Does Minimum Wage Increase Labor Productivity? Evidence from Piece Rate Workers

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I examine worker effort as a potential margin of adjustment to a minimum wage hike using unique data on piece rate workers who perform a homogenous task and whose individual output is rigorously recorded. By employing a difference-in-differences strategy that exploits the increase in Florida's minimum wage from \$6.79 to \$7.21 on January 1, 2009, and worker location on the pre-2009 productivity distribution, I provide evidence consistent with incumbent workers' positive effort responses.

I. Introduction

Worker effort as a potential margin of adjustment to a minimum wage was raised in early studies, such as Obenauer and von der Nienburg (1915)

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and Stigler (1946). Yet rigorous empirical investigation of this issue has been lacking in the literature, despite the significant progress made in recent decades on the minimum wage's (dis)employment effect.[1]

In this paper, I employ a direct and high-frequency measure of individual worker productivity on a homogenous task to examine possible worker effort responses to a minimum wage increase. In particular, I use personnel records from a large tomato farm in Florida—where piece rate workers hand harvest tomatoes in the field—together with the change in the state minimum wage from \$6.79 to \$7.21 on January 1, 2009. In piece rate settings, the employer must make up any shortfall between a worker's raw productivity (output in dollars per hour) and the minimum wage for all work hours during a given pay period (in this context, 1 week).[2] Hence, a firm's compliance costs increase with the minimum wage, which may (at least in part) be offset by the increased effort of low-productivity workers.

This is a unique setting conducive to examining worker effort responses to a minimum wage increase for several reasons. First, because the pay scheme is piece rate based, the productivity of individual workers is rigorously recorded.[3] Not only do the workers clock in and out for each work spell, but an electronic system keeps track of their output in the field. Second, the minimum wage increase of January 1, 2009, occurs within a given harvesting season (autumn 2008 season), which allows me to compare the same worker's productivity before and after the hike. Third, the nature of the task and workforce allows me to rule out other potential determinants of worker productivity. In particular, hand harvesting of fresh tomatoes is a low-skilled, labor-intensive process, and there is little scope for technological adjustments (e.g., shift toward capital) or innovation, at least in the short run (i.e., within season).[4] In addition, because of the seasonal nature of the harvesting task and high workforce turnover, firm investment in worker training is virtually nonexistent and largely irrelevant in this sector.

[1] See Card and Krueger (1995), Brown (1999), and Neumark, Salas, and Wascher (2014) for reviews, and see Cengiz et al. (2019) and Harasztosi and Lindner (2019) for more recent evidence.

[2] Workers whose raw productivity (output in dollars per hour) is above the minimum wage get paid according to their actual output.

[3] One salient feature of this work environment is that the output of individual workers is readily observable, which is conducive to the adoption of a piece rate pay scheme (Lazear 1986).

[4] In the United States, the markets for fresh and processed tomatoes are entirely separate. Not only are different varieties of tomatoes grown to serve each market, but they are harvested differently. In particular, processed tomatoes (which are common in California) are machine harvested, whereas fresh tomatoes are hand harvested. The Florida farm studied here serves the market for fresh tomatoes only, and the incidence of hand harvesting is 100%.

To isolate the effects of worker effort from external determinants of labor productivity (e.g., field life cycle or weather), I employ a difference-in-differences (DID) strategy. Similar to Mas and Moretti (2009), I first capture each worker's "baseline" or "permanent" productivity by estimating his fixed effects using data from outside my main estimation window. I then look for possibly differential productivity changes of individual workers around January 1, 2009, by their baseline productivity. Using high-productivity workers (who are always above the minimum wage in either the old or the new regime) to difference out the effects of farm-level common shocks, I isolate the minimum wage–induced effort responses based on a disproportionate productivity increase in the lower part of the fixed effects distribution when the minimum wage increases. This is analogous to the approach in Cengiz et al. (2019) and Dustmann et al. (2022), for instance, where workers in the upper part of the wage distribution are viewed as a control when evaluating the effect of a higher minimum wage on low-wage workers.

I find evidence consistent with incumbent workers' positive effort responses. As the minimum wage increases by 6% ($6.79 to $7.21) on January 1, 2009, worker productivity (i.e., output per hour) in the bottom 40th percentile of the worker fixed effects distribution increases by about 4.6% relative to that in the higher percentiles. Examining the employment outcomes of individual workers over time, I find that while low-productivity workers have 6%–10% lower chances of being employed on any given day than high-productivity workers, this existing difference is not further amplified when the minimum wage increases. This lack of significant employment effects attributable to the minimum wage hike may have several explanations. In a competitive framework, the positive effort responses of sub-minimum-wage workers should obviate the need for reducing employment opportunities assigned to these workers. Moving beyond competition, it is also possible that workers simply reacted to a perceived threat, even in the absence of any actual pressure coming from the employer, and/or are driven by other motives, such as gift exchange (Akerlof 1982). Overall, my back-of-the-envelope calculation shows that the increased productivity among the low-fixed-effect workers can offset about half of the projected rise in the firm's wage bill, suggesting a roughly equal sharing of the minimum wage cost between the employer and the workers.

By taking advantage of rare data on piece rate workers whose physical output (pieces per hour) is rigorously recorded around a minimum wage hike where the piece rate itself remains the same throughout, I am able to test for workers' effort responses as a plausible channel of adjustment to a minimum wage hike. Such responses are extremely difficult to detect in observational data, since in most settings data that repeatedly measure the same worker's productivity in the same task around a minimum wage hike are lacking. Although it is difficult to know the exact extent to which the effort responses shown here will apply to other low-wage settings, the hypothesized effort responses do not rest on the pay scheme being piece rate based. For instance, a recent study by Coviello, Desseranno, and Persico (2019) illustrates a minimum wage–related productivity increase among salespeople of a retail chain, where the compensation scheme at use is base pay plus a performance-based commission. Moreover, even in settings where workers are paid a fixed hourly wage, it is known that the employer and coworkers can to a varying extent assess/observe the productivity of different employees.[5] It is the ability to tell apart low- versus high-productivity workers, not the pay scheme per se, that dictates the relevance of the effort margin as a possible response to minimum wage changes. An added advantage of my study is that it provides rare insights into the labor market behavior and outcomes of US farm laborers, a relevant yet understudied group when it comes to analyses of the impact of minimum wages. In particular and as shown in table A1, the wages of farmworkers are not dissimilar to those of workers at fast food restaurants (see, e.g., Card and Krueger 1994) or care homes (see, e.g., Machin, Manning, and Rahman 2003), the subgroups often studied in leading papers in the minimum wage literature.

By providing clean evidence on the minimum wage effect on worker effort, I add to the recent and growing literature that explores alternative channels (other than employment) through which firms may absorb the rising labor cost associated with the minimum wage (for a review, see Clemens 2021). These channels include increased worker retention and reduced turnover (Portugal and Cardoso 2006; Dube, Lester, and Reich 2016; Gittings and Schmutte 2016), labor-labor substitution (Giuliano 2013), changes in hiring standards (Clemens, Kahn, and Meer 2021), an increase in prices (Aaronson 2001; Aaronson, French, and MacDonald 2008; Leung 2021; Harasztosi and Lindner 2019), and a decrease in profits (Draca, Machin, and Van Reenen 2011; Bell and Machin 2018). In particular, I speak directly to effort-driven labor productivity by employing reliable data on the physical output (pieces per hour) of harvesting employees around an increase in the statutory minimum wage.[6]

This paper also relates to the personnel economics literature that explores how incumbent workers' productivity may be related to labor market

[5] Observable characteristics (such as experience, for instance) may serve as a proxy for productivity. In Jardim et al.'s (2018) evaluation of Seattle's minimum wage, they find that all of the earnings increases from a higher minimum wage accrue to the more experienced half of the low-wage workforce, whereas the less experienced half saw no significant change in earnings due to decreases in their hours worked offsetting their wage gains.

[6] This is in contrast to approaches that are based on firm-level, revenue-based productivity, such as total factor productivity (TFP). For instance, Mayneris, Poncet, and Zhang (2018) document in the context of China that a minimum wage leads to the exit of low-productivity firms and increases firm-level TFP conditional on survival.

conditions. In an earlier work, Rebitzer (1987) showed that the level of unemployment raises productivity growth using US data at two-digit manufacturing industries for 1960–80. In addition, a recent work of Lazear, Shaw, and Stanton (2016) shows that incumbent workers may work harder during recession and when the unemployment rates are higher. While similar in the usage of personnel records from a US firm, Lazear, Shaw, and Stanton's (2016) study of recession effects focuses on the increased cost in case of discharge for workers with a relatively long employment contract, whereas my analysis of minimum wage effects concentrates on the increased risk of not being picked up for daily employment for workers operating in a casual labor market, where daily employment is decided on an ad hoc basis in the absence of any longer-term contract.

II. Background and Data

A. Minimum Wage for Piece Rate Workers

For a given pay period (here, one calendar week), consider a worker i with a transaction profile of (h_i, Y_i), where h_i denotes the total field hours spent and Y_i the total output (in pieces) produced. Applying the constant piece rate (dollars per piece) p, the total output can be expressed as pY_i in dollars. This worker's average productivity is then $pY_i/h_i \equiv py_i$ (dollars per hour). Since the piece rate p remains constant throughout, there is a one-to-one correspondence between a worker's physical productivity y_i (pieces per hour) and his productivity expressed in dollars py_i.

For all hours employed during the pay period, workers whose average raw productivity is above (below) the minimum wage are paid according to actual output (minimum wage).[7] Hence, worker i's hourly wage is

$$Hourly\ wage_i = \begin{cases} py_i & \text{if } py_i \geq \text{MW}, \\ \text{MW} & \text{if } py_i < \text{MW}, \end{cases}$$

where MW denotes the minimum wage. Worker i's total weekly earnings are

$$Earnings_i = \begin{cases} pY_i & \text{if } py_i \geq \text{MW}, \\ h_i\text{MW} & \text{if } py_i < \text{MW}, \end{cases}$$

so the firm's total wage bill is

$$\sum_j pY_j + \sum_{py_{j'} < \text{MW}} h_{j'}\left(\text{MW} - py_{j'}\right),$$

[7] This is similar to the piece rate scheme with a guarantee modeled in Lazear (2000). The difference is that in Lazear (2000) the guarantee is chosen by the firm, whereas here the minimum wage is imposed by the government.

Minimum Wage:								**Pre (6.79) ←**	**→ Post (7.21)**			
Week:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
	estimate worker FE								**Jan 1**			

FIG. 1.—Timeline of the 2009 minimum wage hike. The harvesting season being investigated spans 12 weeks from November 2008 to January 2009, during which Florida's state minimum wage rose from \$6.79 to \$7.21 on January 1, 2009, a date that falls in week 9 of the analytic window. The preperiod is defined as weeks 1–8, and the postperiod is defined as weeks 9–12. The estimation of worker fixed effects (FE) is based on transactions during the initial 5 weeks, and that of worker effort responses is based on those during weeks 6–12.

where the first and second parts represent (i) the unadjusted wage bill for all workers and (ii) the compliance cost for the minimum wage expended on sub-minimum-wage workers, respectively.

