, the wage and its relationship with income and hours targets. The most general form of this model is written as:

$$\begin{aligned}(5)\qquad \ln(h_i) = {} & \phi_1 \ln(w_i) + \phi_2 \ln\left(w_i{*}m^{-T}\right) \\ & + \phi_3 \ln\left(w_i{*}m^{+T}\right) + \phi_4 \ln\left(w_i{*}h^{-T}\right) \\ & + \phi_5 \ln\left(w_i{*}h^{+T}\right) + \phi_6 CF_i + \psi_t + \omega_j + \varepsilon_i,\end{aligned}$$

where h_i is the number of hours logged by worker i, w_i is the imputed hourly wage for worker i, m^{-T} and h^{-T} are indicators that define when the worker is below either her income or hours target, respectively, m^{+T} and h^{+T} are similar indicators for when the worker is above her income or hours targets, CF_i is the control function, ψ_t are yearly fixed-effects, ω_j are occupation fixed-effects, and ε_i is an i.i.d. error term. We estimate this function using ordinary least squares (OLS).

The first set of results are shown in table 3 below. In this table, model 1 contains only the wage and constant term, and no year or task fixed effects. The second model (model 2) includes both year and task effects but does not address measurement errors nor wage endogeneity. Model 3 isolates the effect of controlling for these sources of bias by dropping the fixed effects estimator but adds a control function (using the instrument described above). Finally, model 4 includes both a full set of fixed effects and the wage instrument.

Our findings are consistent with those reported in the daily labor-supply literature. In model 1, with no controls, we find that the labor supply elasticity is positive and significant, which reflects a somewhat naive set of assumptions regarding worker behavior. In the second model, we consider the fact that worker behavior likely varied over time, and by task. In controlling for this level of unobserved heterogeneity, we find a negative supply elasticity, somewhat akin to the results from the simplest model in Camerer et al. (1997). However, when we control for wage endogeneity, and likely errors in wage measurement, the labor-supply elasticity again turns positive, significant, and plausible in magnitude. We interpret this finding as suggesting that the negative bias caused by the "division effect" of Farber (2008) and Stafford (2015) is indeed important. Finally, after adding back the year and task effects, we still find a positive labor-supply elasticity, but slightly lower than prior results would suggest is reasonable.

None of the models in table 3, however, allow for either income or hours targeting. Crawford and Meng (2011) and Farber (2015) differ as to whether either of these targets are likely to be important. In table 4, therefore, we examine how wage response differs whether workers are above or below hours or income targets, following the same progression of covariates and controls as in table 3. In the simplest case (Model 1), we find a positive and significant base-wage effect, consistent with the neoclassical model, but a

[14] See the online appendix for details of this multinomial regime-selection procedure.

Table 3. Reduced-Form Evidence, No Targeting

	Model 1		Model 2		Model 3		Model 4	
	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
log(Wage)	0.0388*	0.0156	−0.0218	0.0184	0.1324*	0.0220	0.0779*	0.0335
Constant	Y		N		Y		N	
Year effects	N		Y		N		Y	
Task effects	N		Y		N		Y	
Instrument	N		N		Y		Y	
R^2	0.002		0.094		0.012		0.097	
LLF	−1,428.825		−1,255.921		−1,410.684		−1,249.515	

Notes: Model 1 includes only constant term; model 2 includes year and task effects, and worker attributes; model 3 is estimated with instrumental variable (control function) and no fixed effects, or attributes; model 4 is estimated with control function, fixed effects, and worker attributes. A single asterisk indicates significance at a 5% level. Dependent variable is the natural log of hours.

significant negative wage effect for workers who are below their income target, exactly as predicted by Kőszegi and Rabin (2006) and Crawford and Meng (2011). This pattern persists if we allow for the full range of controls (model 2). Model 2 is akin to the Farber (2015) approach as he considered income targets but not hours targets. In model 3, we extend the targeting logic to hours as well as income and find that the income-targeting effect goes away. Workers appear to reach their hours target first, as the negative hours targeting effect dominates the other targeting hypotheses for workers who are below target. If we add the full set of controls, and the instrument in model 4, we see that this effect continues, but targeting again exerts a negative effect for workers who are below both their hours and income targets, producing a net-negative supply–response elasticity. Again as in Crawford and Meng (2011), workers above target respond to wage changes as the neoclassical model suggests.