When worker productivity is held constant, firm's compliance costs increase with the minimum wage for two reasons: first, a higher minimum wage makes the minimum wage bite for more workers than previously; and second, it increases the gap between the (new) minimum wage and the raw productivity of sub-minimum-wage workers. A minimum wage increase thus creates an incentive for firms to reduce (at either the extensive or the intensive margin) the employment hours assigned to low-productivity workers. On the other hand, low-productivity workers can preempt the firm's action by increasing their efforts and productivity, thereby (at least partially) relieving the firm of the expanding compliance cost.[8] Whether either or both effects exist is examined empirically below.

B. Setting and Data

The setting of my analysis is a large tomato farm in Florida, where piece rate workers hand harvest fresh tomatoes in the field. My main data come from the personnel records of the farm covering the 12-week autumn harvesting season from November 2008 to January 2009. Because this firm uses one calendar week pay periods, the timeline in figure 1 shows the harvesting periods by week. During the ninth week of this season—specifically, on January 1, 2009—the state minimum wage rose from \$6.79 to \$7.21, an increase of 42 cents, or 6% of the baseline minimum wage.

The minimum wage increase comes from Article X, Section 24, of the Florida Constitution. Enacted in 2004 and first implemented in 2005,

[8] Note that increased productivity of workers who are above the minimum wage makes little difference for the firm's labor cost since compensation is purely piece rate based, which means that the total wage bill is determined by the total output (pieces) harvested and the piece rate only, not by the speed or productivity (output per hour) of (above-minimum-wage) workers.

Florida's minimum wage is indexed to inflation. In particular, on September 30 of each year, an adjusted minimum wage rate is computed on the basis of the current minimum wage and the inflation rate (based on the consumer price index for urban wage earners and clerical workers [CPI-W]) during the 12 months prior to each September 1, which is then published and takes effect on the following January 1.[9] As table A2 shows, the minimum wage hike on January 1, 2009, is relatively large in absolute magnitude. This has to do with the high inflation rate that prevailed during the 12 months prior to September 1, 2008, as shown in figure A1.

Although the farm operates several different fields and grows different tomato varieties, because of a confidentiality agreement with the firm, this analysis is constrained to the harvesting of two main varieties, round and grape tomatoes, which represent more than 70% of total man hours. All field-workers are paid by piece rate based on individual output, meaning that there is no team element in production or compensation, and may be asked to pick either tomato variety depending on the day's harvesting requirements.

During the season, workers stay in a living quarter located near the farm in rural Florida. The available worker pool may change as new workers arrive and existing workers exit during the season (see sec. IV.C for further details). There is no long-term contract, and employment is decided on a day-to-day basis. Specifically, the harvesting manager decides on the basis of field capacity (i.e., how many mature crops are there to be harvested on that day, which is predetermined by the acreage planted and the field life cycle) and weather conditions whether they will harvest or not for a given day and how many workers will be needed (based on some heuristic he has figured out through many years of experience). As shown in figure A2, the number of workers employed each day is closely related to field capacity, with an R^2 of 0.7695.[10] Once the day's harvesting plan is known, an appropriate number of workers are recruited from the available worker pool. It is

[9] Specifically, part (c) of Article X, Section 24, of the Florida Constitution reads as follows: "MINIMUM WAGE. Employers shall pay Employees Wages no less than the Minimum Wage for all hours worked in Florida. Six months after enactment, the Minimum Wage shall be established at an hourly rate of $6.15. On September 30th of that year and on each following September 30th, the state Agency for Workforce Innovation shall calculate an adjusted Minimum Wage rate by increasing the current Minimum Wage rate by the rate of inflation during the 12 months prior to each September 1st using the CPI-W or a successor index as calculated by the United States Department of Labor. Each adjusted Minimum Wage rate calculated shall be published and take effect on the following January 1st. For tipped Employees meeting eligibility requirements for the tip credit under the Fair Labor Standards Act (FLSA), Employers may credit toward satisfaction of the Minimum Wage tips up to the amount of the allowable FLSA tip credit in 2003."

[10] Since it is not possible to measure the (predetermined) field capacity, I use the actual output as a proxy.

not known exactly how this is achieved in practice, but in the data it can clearly be seen that it is not the same number of workers or the same set of workers being employed each day. In section IV.C I investigate whether workers' employment outcomes are in any way related to their productivity.

The harvesting workers, if working that day, arrive in the field by buses organized by crew leaders, and once the day's harvesting is finished, they leave by the same buses. To track each worker's output and work hours electronically, an ID card with a magnetic chip is attached to each worker's bucket and scanned at the beginning and end of each work spell. Although a workday may comprise multiple work periods, there is typically a morning and afternoon work spell, with a lunch break separating the two. During a work period, workers spread around the field to pick tomatoes from different rows of thick, tall bushes and then carry their filled buckets to a truck parked in the middle of the field. Several "dumpers" standing on the back of the truck empty the full buckets into a large collection bin and scan the worker's ID card with a scanning device to add the output unit to the system. This procedure is repeated throughout the day until the day's designated fields are completely picked.

Output is measured in 32-pound buckets, for which the piece rate for round (grape) tomatoes is a constant \$0.50 (\$3.75) throughout. Therefore, for ease of comparison, workers' physical output is always converted to dollars (pieces times piece rate for the relevant variety), and productivity (output per hour) is expressed in dollars per hour. For each variety separately, I remove the transactions that fall in the bottom and top 1% of the productivity distribution to ensure that the results are not driven by outliers. Furthermore, I focus on workers with at least five spells (transactions) during weeks 1–5 (so that I can obtain reliable estimates of their fixed effects).[11] This results in 31,762 transactions for 974 unique workers. The average output per hour (dollars per hour) in the sample is \$9.54, with a standard deviation of \$3.62. In table A3 I report the mean daily employment (1 if working and 0 otherwise), daily hours worked (if working that day), and productivity (output per hour) by quintiles of worker fixed effects (see sec. III) and by time period (weeks 1–5, 6–8, and 9–12).

To address the relevant question of how substantive this new \$7.21 minimum wage is, the incidence and extent of the old and the new minimum wages are tabulated in table 1. As the minimum wage rises from \$6.79 to \$7.21, the share of worker-weekly paychecks for which the minimum wage binds rises from 12% to 16%. Moreover, the share of workers for whom the minimum wage will ever bite increases from 42% to 52%. At the same time, the share of farm-level employment hours assigned to worker-weeks below

[11] My main results are robust to alternative choices of minimum spell numbers in the vicinity.

Table 1
Incidence and Extent of the New Minimum Wage

	Minimum Wage	
	$6.79	$7.21
Minimum wage bites for the following share of:		
Worker-weekly paychecks	.118	.158
Workforce (for whom minimum wage ever bites)	.422	.521
Employment hours	.096	.135
Minimum wage compliance cost ($)	8,340	13,217

NOTE.—Both columns are based on 5,400 worker-weekly observations (974 unique workers) for weeks 1–8. The first column applies the low minimum wage of $6.79 (the current minimum wage in weeks 1–8), and the second column applies the high minimum wage of $7.21 (the new minimum wage to take effect in weeks 9–12).

the minimum wage rises from 10% to 14%, and the minimum wage compliance cost increases from $8,340 to $13,217 (an increase of about 58%).

C. Compliance

The minimum wage is part of the Fair Labor Standards Act (FLSA), which also sets overtime, record keeping, and child labor standards. Contrary to popular misconceptions, all agricultural workers on any but small farms, while exempt from the law's overtime pay provision, are covered by its minimum wage requirement.[12] Since the state of Florida has its own minimum wage, whichever one is higher binds between the federal and state minimum wages (see table A2).

As with any empirical research on the minimum wage, one important concern here is noncompliance.[13] The most common violation of minimum wage regulations is manipulating the manual records of workers' compensable hours. The record-keeping standards at the farm studied here, however, makes ex post manipulation of employment hours highly implausible. Workers are clocked in and out in the field by magnetic chips. Nevertheless, I perform several tests to eliminate this possibility, including an inspection of workers' actual pay stubs to verify that sub-minimum-wage workers were indeed paid the minimum wage. To illustrate, the worker whose weekly pay stub is shown in figure A3 worked a total of 15.28 hours over 2 days during the reference week in 2008. Based on his output, his raw (unadjusted) earnings were $87.75 dollars ($29.00 + $7.50 + $11.25 + $40.00), which translates into an hourly productivity (dollars per hour) of $5.74. Because the

[12] An agricultural employer who does not use more than 500 man-days (days on which a worker provides at least one hour of agricultural work) in any calendar quarter of the preceding calendar year is exempt from the FLSA minimum wage provision for the current calendar year. The farm studied here hires 300–600 workers per day and thus is not exempt from the provision.

[13] See Ashenfelter and Smith (1979) and Clemens and Strain (2020) for discussion of employer noncompliance with the minimum wage.

relevant minimum wage for this period was \$6.79, the worker was paid \$6.79 and not \$5.74 for all 15.28 hours worked, resulting in a total earnings of \$103.75 (\$6.79 times 15.28). The firm's compliance costs were thus \$16 (\$103.75 minus \$87.75), which appears as a line item labeled "minimum wage."

I also check for any sign of ex post manipulation in the payroll data, in particular, any downward adjustment of employment hours for workers whose raw hourly productivity falls below the minimum wage. Figure A4 plots the mean of worker-weekly total hours of employment by 5-cent bins of worker-weekly average productivity (output per hour) for a 2-dollar window around the relevant minimum wage. Data are pooled across weeks with week fixed effects controlled for. The plot for weeks 1–8 (minimum wage = \$6.79) is in figure A4*A*, whereas that for weeks 9–12 (minimum wage = \$7.21) is in figure A4*B*. As the figure illustrates, the individual work hours in any given (calendar week) pay period are smooth along the distribution of each worker's contemporaneous productivity. That is, there is no sign of a discontinuous drop in field hours for workers below the productivity threshold of \$6.79 (or \$7.21), which could be expected if the firm had adjusted sub-minimum-wage workers' field hours downward.[14]

On the other hand, if the firm were to make a uniform downward adjustment to everyone's employment hours, such an adjustment could not be detected without having access to the unadulterated records. Even if such uniform downward adjustment were to happen, it would not threaten the analysis because the DID strategy used examines possible differential changes in the outcomes of low- versus high-productivity workers when both groups are exposed to the same shocks at the firm level. Such shocks would include both the January 1 minimum wage hike and the (highly unlikely) uniform downward adjustment of everyone's employment hours.

III. Empirical Strategy

Outdoor production of agricultural crops tends to be characterized by natural fluctuations in average productivity due to external factors, such as weather conditions and the field life cycle. It is therefore tenuous to attribute to effort any changes in worker productivity observed before and after a minimum wage hike. To isolate the effects of worker effort from external determinants of labor productivity, I therefore employ a DID strategy. Similar to Mas and Moretti (2009), I first capture each worker's "baseline" or "permanent" productivity by estimating his individual fixed effects using data

[14] Relatedly, fig. A5 shows the McCrary plot, which tests for selective sorting around the threshold of the worker-weekly average productivity (output per hour). Consistent with no ex post manipulation of production records by the firm, the figure shows no discontinuity in the density of observations around the minimum wage either in the preperiod or in the postperiod.

from weeks 1–5 of the harvesting season. Based on the estimated fixed effects, I classify workers into high- versus low-productivity types.

I then look for possibly differential productivity changes in individual workers from weeks 6–8 to weeks 9–12 by their baseline productivity. Since low-fixed-effect workers are more likely to fall below a minimum wage than are high-fixed-effect workers when subject to a common production environment, to the extent that workers respond to the fear of selective nonemployment (or other related motives) a disproportionate increase in observed productivity in the lower part of the fixed effects distribution should be expected as the minimum wage increases.

Based on data from weeks 1–5, I first estimate by ordinary least squares the following regression:

$$y_{ivft} = \phi_{vf} + \psi_t + \gamma_1 Z_{it} + \gamma_2 X_{vft} + \alpha_i + u_{ivft}, \tag{1}$$

where y_{ivft} denotes (log) worker i's output per hour for variety v in field f on day t. I include variety-field fixed effects (ϕ_{vf}) to capture any between-variety differences that are also field specific as well as day fixed effects (ψ_t) to account for such day-specific common shocks as weather. Worker fixed effects, which capture each worker's baseline productivity, are denoted by α_i. As a result, the estimates of α_i capture the differences between workers who harvest the same variety in the same field while eliminating day-specific common shocks. Furthermore, I also include variety-field-day–specific observed characteristics, such as a cubic polynomial of the variety-field life cycle,[15] supervisor fixed effects (collected in X_{vft}), and a cubic polynomial of worker experience, measured as cumulative work hours from the beginning of the season to day t, Z_{it}. Essentially, I want to capture in α_i a worker's fixed characteristic, which I refer to as baseline productivity, while accounting for other determinants of worker's observed productivity.

Next, based on the estimated fixed effects $\hat{\alpha}_i$, I classify workers into different bins (e.g., percentiles or quintiles) and then estimate variants of the following regression (based on transactions over weeks 6–12):

$$y_{ivft} = \delta(Post_t \times D_i) + \pi_i + \psi_t + \phi_{vf} + \beta_1 Z_{it} + \beta_2 X_{vft} + e_{ivft}, \tag{2}$$

where y_{ivft} again denotes (log) worker i's output per hour for variety v in field f on day t. The variable $Post_t$ assumes the value of unity if day t belongs to weeks 9–12 and zero otherwise, while D_i indicates whether worker i is, say, in the bottom 40th percentile on the (preestimated) worker fixed effects distribution.[16] I include dummies indicating each percentile of the

[15] The variety-field life cycle is computed as the number of days the variety has been picked in that field by day t divided by the total number of days it has been harvested in that field during the season.

[16] I also consider a more flexible approach where I allow quintile-specific productivity changes.

preestimated worker effects π_i (which subsumes D_i) and day fixed effects ψ_t (which subsumes $Post_t$). As in equation (1), I also control for variety-field fixed effects ϕ_{vf} and for the variables in $\boldsymbol{Z}_{it}$ and $\boldsymbol{X}_{vft}$. The DID estimate δ measures the disproportionate productivity changes of workers in the bottom 40th percentile of the fixed effects distribution relative to those in the upper part. All standard errors are clustered by day.[17]

I start by comparing the productivity changes in the bottom two quintiles with those in the upper quintiles. Because the quintiles are based on predefined characteristics (i.e., worker fixed effects in weeks 1–5), this method of classifying treatment status is exogenous to workers' actual effort choices during the analytic window (weeks 6–12). The identifying assumption for this approach is that conditioning on the included controls—in particular, the harvesting day fixed effects that capture farm-level common shocks specific to each day (e.g., weather)—there are no significant changes on or around January 1, 2009, other than the new minimum wage that might differentially influence the effort choices of workers in the lower versus upper part of the worker fixed effects distribution.

IV. Results

A. Worker Fixed Effects

Based on a sample of 13,291 transactions (974 unique employees) from weeks 1 to 5, I first estimate equation (1). Based on the estimated fixed effects (whose mean is zero by normalization with a standard deviation of 0.2254), I classify workers into different bins (quintiles or percentiles).[18] I then examine the relationship between workers' observed productivity in weeks 6–8 (the preperiod with respect to the minimum wage hike) and their baseline productivity (i.e., fixed effects).[19]

Below I present evidence that the preestimated fixed effects are indeed a good predictor of workers' observed productivity and hence the risk of falling below the minimum wage. In the graphical analysis below, I use worker-week as the unit of observation—the unit at which paychecks are issued and minimum wage adjustments are made—without using additional controls. In my regression analysis (sec. IV.B), I use a finer variation with an extensive list of controls to account for external determinants of productivity.

Figure 2 plots the worker-week-level productivity distribution for weeks 6–8 by quintiles of the worker fixed effects based on weeks 1–5. Because of such external factors as weather and field life cycle, there is a

[17] My main results are robust to clustering at the worker level.

[18] The distribution of the estimated worker fixed effects is presented in fig. A6.

[19] The correlation in the observed productivity of each worker between periods is 0.6886 between periods 1 and 2, 0.5544 between periods 1 and 3, and 0.6597 between periods 2 and 3, where periods 1, 2, and 3 refer to weeks 1–5, 6–8, and 9–12, respectively.

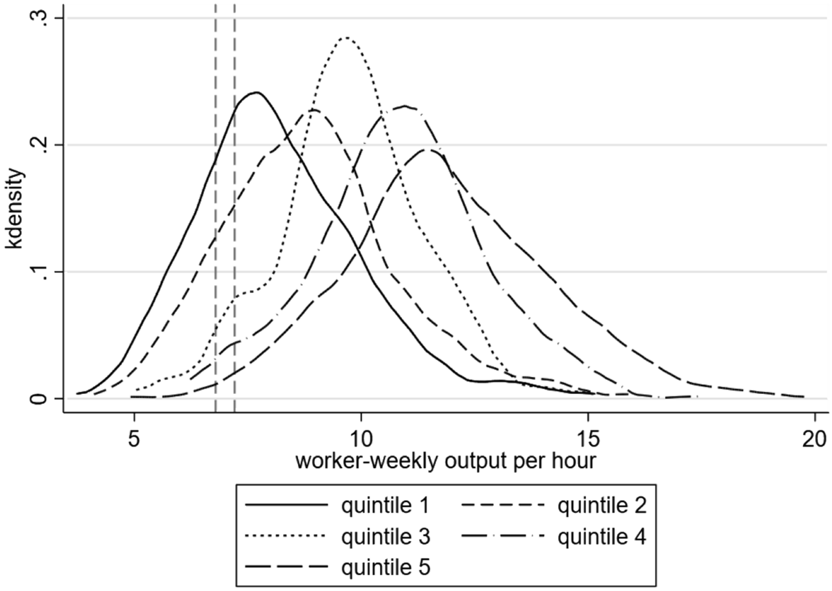

FIG. 2.—Distribution of worker productivity by quintiles of worker fixed effects. This figure plots worker-weekly output per hour during weeks 6–8. The worker fixed effects are preestimated by equation (1) using transactions during weeks 1–5. The dashed vertical lines indicate the old and new minimum wages of \$6.79 and \$7.21, respectively.

fair amount of dispersion in worker productivity even for the same quintiles. However, on average workers in the lower quintiles tend to have lower productivity, suggesting that the estimated worker fixed effects (from weeks 1 to 5) are indeed informative. The monotonic relationship between worker productivity (in weeks 6–8) and the preestimated worker fixed effects is also visualized in figure 3, which displays the mean of worker-weekly productivity against the percentile of the worker fixed effects. Based on these figures, the preestimated worker fixed effects (based on weeks 1–5) seem to be a good proxy for workers' baseline productivity.[20]

Given the monotonicity in figure 3, it is easy to imagine that workers in the lower part of the fixed effects distribution are more likely to fall below the new (and old) minimum wage than those in the upper part. Figure 4 illustrates this. Based on worker-weekly productivity observations (from weeks 6–8), I compute for each percentile of the worker fixed effects the share of observations that fall below the current and new minimum wages. As shown,

[20] This stability can also be established using fixed effects based on weeks 1–3 and observed productivity in weeks 4–5, albeit for a smaller sample than used here.

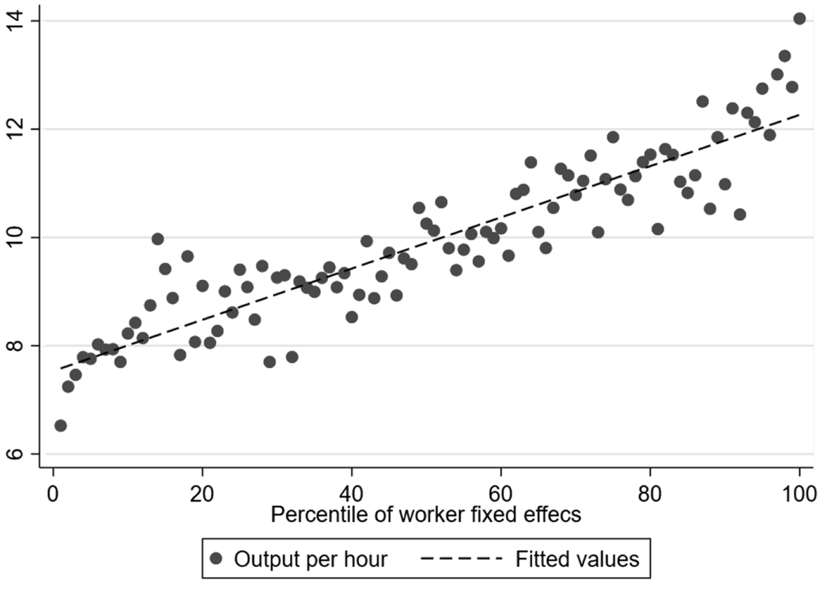

FIG. 3.—Average productivity by percentile of worker fixed effects. This figure plots the mean of worker-weekly productivity during weeks 6–8 by percentile of worker fixed effects. The worker fixed effects are preestimated by equation (1) using transactions during weeks 1–5. The coefficient (standard error) of the fitted line is 0.0473 (0.0021), and the R^2 is 0.8302.

the probability of falling below the minimum wage is greater in the lower part of the distribution than in the higher part. Moreover, the probability shifts upwardly as the new minimum wage is applied to the same productivity data, and the upward shift is more pronounced in the lower part of the fixed effects distribution than in the upper part. Therefore, low-fixed-effect workers have a greater incentive to increase effort than high-fixed-effect workers when both are subject to the minimum wage hike on January 1, 2009.