To summarize the reduced-form evidence to this point, we find strong evidence in support of the reference-dependent preference model and reject the neoclassical model in our data. Neither Crawford and Meng (2011), nor Farber (2015), however, control for the possibility that regime membership is not randomly assigned.

Table 5 shows our final reduced-form evidence in which we control for both wage endogeneity and endogenous regime selection. In this table, we assume workers select into each regime based on the hours they decide to work and income they earn. We control for this multinomial selection mechanism using the endogenous switching regression method described above (Dahl 2002). By estimating both the selection model and wage-response model, we are able to test hypotheses regarding both regime membership and behavior conditional on regime choice.[15]

Note that the base labor-supply elasticity estimates are uniformly larger in magnitude and are estimated more efficiently (lower standard errors) in each of the four cases. We interpret this as evidence of a relatively substantial, and negative, regime-selection bias. That said, the general pattern of response elasticities remains, that is, when workers are

[15] Estimates of the regime-selection model are available in the online appendix. Consistent with the exclusion restriction described above, we define regime membership as depending on worker attributes and labor supply on job attributes.

Table 4. Reduced Form, Targeting Model

	Model 1		Model 2		Model 3		Model 4	
	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
Log(Wage)	0.1636*	0.0571	0.0973	0.0592	0.1909*	0.0523	0.1441*	0.0537
Log(Wage*Below m^T)	−0.1331*	0.0537	−0.1424*	0.0521	−0.0513	0.0519	−0.1005*	0.0497
Log(Wage*Above m^T)	0.0459	0.0534	0.0375	0.0519	0.0415	0.0516	−0.0086	0.0495
Log(Wage*Below h^T)					−0.1165*	0.0171	−0.0778*	0.0181
Log(Wage*Above h^T)					0.0296	0.0170	0.0698*	0.0182
Constant	Y		N		Y		N	
Year effects	N		Y		N		Y	
Task effects	N		Y		N		Y	
Instrument	Y		Y		Y		Y	
R^2	0.208		0.291		0.337		0.418	
LLF	−1,017.67		−821.895		−703.296		−470.676	

Note: Model 1 allows for wage effect above and below income targets; model 2 is model 1 with year and task fixed effects, and worker attributes; model 3 allows for income and hours targets; and model 4 is model 3 with year and task fixed effects and worker attributes. All models estimated with control function method, with other-worker average wage as instrument. A single asterisk indicates significance at a 5% level. Dependent variable is the natural log of hours.

below both their hours and income targets, the supply curve tends to bend backward, although it has a more conventional positive slope above the income target. More intuitively, if a worker is below both her income and hours targets, then during any given work week an increase in the implicit hourly wage (income from piece rate/hours worked) is likely to mean that her income target will be reached before her hours target, and she will either go home early some day or simply work fewer days.[16]

Importantly, however, the findings of this model differ from those in table 4 in the behavior around the hours target. Although the non-selected results in table 4 suggest that workers above their hours target will increase the number of hours supplied in response to higher wages, this model suggests that supply elasticities are negative when workers are both above and below their hours targets. Moreover, both of these effects are strongly significant. In other words, workers will only supply more labor in response to higher wages when they perceive a possible “windfall” in the sense that they are making more than others in their job. But, they tend to set specific hours targets, whereby any deviation in wages is likely to induce less work. These findings are, again, consistent with the reference-dependent model of Crawford and Meng (2011) as applied to the daily-labor supply of NYC taxi drivers.

Structural Evidence

In this section, we present estimates of the structural model in equation (4) that account for the endogeneity of both wages and regime membership. That is, we use a structural approach to estimate regime-specific wage elasticities of labor supply, controlling for the fact that workers endogenously select into each regime. Although Crawford and Meng (2011) and Farber (2015) also estimate structural version of their daily-labor supply models, they both estimate discrete-choice, optimal-stopping models using data instances

[16] We estimated a version of this model with non-piece-rate data as well as a falsification test for this model. Although some of the point estimates are the same sign, few are statistically significant, and the model has approximately half the explanatory power of the model reported in table 5. We interpret this as evidence in support of our maintained model. We also estimated the model using only undocumented workers and found a slightly lower supply elasticity but very similar qualitative results. Both tables are available in the online appendix.

in which drivers stopped working before their shift was up. Because we do not have intra-day data of this type, we estimate the optimal labor-supply equations implied by the theoretical model of reference-dependent preferences and derive elasticities from our estimates.

Estimates of the structural model are in table 6 below. First, note that there appears to be very little bias in the structural parameter estimates in failing to account for wage endogeneity, as the estimates from model 1 are very similar to those in models 2 and 3. Second, our estimates of θ, the disutility of hours, are not statistically significant (at a conventional, 5%, level). This finding could either be due to the fact that we have less variation in hours than in the canonical taxi-driver case or a small number of observations in each regime. Regardless, the fact that the point estimates are consistent from one model to the next and are similar to analogous estimates from Crawford and Meng (2011) suggest that they should remain in the utility model.

Next, we find that $\eta(\lambda - 1)$ is consistently below zero. Given that η is the relative importance of gain–loss utility, and λ the loss in utility from not making a target, this finding suggests that the component of utility attributed to gain–loss is important relative to the marginal loss that may result from missing a target. Because the combination of these parameters is a critical determinant of the elasticity of labor supply, we expect to find that gain–loss utility drives wage response in regimes 1 and 4 in equation (4).

Recall that gain–loss utility arises in the regimes in which the worker is below her income and hours goals (regime 1) and above income and hours goals (regime 4). In the other two regimes, we expect neo-classical wage responses. Because our structural parameters provide no information on workers' wage responses, we derive the implied elasticities and present them in table 6. As expected, the elasticity of labor supply is negative in regime 1 ($-$ 0.36) and in regime 4 ($-$ 0.24), although it is positive in regimes 2 and 3. These findings are consistent with the negative wage-hours correlation documented in Crawford and Meng (2011) and with our own, reduced-form, elasticities shown in table 5. Importantly, these elasticity estimates suggest that for workers in the gain–loss utility domain, wage changes may induce negative labor-supply responses. Higher piece-rate wages for these workers may, in fact, have the opposite effect to what is expected and exacerbate any labor-shortage issues.

It is important to remember, however, that these worker-level responses are only on the intensive margin and do not refer to changes in aggregate labor supply. Higher piece rates, if communicated generally, may indeed have the expected effect of bringing more workers into the market and helping alleviate any shortage of farm labor. Further, although reference-dependent preferences appear to explain the existence of backward-bending supply curves for some workers, we are under no illusion that institutional factors, such as fixed work weeks, changes in the weather, agronomic conditions, or daylight hours, are not also important in determining workers' total hours of work on a weekly basis.

Simulation and Implications

In this section, we use the structural model estimates from the previous section to conduct a series of counter-factual simulations that demonstrate the practical importance of our findings. Recall that the primary objective of this paper is to determine how the aggregate supply of labor can be expected to change on the intensive margin through changes in the piece rate or by influencing the amount existing workers supply. We begin from observed wage levels and examine how labor supply changes on the intensive margin whether a worker is above or below his or her hypothetical income or hours targets. With these simulations, we show how the aggregate quantity of labor supplied can actually fall in response to an increase in wages.

For this exercise, we assume baseline parameters for the structural model as shown in table 6 above. We do not simply use the estimated elasticities for this exercise, because they are point estimates from the structural model. Further, because our data includes observations from 1989–2014, we seek to make our findings as relevant as possible to the current labor market by calibrating our simulation to the most current, 2013–14 data.[17] That is, we assume the most current wage conditions to simulate expected changes in labor supply. For workers in each regime, we examine changes in labor supply for wages that are

[17] A reviewer pointed out that the NAWS is designed to be representative over two-year cycles, the most current of which is 2013–14.