B. Minimum Wage Effect on Worker Effort

1. *Main Results*

Panel A of table 2 presents the estimates of equation (2) (or its variants), which contrasts the effort responses of workers in the lower part of the distribution with those of workers further up the distribution. Column 1 compares the productivity change in quintiles 1 and 2 of the worker fixed effects distribution with that of the upper quintiles (quintiles 3–5). The estimates reveal that there is a positive productivity change in the bottom two quintiles relative to the upper quintiles. Here, the coefficients on $Post_t \times Quintile1_i$ and $Post_t \times Quintile2_i$ are not significantly different from each other. In

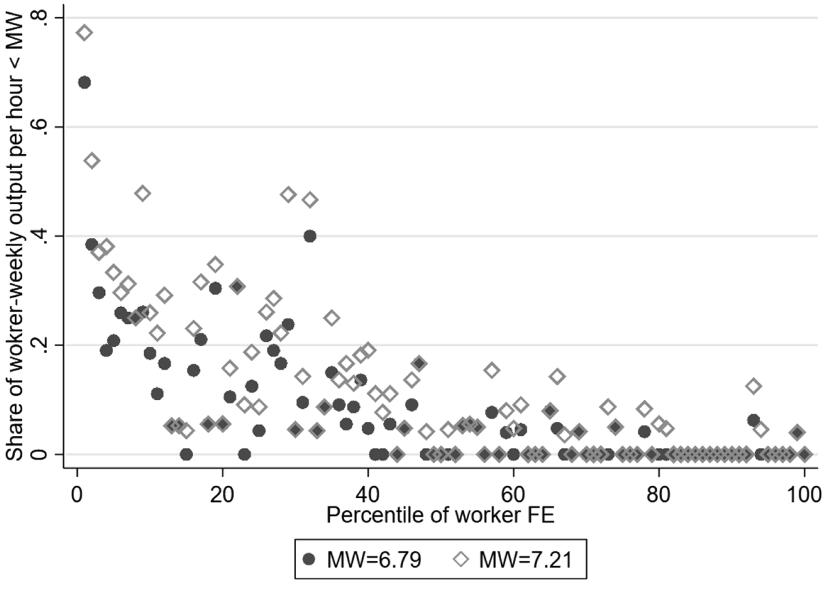

FIG. 4.—Propensity to fall below the minimum wage by worker fixed effects. This figure plots for each percentile of worker fixed effects the share of worker-weekly productivity observations during weeks 6–8 that fall below the current ($6.79) and new ($7.21) minimum wages, respectively. Worker fixed effects (FE) are preestimated by equation (1) using transactions during weeks 1–5.

column 2, I then estimate the average changes among quintiles 1 and 2 relative to quintiles 3–5. The estimates show that the output per hour for workers below the 40th percentile increases a disproportionate 4.6% relative to workers in the comparison group (above the 40th percentile).[21]

To address the concern that what constitutes the preperiod and the postperiod may not be so clear-cut, I exclude the transition weeks (weeks 8, 9). While January 1 falls in week 9, the new and higher minimum wage may take time to sink in with the workers rather than have an immediate effect. On the contrary, workers may respond proactively in the week before the scheduled increase in the minimum wage. When focusing on these pre- and postperiods that are more clearly separate, the coefficient becomes larger (see cols. 3, 4).

[21] In table A4 I present estimates using alternative ways to account for workers' baseline productivity. Columns 1 and 2 replicate my baseline estimates from cols. 1 and 2 of table 2. In cols. 3 and 4, I include dummies for each quintile of the preestimated worker fixed effects, requiring coarser information on worker types than in the baseline. In cols. 5 and 6, I include the preestimated worker fixed effects in levels, imposing a linear effect and reducing the number of parameters to be estimated. As shown, the results are robust to these alternative (and less demanding) specifications to account for the baseline productivity.

Table 2
Worker Output per Hour by Quintiles of Worker Fixed Effects

	Dependent Variable: log(Output per Hour)					
	All		Exclude Transition Weeks		Exclude Final Week	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Full sample:						
Post × low fixed effects		.046***		.070***		.043**
		(.016)		(.020)		(.017)
Post × quintile 1	.045*		.080***		.044*	
	(.024)		(.028)		(.025)	
Post × quintile 2	.052***		.065***		.046***	
	(.012)		(.016)		(.012)	
Observations	18,471	18,471	12,675	12,675	17,445	17,445
R^2	.565	.564	.577	.577	.536	.536
B. Balanced sample:						
Post × low fixed effects		.043**		.068***		.040**
		(.016)		(.019)		(.017)
Post × quintile 1	.043*		.080***		.041	
	(.024)		(.028)		(.026)	
Post × quintile 2	.049***		.061***		.044***	
	(.012)		(.015)		(.012)	
Observations	16,756	16,756	11,247	11,247	15,730	15,730
R^2	.567	.567	.574	.574	.538	.538

NOTE.—Panel A is based on the full sample. Panel B is based on the balanced sample including workers who worked in both the preperiod (weeks 6–8) and the postperiod (weeks 9–12). Based on transactions during weeks 6–12. *Post* = 1 if week 9 or later. Transition weeks refer to weeks 8 and 9. The quintiles are based on the worker fixed effects estimated based on eq. (1) using data from weeks 1–5. Low fixed effects indicates that worker fixed effects are in the bottom 40th percentile. All regressions include percentile dummies for preestimated worker effects, day fixed effects, a cubic polynomial of worker experience, variety-field fixed effects, a cubic polynomial of the variety-field life cycle, and supervisor fixed effects. Robust standard errors clustered by day are in parentheses.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

In columns 5 and 6, I exclude the final week from the sample, as the incentives may be weaker when workers know that the season will end after that. The magnitude of the main estimates changes only slightly. Overall, these findings suggest that the increase in the minimum wage from \$6.79 to \$7.21 increases the relative productivity of workers in the bottom 40th percentile by 4%–7%.

So far I have focused on the dichotomous distinction between low- and high-productivity workers. I now take a more flexible approach and estimate a variant of equation (2) where $Post_t \times D_i$ is replaced by $Post_t$ interacted with dummies for each quintile, using quintile 3 as the reference category. The estimated coefficients along with 95% confidence intervals are plotted in figure 5. As expected, the productivity response of quintiles 1 and 2 are clearly positive relative to that of quintile 3 (the reference category). Moreover, there are also modest increases in the productivity of quintiles 4 and 5, albeit

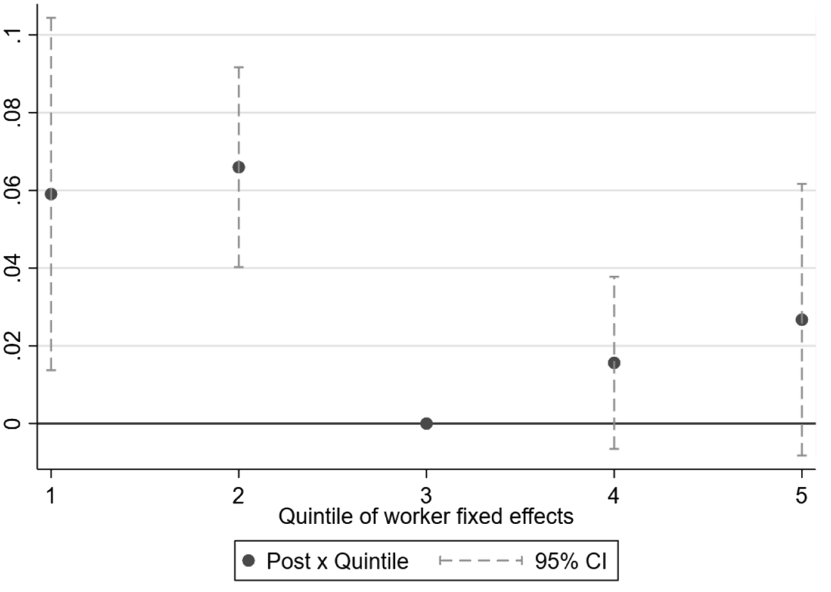

FIG. 5.—Productivity change from before to after the minimum wage hike by quintiles of worker fixed effects. Based on transactions during weeks 6–12. *Post* = 1 if week 9 or later. This figure plots the changes in productivity (output per hour) from the preperiod to the postperiod by quintiles of worker fixed effects (relative to quintile 3). It plots the DID coefficients from estimating a variant of equation (2), where $Post \times D$ is replaced with $Post \times$ dummy for each quintile except for quintile 3. The regression includes percentile dummies for preestimated worker effects, day fixed effects, a cubic polynomial of worker experience, variety-field fixed effects, a cubic polynomial of the variety-field life cycle, and supervisor fixed effects. Standard errors are clustered by day. CI = confidence interval.

smaller in magnitude than that for quintiles 1 and 2 and imprecisely estimated.[22] Such responses in the upper part of the distribution may be driven by peer pressure, as in Mas and Moretti (2009), and/or high-productivity workers' preferences for maintaining their rank ordering, as in Kuziemko et al. (2014). The pattern shown in figure 5 also ensures that the estimates in table 2 are indeed driven by positive effort responses of low-productivity workers (who are more "at risk" than others) rather than potentially negative effort responses of high-productivity workers who may be activated by fairness concerns, as in Breza, Kaur, and Shamdasani (2017) and Dube, Giuliano, and Leonard (2019).

[22] The difference between the estimated coefficients plotted in fig. 5 and the p-value associated with each test are as follows: $\widehat{Post \times Q2} - \widehat{Post \times Q4} = 0.0503$ ($p = .004$), $\widehat{Post \times Q2} - \widehat{Post \times Q5} = 0.0392$ ($p = .015$), and $\widehat{Post \times Q2} - \widehat{Post \times Q1} = 0.0068$ ($p = .684$).

2. *Robustness Checks*

My DID estimates show a disproportionate increase in observed productivity in the lower part of the fixed effects distribution than in the upper part as the minimum wage increases from the preperiod to the postperiod. There are potential threats to interpreting these effects as an "effort response" to the minimum wage, including composition changes and reliability of the estimated worker effects. Below I report a series of additional robustness checks to address these concerns.

First, I investigate whether the baseline effects detected might result from changes in worker composition (i.e., differential selection within high- vs. low-quintile bins over time). I repeat my main analysis using a balanced sample of workers who worked in both the preperiod (weeks 6–8) and the postperiod (weeks 9–12). In these estimates, reported in panel B of table 2, the sample size becomes slightly smaller, but the patterns are similar to those in panel A of the same table.[23] Thus, the increase in output per worker detected is unlikely to be driven by differential compositional changes within high- versus low-quintile bins.

Next, I address concerns regarding the reliability of the estimated worker effects. In estimating worker fixed effects in equation (1), I imposed the restriction of at least five spells per worker, resulting in on average 13 spells per worker, which should be considered "large" by the standard of panel data models (see Fernández-Val and Weidner 2018). To nevertheless check whether smaller spell numbers for some workers may be an issue, I vary the minimum number of spells required when estimating equation (1). In table 3, column 3 replicates the results in column 2 of table 2. Columns 1 and 2 show results with lower numbers of minimum spells, and columns 4–6 show results with higher numbers. When moving from column 1 through column 6, the DID estimate of productivity changes remains largely stable.

As an additional check for the reliability of my estimated worker effects, I also conduct a simulation exercise. In particular, I randomly draw individual effects from a distribution with a mean of zero and a standard deviation of 0.2254 (see fig. A6) and estimate the δ in equation (2) with these randomly assigned individual effects. I repeat this exercise 500 times and plot the distribution of the estimated δ's in figure A7. To assess how likely it is that the baseline estimate of 0.046 (col. 2 of table 2) happens "by chance" even when the underlying worker effects are completely random, the dashed line indicates the 95th percentile of the distribution of $\hat{\delta}$'s based on randomly

[23] Note that in either sample, the main coefficient of interest, *Post* $\times$ low fixed effects, is identified from workers who worked in both the preperiod and the postperiod. However, in panel A the part-season workers still contribute to the estimation of other included controls, such as day fixed effects or variety-field fixed effects.

Table 3
Imposing Restrictions on the Minimum Number of Spells When Estimating Worker Fixed Effects

	Dependent Variable: log(Output per Hour)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post × low fixed effects	.050***	.049***	.046***	.034**	.043**	.041**
	(.016)	(.015)	(.016)	(.016)	(.016)	(.016)
Observations	19,446	19,249	18,471	17,827	17,460	16,752
R^2	.566	.568	.564	.567	.570	.568
Minimum number of spells	3	4	5	6	7	8
Average number of spells	12	13	13	14	14	15

Note.—Column 3 replicates the result in col. 2 of table 2. Columns 1 and 2 show results with lower numbers of minimum spells, and cols. 4–6 show results with higher numbers. Based on transactions during weeks 6–12. *Post* = 1 if week 9 or later. The quintiles are based on the worker fixed effects estimated based on eq. (1) using data from weeks 1–5. All regressions include percentile dummies for preestimated worker effects, day fixed effects, a cubic polynomial of worker experience, variety-field fixed effects, a cubic polynomial of the variety-field life cycle, and supervisor fixed effects. Robust standard errors clustered by day are in parentheses.
** $p < .05$.
*** $p < .01$.

assigned individual effects. The baseline estimate of $\hat{\delta} = 0.046$ clearly lies outside this threshold.

C. Employment Outcomes

My analysis so far has focused on the effort responses of workers. In this section, I examine (i) whether the employment outcomes differ between high- and low-productivity workers (irrespective of the minimum wage) and (ii) whether any preexisting differences may be further amplified because of the minimum wage increase.

Before proceeding, it is worthwhile to understand the evolution of farm-level employment during the season. As figure 6*A* shows, the farm's life cycle and hence its labor demand cycle peaks in the middle of the season. In keeping with these employment requirements, the farm needs to build up its worker pool at the beginning of the season and shed it once the peak has been reached and as the season is winding down. Figure 6*B* plots the cumulative inflows, the cumulative outflows, and the stock of workers in each week. The inflows in week K are measured as workers whose first harvesting day occurs in week K, and the outflows in week K are defined as those whose last harvesting day occurs in week $K - 1$. The stock of workers in week K are the cumulative inflows by week K minus the cumulative outflows by week K, proxying for the size of the worker pool available for hire in week K. As the figure shows, large inflows are seen at the beginning of the season, the pace of which then slows down as the season progresses. In contrast, worker outflows are negligible at the beginning of the season but then steadily increases over time.

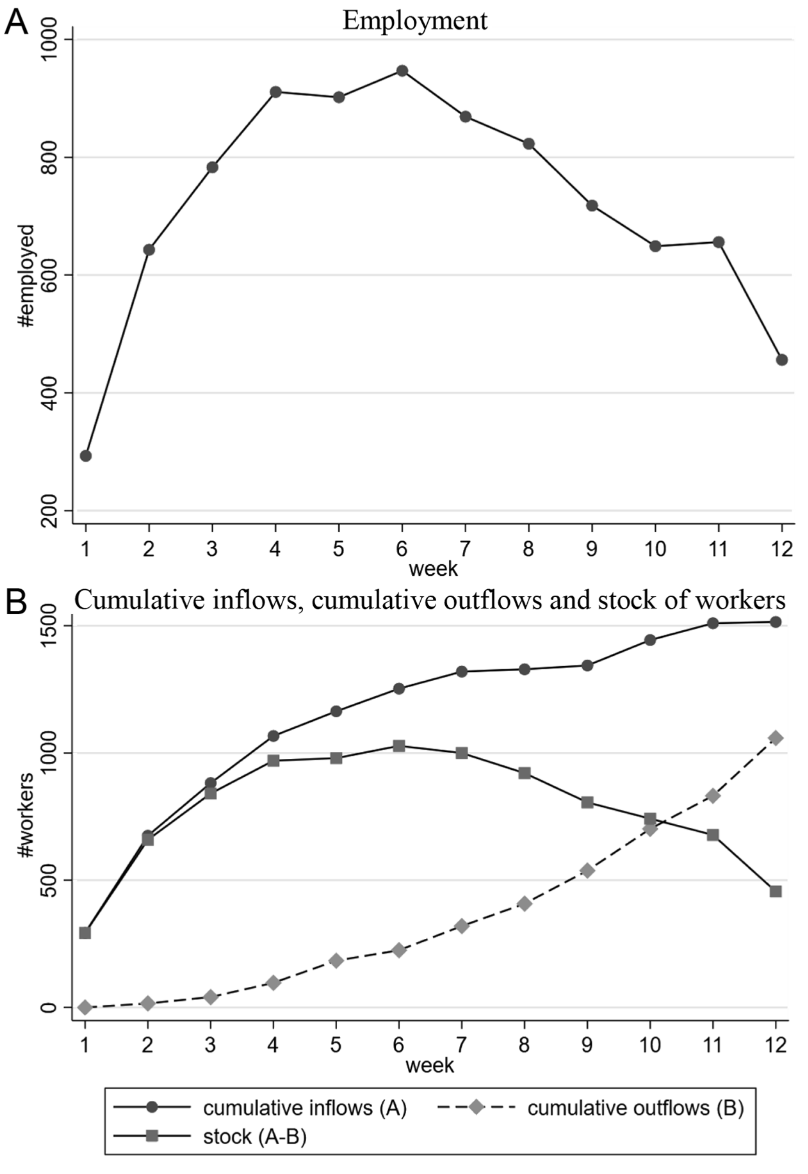

FIG. 6.—Employment and worker flows during the season. *A* shows the total number of workers employed in each week. *B* shows the cumulative inflows, cumulative outflows, and stock of workers in each week. The inflows in week *K* are measured as workers whose first harvesting day occurs in week *K*, and the outflows in week *K* are defined as those whose last harvesting day occurs in week $K - 1$. The stock of workers in week *K* are the cumulative inflows by week *K* minus the cumulative outflows by week *K*, proxying for the size of the worker pool available for hire in week *K*.

To understand whether worker productivity matters at all in the day-to-day allocation of employment opportunities, I estimate the following equation:

$$Employment_{it} = \eta_1 D_i + \eta_2(Post_t \times D_i) + \psi_t + \omega_{it}, \tag{3}$$

where $Employment_{it}$ is worker i's employment outcome on day t. The variable D_i indicates whether worker i is below the 40th percentile in the baseline productivity distribution. The variable $Post_t$ assumes the value of unity if day t belongs to weeks 9–12 and zero otherwise. Day fixed effects are absorbed in ψ_t (which subsumes $Post_t$). As before, the treatment status D_i is based on the worker's predetermined characteristic (from weeks 1 to 5) and is orthogonal to his contemporaneous decisions. Standard errors are clustered by day.

In the absence of the second term, the equation estimates the simple difference between low- versus high-productivity workers, that is, whether low-productivity workers are overall employed less frequently than high-productivity workers. Once the interaction term is included ($Post_t \times D_i$), the coefficient η_2 picks up the excess selectivity in the postperiod (weeks 9–12) over and above that (η_1) in the preperiod (weeks 6–8), which may be attributed to the minimum wage hike.

Table 4 displays the estimates of equation (3) (or its variants) using worker-day as the unit of analysis. Columns 1–4 use daily employment (1 if working that day and 0 otherwise) as the dependent variable. The estimate in column 1 shows that overall, workers below the 40th percentile have a 0.025 percentage point lower probability of being employed each day than those above the 40th percentile, which is about 6% (0.025/0.397) of the mean. Column 2 shows that the preexisting difference (−0.019) is about twice as large as the additional effect in the postperiod (−0.011).

So far, I have included all worker-days in the sample, including workers who may have already left the farm and are no longer available for hire on a given day. For instance, a worker whose last day of employment during the season falls in week $K - 4$ is unlikely to be available for hire in week K. By including such workers and recording them as not working, the true extent of nonworking status at this farm may be overstated. In columns 3 and 4, I therefore exclude worker-days from the sample if the worker's last day of employment at this farm during this season occurs in any week prior to the week of the present worker-day. The mean employment probability in this restricted sample is 0.642, as opposed to 0.397 in the full sample. The estimates in columns 3 and 4 show that while low-productivity workers are 8.4% (0.054/0.642) less likely to be employed than high-productivity workers in general, there is no strong evidence that this preexisting employment gap widens when a higher minimum wage takes effect. Based on columns 2 and 4, a possible reduction in the employment of low-productivity workers attributable to the minimum wage hike is at most 4.6% (0.030/0.642).

Table 4
Daily Employment Outcomes by Low- versus High-Fixed-Effect Workers

	Dependent Variable					
	Daily Employment (Extensive Margin)				Daily Hours Worked (Intensive Margin)	
	All Workers		Exclude Workers Who Likely Exited the Farm		Conditional on Working That Day	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of dependent variable	.397		.642		5.596	
Post × low fixed effects		−.011		−.030		.028
		(.020)		(.027)		(.125)
Low fixed effects	−.025**	−.019	−.066***	−.054***	−.312***	−.323***
	(.010)	(.016)	(.013)	(.015)	(.070)	(.109)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,038	36,038	22,313	22,313	14,323	14,323
R^2	.106	.106	.167	.167	.340	.340

NOTE.—Based on worker-day-level data for weeks 6–12. *Post* = 1 if week 9 or later. Low fixed effects indicates that preestimated worker fixed effects are in the bottom 40th percentile. Daily employment is 1 if the worker is working that day and 0 otherwise. Daily hours worked are total hours worked by the worker conditional on working that day. Columns 1 and 2 include all workers in the sample. Columns 3 and 4 exclude worker-days if the worker's last day of employment at this farm during this season occurs in any week prior to the week of the present worker-day. Columns 5 and 6 restrict the sample to worker-days with nonzero employment hours. All regressions include day fixed effects. *Post* is subsumed in day fixed effects. Robust standard errors clustered by day are in parentheses.
** $p < .05$.
*** $p < .01$.