Table 5. Reduced Form, Targeting Model, w Non-Parametric Selection Correction

	Model 1		Model 2		Model 3		Model 4	
	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
Log(Wage)	0.4789*	0.1053	0.4943*	0.1061	0.5572*	0.0814	0.6097*	0.0819
Log(Wage*Below m^T)	−0.6952*	0.0992	−0.6552*	0.0998	−0.2097*	0.0817	−0.2047*	0.0814
Log(Wage*Above m^T)	0.0918	0.0992	0.1315	0.0998	0.3131*	0.0817	0.3170*	0.0814
Log(Wage*Below h^T)					−0.5889*	0.0291	−0.5845*	0.0301
Log(Wage*Above h^T)					−0.1419*	0.0290	−0.1362*	0.0300
Constant	Y		N		Y		N	
Year effects	N		Y		N		Y	
Task effects	N		Y		N		Y	
Instrument	Y		Y		Y		Y	
R^2	0.571		0.575		0.744		0.748	
LLF	−3,475.481		−3,452.032		2,559.024		−2,525.082	

Note: Model 1 allows for wage effect above and below income targets; model 2 is model 1 with year and task fixed effects; model 3 allows for income and hours targets; and model 4 is model 3 with year and task fixed effects. All models estimated with control function method, with other-worker average wage as instrument. Non-parametric regime correction through Dahl (2002) method. A single asterisk indicates significance at 5%. Dependent variable is the natural log of hours worked per week.

10% and 25% above their baseline values. In order for our simulation to represent a clean experiment, we hold all other variables constant at their baseline (2013–14) values and focus only on the response to changes in the prevailing wage.

Our simulation results are shown in table 7 below. As expected, an increase in the wage by 10% leads to a slight reduction in the number of hours worked in regimes 1 and 4, whereas workers in regimes 2 and 3 increase the amount of labor supplied. Raising the wage by 25% produces a more dramatic reduction in the number of hours worked in regimes 1 and 4, and a stronger neo-classical (positive) effect on hours worked in regimes 2 and 3. When gain–loss utility is important, as in regimes 1 and 4, workers who are either below their income goals or above their hour goals are in the domain of losses, so the negative marginal utility of extra hours exceeds the positive marginal utility of more income, and they cut back the number of hours worked. In regimes 2 and 3, the opposite occurs. Namely, because gain–loss utility is not important, higher wages uniformly produce a positive response in the number of hours worked. The net effect, accounting for the proportion of workers in each regime, is a loss of 0.41 hours worked per week with a 10% increase, and 0.62 hours worked with a 25% increase. Relative to the total number of hours worked reported in this table, these net changes are small, yet show the potential for counter-productive wage changes to reduce net labor supply.[18]

These results show that the backward-bending labor supply curve of Camerer et al. (1997), Crawford and Meng (2011), and others is not simply an artifact of the taxi industry nor of work environments in which workers are free to, essentially, be their own bosses. In more general working environments, such as the agricultural context here, workers also reduce their hours worked in response to higher wages. From a practical perspective, if a farm manager is considering a higher piece wage in order to induce more work from her employees, or is considering technological changes that may increase the effective hourly wage (planting shorter trees, for instance) workers may instead work only until a certain

[18] Our findings in this table may, in fact, understate the change in hours worked and the net change across regimes because we do not account for the fact that wage changes may produce changes in regime membership.

Table 6. Structural Models of Labor Supply, and Targeting Behavior

	Model 1		Model 2		Model 3	
	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
$\eta(\lambda - 1)$	−0.7201*	0.0636	−0.7500*	0.0692	−0.7210*	0.0684
θ	0.0101	0.0093	0.0119	0.0252	0.0333	0.0885
ρ	0.2155*	0.0343	0.2285*	0.0440	0.2493*	0.0460
Constant	Y		Y		Y	
Task effects	N		N		Y	
Instrument	N		Y		Y	
LLF	−3,837.55		−3,761.41		−3,752.56	
Chi-square	8,092.30		8,244.57		8,262.27	
Implied elasticities from preferred model:						
Regime 1					−0.3597	0.0111
Regime 2					0.2135	0.0012
Regime 3					0.3096	0.0044
Regime 4					−0.2379	0.0012

Notes: Estimated using non-linear least squares with control-function and regime-selection correction model of Dahl (2002). A single asterisk indicates significance at 5%. Recall worker in Regime 1 is below income and hours targets, worker in regime 2 is below income target, but above hours target, worker in regime 3 is above income target, but below hours target, and worker in regime 4 is above both income and hours targets. Gain–loss utility is expected in regimes 1 and 4.

income threshold is reached and then leave for the day. Of course, the goal of the wage hike was thwarted.