Furthermore, I examine in columns 5 and 6 the intensive margin effect (i.e., total hours worked conditional on working that day) on employment.[24] While low-productivity workers work 5.7% (0.323/5.596) fewer hours than high-productivity workers, I do not find any evidence of a further reduction in the hours worked by low-productivity workers after the minimum wage hike. This is consistent with the fact that harvesting workers, once in the field, tend to work the same hours until the day's harvesting finishes (and leave by the same buses on which they arrived in the morning), leaving little scope for intensive margin adjustments.

Based on table 4, it appears that while low-productivity workers in general have lower chances of being employed than high-productivity workers, this existing employment gap is not further widened because of the higher minimum wage. This lack of significant employment effects attributable to the minimum wage hike may be reconciled on the basis of various grounds. In a competitive framework, the positive effort responses of sub-minimum-wage workers should obviate the need for reducing employment opportunities

[24] Columns 5 and 6 include worker-days with nonzero employment hours only; hence, the smaller number of observations than in other columns.

Table 5
Implication of Worker Effort Responses on the Firm's Minimum Wage Compliance Cost

	Minimum Wage = \$6.79	Minimum Wage = \$7.21		
	(1)	(2)	(3)	(4)
Minimum wage compliance cost (\$)	8,340	13,217	10,660	10,286
Worker effort response		No	Yes	Yes
Change in the allocation of employment hours		No	No	Yes
Implied reduction in compliance cost (\$)		NA	2,557	2,931

Note.—Based on 5,400 worker-weekly observations (974 unique workers) for weeks 1–8. Columns 3 and 4 apply a productivity increase of 4.6% for workers in the bottom 40th percentile. Column 4 additionally applies a decreased share of employment hours for workers in the bottom 40th percentile by 4.6%. NA = not applicable.

assigned to these workers. The fact that not all workers whose raw productivity falls below the minimum wage are discharged is also in line with earlier findings of Holzer, Katz, and Krueger (1991) that some positive rents (for workers) are associated with minimum wage jobs. Moving beyond competition, it is also possible that workers simply reacted to a perceived threat—even in the absence of any actual pressure coming from the employer—and/or are driven by fairness concerns between the worker and the employer in the spirit of gift exchange (Akerlof 1982).

D. Discussion

The results of my analysis described above indicate that in response to the January 1, 2009, minimum wage hike, the productivity of workers in the bottom 40th percentile of the productivity distribution increased by a disproportionate 4.6% relative to those in the higher percentiles (col. 2 of table 2). In the absence of such worker responses, a higher minimum wage means a higher labor cost for the firm because of higher associated compliance costs. If, however, some sub-minimum-wage workers increase their efforts, it may (at least partially) offset these rising costs.[25] I examine these alternatives in table 5. Based on data for weeks 1–8, when the prevailing minimum

[25] The positive productivity response to the minimum wage may suggest that the new minimum wage is functioning as an efficiency wage (Shapiro and Stiglitz 1984; Rebitzer and Taylor 1995). However, the concept of an efficiency wage is applicable to settings where workers are paid a fixed wage (salary) while their effort or output is difficult to monitor. In my context, workers are compensated by pure piece rate and their output is readily observable by the employer, which obviates the firm's need to employ an efficiency wage. See Shapiro and Stiglitz (1984) and Katz (1986) for further discussion of the characteristics of workplaces conducive to adoption of an efficiency wage.

wage is $6.79, I compute a compliance cost by sub-minimum-wage workers of $8,340.[26]

I then consider the consequence of a minimum wage increase from $6.79 to $7.21. In the absence of worker effort responses, this will raise the firm's compliance cost by $4,877 (from $8,340 to $13,217). However, as earlier analyses show, low-productivity workers may increase their efforts, which would bring the firm's compliance cost down to $10,660, which is $2,557 (or 52%) less than the projected increase of $4,878. On the other hand, any additional saving implied by possible employment adjustment is rather minor (at most $374 or 8%) even if I allow for a significant reduction in the employment hours assigned to low-productivity workers by 4.6% (0.030/0.642, based on col. 4 of table 4). Overall, this calculation indicates that increased worker productivity can offset about half of the projected rise in the minimum wage compliance cost, suggesting a roughly equal sharing of the projected increase between the employer and the workers.

V. Conclusions

By employing a direct and high-frequency measure of individual-level productivity on a homogenous task in the context of Florida's minimum wage hike on January 1, 2009 (from $6.79 to $7.21), I examine worker effort responses as a possible margin of adjustment to a minimum wage hike. When the statutory minimum wage increases, workers in the lower part of the productivity distribution face increased risk of falling below the minimum wage relative to those in the upper part of the distribution. Low-productivity workers may therefore increase their efforts (and hence productivity) to preempt possible discharge. I find that in response to the 42-cent (or 6%) increase in the minimum wage, worker productivity (i.e., output per hour) in the bottom 40th percentile of the worker fixed effects distribution increases by about 4.6% relative to that in the higher percentiles, suggesting that productivity increases driven by worker effort may help mitigate the higher labor costs associated with the minimum wage.

Several cautions are warranted. First, this margin of adjustment can work only within relatively low ranges of the minimum wage. If the minimum wage continues to rise to a higher level, workers may no longer be able to keep up their effort (and productivity) with the minimum wage due to physical or cognitive limits. At that point, the firm may adopt an entirely different personnel policy (or different production technology) than that observed here, and worker effort responses may no longer be a valid channel to absorb the rising labor cost associated with the minimum wage.

[26] For this counterfactual exercise, I fix the production schedule at the period of the pre-minimum-wage hike so as not to confound the minimum wage effect with a seasonality effect.

Second, I focus here on workers who do not have a long-term contract and are hired on a day-to-day basis within a harvesting season. If workers had extended-term contracts, the incentive structure in place may look quite different. On the one hand, the fact that the job is more or less guaranteed—at least for the fixed term—may reduce the incentive to increase effort in response to the minimum wage. On the other hand, the job is worth more (in present discounted values) than performing daily labor; hence, the workers may find a greater incentive to increase effort to keep it.

Although a plausible channel of adjustment to the minimum wage, incumbent workers' effort responses have been largely overlooked in the literature, probably because in most settings, measuring individual-level productivity around a minimum wage hike—without convolution with task and workforce composition—is difficult. This work, although focused on a particular firm in a particular industry, opens a new avenue for future research, particularly in terms of whether labor productivity serves as a mechanism for adjusting to a minimum wage in other firms or industries.

Appendix

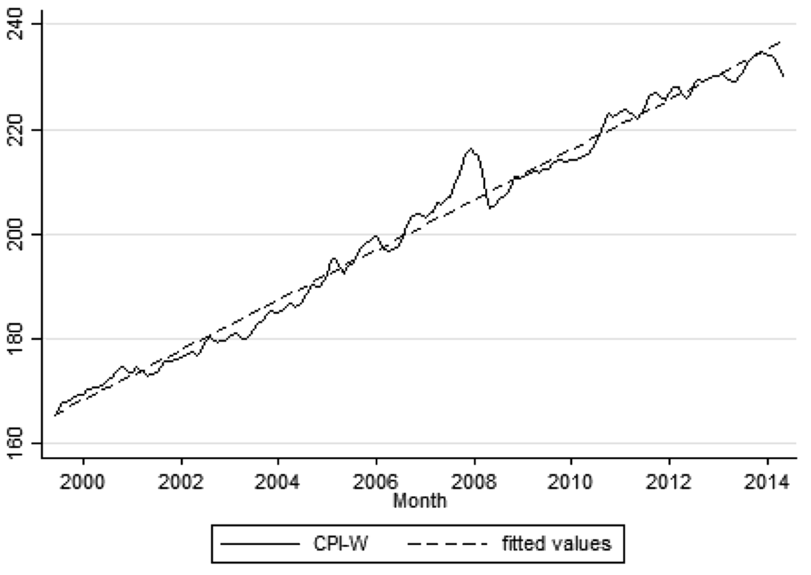

Fig. A1.—Monthly CPI-W. 1982–84 = 100. August for each year is marked on the horizontal axis. Source: US Bureau of Labor Statistics (series CWUR0000SA0).

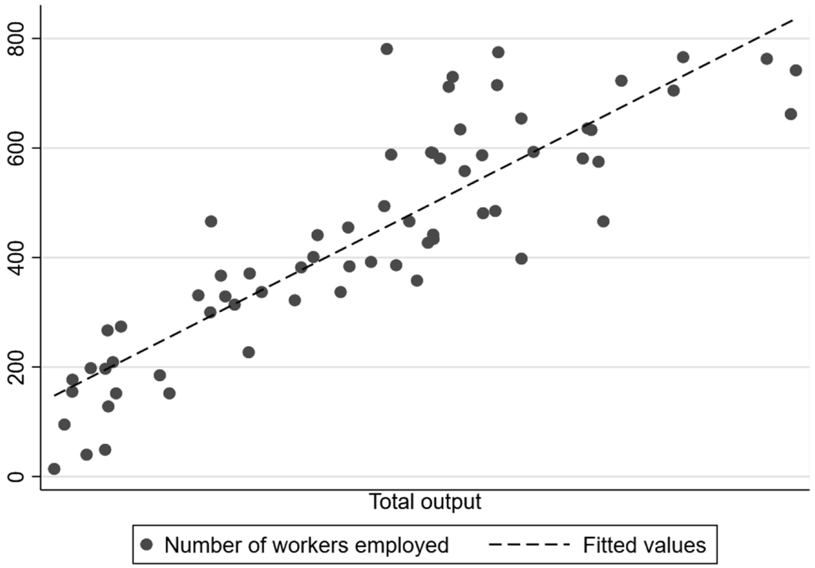

FIG. A2.—Daily number of workers employed and daily total output. This figure plots the relation between the number of workers employed each day and the "field capacity" proxied by the total output. The label for the *x*-axis (total output) is suppressed so as to not reveal the farm's day-specific scale of operation. The R^2 associated with the regression line is 0.7695.

Employee ID: ABCXYZ
From: Nov 16, 2008 To: Nov 22, 2008

Date	**Type**	**Hours**	**Rate**	**Pieces**	**Earnings**
Nov 16, 2008	Minimum Wage				16.00
Nov 16, 2008	Round	5.33	0.5	58	29.00
Nov 16, 2008	Grape	1.67	3.75	2	7.50
Nov 17, 2008	Grape	3.65	3.75	3	11.25
Nov 17, 2008	Round	4.63	0.5	80	40.00
Total		15.28			103.75

FIG. A3.—Example worker pay stub.

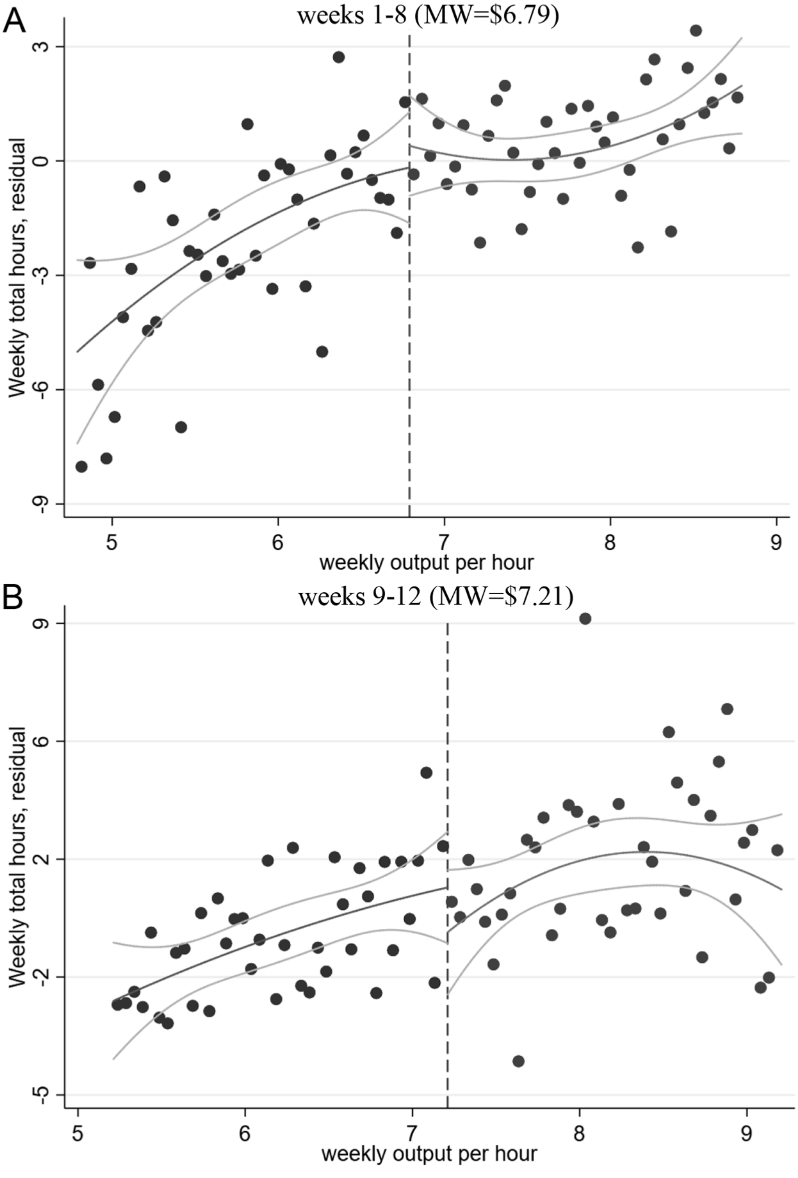

FIG. A4.—Worker-weekly total hours of employment against worker-weekly average productivity. This figure plots the mean of the residual of worker-weekly total hours of employment (after accounting for week fixed effects) by 5-cent bins of worker-weekly average productivity (output per hour) for a 2-dollar window around the relevant minimum wage ($6.79 in *A*, $7.21 in *B*). The quadratic fit with the 95% confidence interval is shown on either side of the minimum wage. It shows that the employment hours in the record are smooth around the minimum wage, with no sign of a discontinuous drop before the minimum wage.

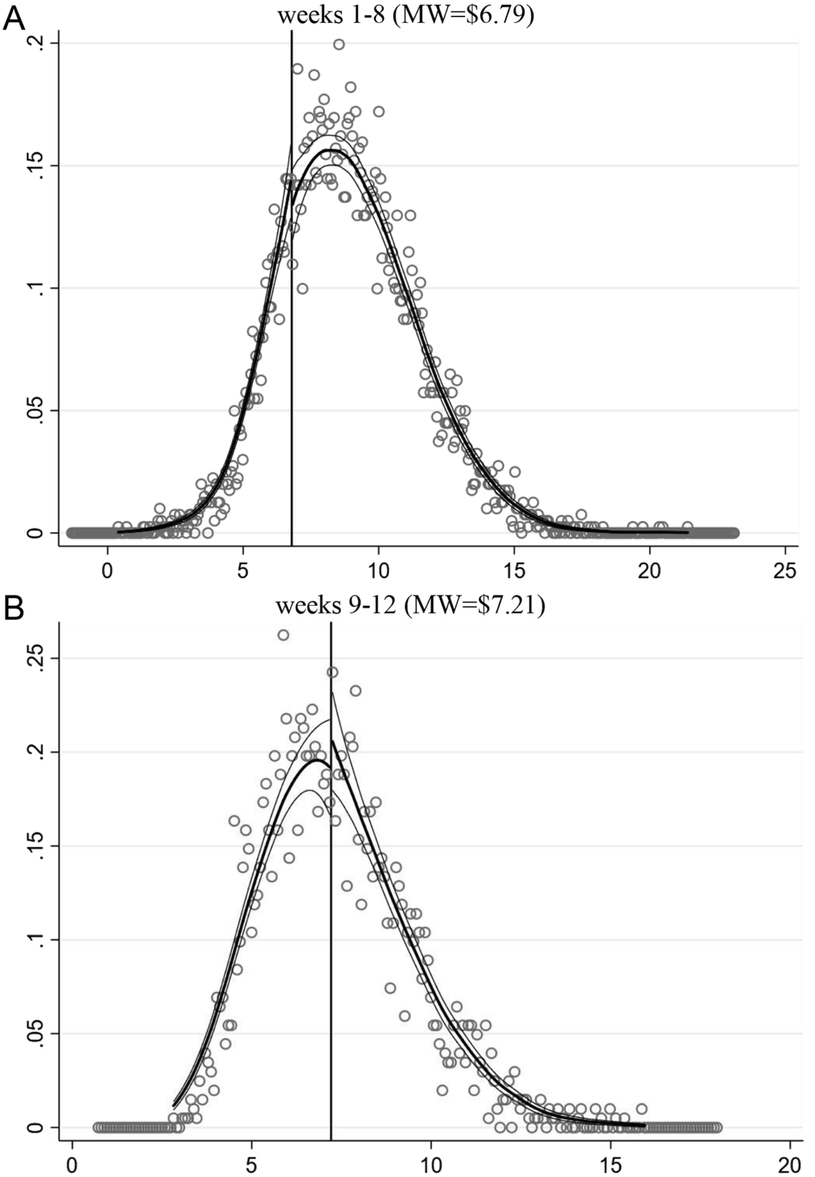

FIG. A5.—McCrary test: density of worker-weekly productivity around the minimum wage threshold. This figure shows the McCrary plot, which tests for selective sorting around the threshold of the worker-weekly average productivity (output per hour). The vertical line shows the relevant minimum wage ($6.79 in *A*, $7.21 in *B*). The figure shows no discontinuity in the density of observations around the minimum wage.

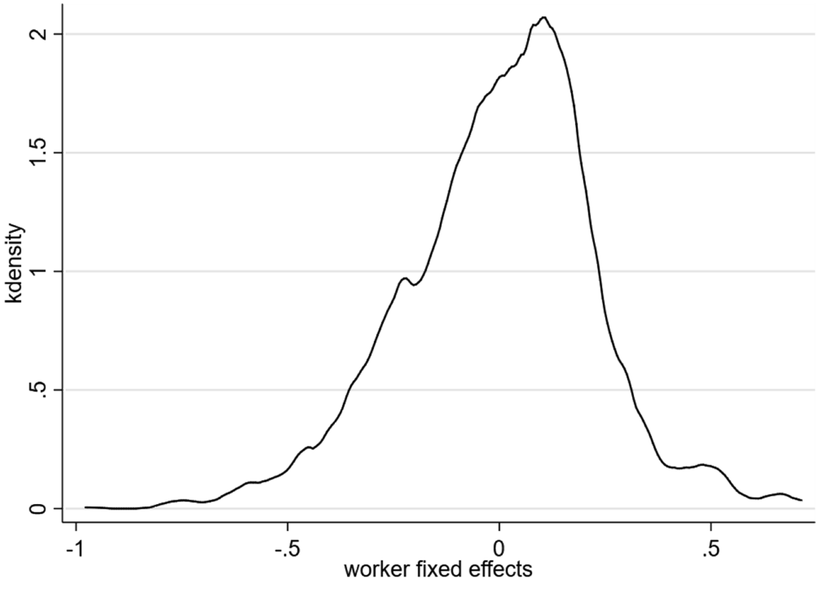

Fig. A6.—Distribution of worker fixed effects. This figure shows the distribution of worker fixed effects as estimated by equation (1), using 13,291 observations from 974 unique workers during weeks 1–5. The mean (standard deviation) of the estimated fixed effects is 0.0000 (0.2254).

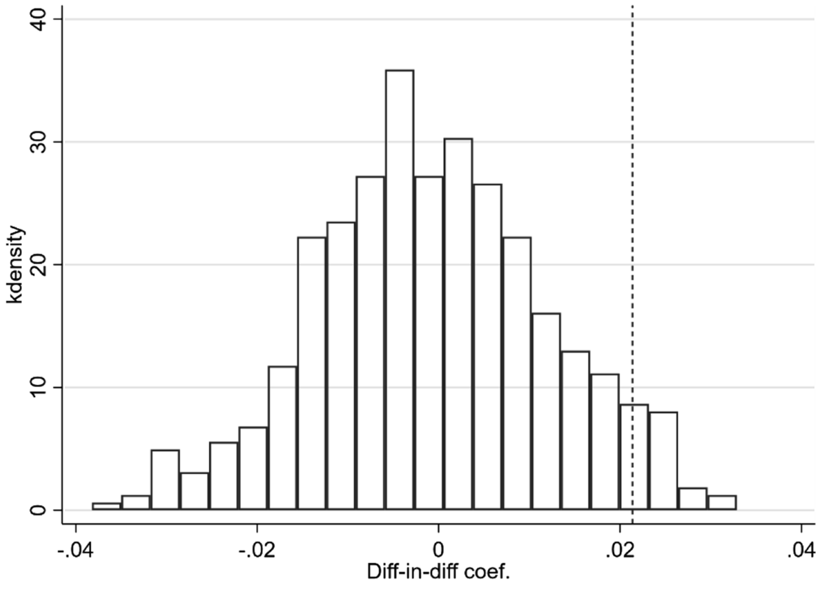

FIG. A7.—Distribution of estimated productivity change based on simulated worker effects. This figure plots the histogram of the estimated productivity change from the preperiod to the postperiod (parameter δ in eq. [2]) based on simulated worker effects. Worker effects are drawn from the normal distribution with mean (standard deviation) of 0.0000 (0.2254), the sample mean and standard deviation among the estimated fixed effects). Based on 500 repetitions. The dashed line shows the 95th percentile.