Conclusion

In this paper, we test for evidence of reference-dependent preferences (Kőszegi and Rabin 2006) manifest in labor-supply decisions made by agricultural workers earning piece-rate wages. Reference-dependent preferences, in a labor-supply context, mean that workers tend to income or hours target and are likely to reduce the amount of work they supply if either of these targets is met. Widely studied in other contexts, workers earning the equivalent of piece-rate wages exhibit negative labor-supply elasticities over relevant wage ranges. If this is true of agricultural workers, then any attempt to increase the supply of labor on the intensive, employed-worker margin may be unsuccessful.

Using a sample of California farm workers (NAWS, from 1989–2014), we estimate several reduced-form models that provide strong evidence in support of the reference-dependent preference hypothesis. Workers in our sample appear to target not only particular levels of income in deciding how much labor to supply each week but the number of hours as well. Workers experience a loss in utility if they find themselves below their peer-based target level of income or above their target level of hours, as both outcomes are undesirable relative to if these targets had been at least met. In each case, workers who deviate from their target hours and income have negative wage elasticities. That is, workers tend to respond to higher hourly wages by reducing the number of hours worked, potentially thwarting any attempt to increase the supply of labor on the intensive margin by increasing wages.[19] We confirm these results through estimates of a structural model of labor supply based on a general model of reference-dependent preferences (Kőszegi and Rabin 2006; Crawford and Meng 2011).

Our findings are consistent with others in the literature who have found broad support for income targeting among workers who are able to vary the amount of labor they supply on a daily basis, but we are the first to report evidence of similar behavior in a more general labor context. Piece rates are an important means of incentivizing productivity in a broad range of industries, so if income and hours targeting is indeed descriptive of behavior in these contexts, we may need to change how we think about how workers respond to attempts to increase the amount of labor supplied. Our findings are particularly important in the specific case of agriculture, because

[19] A reviewer notes that higher wages could have some offsetting effect on the extensive margin, attracting new workers to the labor force. Others, however, argue that this effect is likely to be small given the inherent difficulty and discomfort associated with farm labor (Mercier 2014).

Table 7. Simulation Results: Wage Increase

	Weekly hours							
	Regime 1		Regime 2		Regime 3		Regime 4	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Baseline	31.1446	7.6334	57.1232	13.4102	30.8734	5.4649	48.3594	4.8983
Wage +10%	29.9885	7.3607	58.6444	13.7993	31.7537	5.6093	47.2346	4.7128
Wage +25%	28.2544	6.9543	60.9263	14.3889	33.0741	5.8275	45.5475	4.4363

Note: Regimes 1 and 3 worker is below hours target, and regimes 2 and 4 woker is above hours target. Regimes 1 and 2 worker is below income target, and regimes 3 and 4 worker is above income target. For the simulation, there are 35.07% of workers in regime 1, 18.22% in regime 2, 10.95% in Regime 3, and 33.42% in regime 4. Percentages do not add up to 100% because some observations are at the relevant target.

labor shortages caused by the inherent undesirability of the work and stricter enforcement of immigration laws remain one of the most important issues facing agricultural producers.

Our research is not without weaknesses. First, the NAWS data are not ideal for studying how individual workers set, and respond to, income and hours that deviate from target levels. With a deeper data set, we would have more flexibility in how we define both types of targets. Second, our sample of workers in NAWS is small relative to the total population of farm workers. We conducted the analysis at a national level, and our conclusions remain the same, but sparse sampling remains an inherent weakness of the NAWS data. Third, our data describe the behavior of different workers over a relatively long period of time, and we estimate only representative-worker parameters, conditional on their having selected into a piece-rate regime. With true panel data, we would be in a better position to control for response heterogeneity over individuals. Fourth, the theory of reference-dependent preferences generates a parameter-rich econometric problem that is not easily addressed even in the highest quality data sets. In our structural model, two key parameters are not independently identified, so it is impossible to pinpoint exactly whether the behavior we observe derives from the importance of gain–loss utility or workers' response to utility loss itself. Future research should consider these issues, both on theoretical and empirical levels.

Future research in this area may also consider optimal grower response to the behavioral patterns we reveal here. It would be of considerable practical interest to examine how producers may want to respond to income-targeting workers, perhaps by offering non-linear compensation schedules that offer a base rate and bonus compensation beyond a certain level of production. We leave this question for others to answer in more detail.[20]

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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[20] We thank an anonymous reviewer for pointing out this avenue for future research.

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