Table A1
Lowest-Wage Occupations in Florida

	Hourly Wages					
Occupation Title	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean
A. All occupations	8.02	10.06	14.58	22.58	34.26	18.96
B. Major occupation groups:						
Food preparation and serving-related occupations	7.41	7.71	8.82	11.22	14.69	10.09
Farming, fishing, and forestry occupations	7.43	7.80	8.86	11.35	15.32	10.34
Personal care and service occupations	7.51	8.10	9.75	12.99	18.80	11.63
C. Detailed occupations:						
Combined food preparation and serving workers, including fast food	7.35	7.57	8.10	9.15	10.80	8.66
Dining room and cafeteria attendants and bartender helpers	7.35	7.57	8.16	9.33	11.41	8.81
Cooks, fast food	7.36	7.57	8.20	9.28	10.83	8.65
Dishwashers	7.36	7.57	8.23	9.27	10.78	8.62

Table A1 (*Continued*)

Occupation Title	Hourly Wages 10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean
Amusement and recreation attendants	7.37	7.62	8.39	9.95	12.69	9.27
Counter attendants, cafeteria, food concession, and coffee shop	7.38	7.64	8.39	9.45	11.28	8.83
Cashiers	7.34	7.54	8.44	9.41	11.18	8.83
Waiters and waitresses	7.37	7.61	8.56	11.21	14.54	9.91
Bartenders	7.38	7.62	8.66	11.19	15.29	10.11
Farmworkers and laborers, crop, nursery, and greenhouse	7.41	7.73	8.66	10.58	13.16	9.63

NOTE.—This table shows the mean and various percentiles of hourly wages for the lowest-paying occupations in Florida. Based on May 2009 estimates for Florida from Occupational Employment Statistics provided by the US Bureau of Labor Statistics. Panel A shows the statistics for all occupations in the state. Panel B lists the three lowest-paying major occupation groups, out of 22 in the Standard Occupational Classification (SOC) system. Panel C lists the 10 lowest-paying detailed occupations with an employment count of at least 20,000. There are about 800 detailed occupations in the SOC system.

Table A2
Minimum Wage in Florida, 2000–2015

Year	Federal Minimum Wage ($)	Florida Minimum Wage ($)	Change in Florida Minimum Wage ($)	Florida Effective Dates
2000[a]	5.15	5.15		
2001	5.15	5.15	.00	
2002	5.15	5.15	.00	
2003	5.15	5.15	.00	
2004	5.15	5.15	.00	
2005[b]	5.15	6.15	1.00	5/2/2005–12/31/2005
2006	5.15	6.40	.25	1/1/2006–12/31/2006
2007	5.85	6.67	.27	1/1/2007–12/31/2007
2008	6.55	6.79	.12	1/1/2008–12/31/2008
2009	6.55	7.21	.42	1/1/2009–7/23/2009
2009[c]	7.25	7.25	.04	7/24/2009–12/31/2009
2010[c]	7.25	7.25	.00	1/1/2010–12/31/2010
2011[c]	7.25	7.25	.00	1/1/2011–5/31/2011
2011[d]	7.25	7.31	.06	6/1/2011–12/31/2011
2012	7.25	7.67	.36	1/1/2012–12/31/2012
2013	7.25	7.79	.12	1/1/2013–12/31/2013
2014	7.25	7.93	.14	1/1/2014–12/31/2014
2015	7.25	8.05	.12	1/1/2015–12/31/2015

SOURCE.—Florida Department of Economic Opportunity, October 2015.
[a] 2000–2004, federal minimum wage.
[b] Florida enacted a state minimum wage (Florida Minimum Wage Amendment approved through election ballot on November 2, 2004).
[c] Florida defaulted to the federal minimum wage.
[d] Legal ruling raising the minimum wage to $7.31

Table A3
Mean Employment, Hours Worked, and Productivity

	Daily Employment			
	All Workers (1)	Exclude Workers Who Likely Exited the Farm (2)	Daily Hours If Worked That Day (3)	Output per Hour (4)
A. Weeks 1–5:				
Quintile 1	.49	.53	4.90	7.59
Quintile 2	.51	.55	4.96	8.85
Quintile 3	.53	.59	5.06	9.97
Quintile 4	.55	.57	5.03	11.13
Quintile 5	.52	.55	4.96	11.94
All	.52	.56	4.99	10.00
B. Weeks 6–8:				
Quintile 1	.47	.59	4.98	8.16
Quintile 2	.50	.64	5.33	8.91
Quintile 3	.48	.69	5.36	9.77
Quintile 4	.53	.66	5.41	10.83
Quintile 5	.49	.63	5.45	11.88
All	.49	.64	5.31	9.93
C. Weeks 9–12:				
Quintile 1	.26	.57	5.76	6.84
Quintile 2	.31	.61	5.90	7.59
Quintile 3	.30	.68	6.03	7.86
Quintile 4	.36	.70	6.25	8.76
Quintile 5	.30	.65	6.14	9.70
All	.31	.64	6.03	8.21
D. All weeks:				
Quintile 1	.41	.56	5.12	7.62
Quintile 2	.44	.59	5.30	8.56
Quintile 3	.45	.64	5.37	9.41
Quintile 4	.48	.63	5.45	10.39
Quintile 5	.44	.59	5.39	11.37
All	.44	.60	5.33	9.54
Observations	56,976	41,966	25,252	31,762

NOTE.—Based on 974 unique workers, this table shows the mean employment, hours, and productivity (output per hour) by quintiles of individual fixed effects, separately for weeks 1–5, 6–8, and 9–12 and for the overall season. Observations in cols. 1–3 are at the worker-day level. Observations in col. 4 are at the spell level (more than one spell is possible for a given day). Column 1 includes all possible worker-days. Column 2 excludes worker-days from week *K* if the worker's last day of employment during the season falls in any week prior to week *K*. Column 3 reports daily hours worked conditional on working that day. Column 4 reports output per hour measured in dollars per hour.

Table A4
Results Using Different Specifications in Accounting for the Baseline Productivity of Workers

	Dependent Variable: log(Output per Hour)					
	Percentile		Quintile		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × low fixed effects		.046***		.039**		.048***
		(.016)		(.016)		(.014)
Post × quintile 1	.045*		.037		.061***	
	(.024)		(.024)		(.021)	
Post × quintile 2	.052***		.048***		.044***	
	(.012)		(.012)		(.010)	
Baseline productivity	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,471	18,471	18,471	18,471	18,471	18,471
R^2	.565	.564	.543	.543	.559	.558

NOTE.—This table employs different specifications to account for the baseline productivity of workers. Columns 1 and 2 use the same specification as in table 2 and include dummies for each percentile of the preestimated worker effects. Columns 3 and 4 include dummies for each quintile of the worker effects. Columns 5 and 6 include the preestimated worker effects in levels. Based on transactions during weeks 6–12. *Post* = 1 if week 9 or later. All regressions include day fixed effects, a cubic polynomial of worker experience, variety-field fixed effects, a cubic polynomial of variety-field life cycle, and supervisor fixed effects. Robust standard errors clustered by day are in parentheses.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

References

Aaronson, Daniel. 2001. Price pass-through and the minimum wage. *Review of Economics and Statistics* 83, no. 1:158–69.

Aaronson, Daniel, Eric French, and James MacDonald. 2008. The minimum wage, restaurant prices, and labor market structure. *Journal of Human Resources* 43, no. 3:688–720.

Akerlof, George A. 1982. Labor contracts as partial gift exchange. *Quarterly Journal of Economics* 97, no. 4:543–69.

Ashenfelter, Orley, and Robert S. Smith. 1979. Compliance with the minimum wage law. *Journal of Political Economy* 87, no. 2:333–50.

Bell, Brian, and Stephen Machin. 2018. Minimum wages and firm value. *Journal of Labor Economics* 36, no. 1:159–95.

Breza, Emily, Supreet Kaur, and Yogita Shamdasani. 2017. The morale effects of pay inequality. *Quarterly Journal of Economics* 133, no. 2:611–63.

Brown, Charles. 1999. Minimum wages, employment, and the distribution of income. *Handbook of Labor Economics* 3:2101–63.

Card, David, and Alan B. Krueger. 1994. Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania. *American Economic Review* 84, no. 4:772–93.

———. 1995. *Myth and measurement: The new economics of the minimum wage*. Princeton, NJ: Princeton University Press.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. The effect of minimum wages on low-wage jobs. *Quarterly Journal of Economics* 134, no. 3:1405–54.

Clemens, Jeffrey. 2021. How do firms respond to minimum wage increases? Understanding the relevance of non-employment margins. *Journal of Economic Perspectives* 35, no. 1:51–72.

Clemens, Jeffrey, Lisa B. Kahn, and Jonathan Meer. 2021. Dropouts need not apply? The minimum wage and skill upgrading. *Journal of Labor Economics* 39, no. S1:S107–S149.

Clemens, Jeffrey, and Michael R. Strain. 2020. Understanding "wage theft": Evasion and avoidance responses to minimum wage increases. NBER Working Paper no. w26969, National Bureau of Economic Research, Cambridge, MA.

Coviello, Decio, Erika Deserranno, and Nicola Persico. 2019. Minimum wage and individual worker productivity: Evidence from a large US retailer. Working paper.

Draca, Mirko, Stephen Machin, and John Van Reenen. 2011. Minimum wages and firm profitability. *American Economic Journal: Applied Economics* 3. no. 1:129–51.

Dube, Arindrajit, Laura Giuliano, and Jonathan Leonard. 2019. Fairness and frictions: The impact of unequal raises on quit behavior. *American Economic Review* 109, no. 2:620–63.

Dube, Arindrajit, T. William Lester, and Michael Reich. 2016. Minimum wage shocks, employment flows, and labor market frictions. *Journal of Labor Economics* 34, no. 3:663–704.

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp vom Berge. 2022. Reallocation effects of the minimum wage. *Quarterly Journal of Economics* 137, no. 1:267–328.

Fernández-Val, Iván, and Martin Weidner. 2018. Fixed effect estimation of large-T panel data models. *Annual Review of Economics* 10, no. 1:109–38.

Gittings, R. Kaj, and Ian M. Schmutte. 2016. Getting handcuffs on an octopus: Minimum wages, employment, and turnover. *ILR Review* 69, no. 5:1133–70.

Giuliano, Laura. 2013. Minimum wage effects on employment, substitution, and the teenage labor supply: Evidence from personnel data. *Journal of Labor Economics* 31, no. 1:155–94.

Harasztosi, Péter, and Attila Lindner. 2019. Who pays for the minimum wage? *American Economic Review* 109, no. 8:2693–727.

Holzer, Harry J., Lawrence F. Katz, and Alan B. Krueger. 1991. Job queues and wages. *Quarterly Journal of Economics* 106, no. 3:739–68.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma Van Inwegen, Jacob Vigdor, and Hilary Wething. 2018. Minimum wage increases and individual employment trajectories. NBER Working Paper no. 25182, National Bureau of Economic Research, Cambridge, MA.

Katz, Lawrence F. 1986. Efficiency wage theories: A partial evaluation. *NBER Macroeconomics Annual* 1:235–76.

Kuziemko, Ilyana, Ryan W. Buell, Taly Reich, and Michael I. Norton. 2014. "Last-place aversion": Evidence and redistributive implications. *Quarterly Journal of Economics* 129, no. 1:105–49.

Lazear, Edward P. 1986. Salaries and piece rates. *Journal of Business* 59, no. 3:405–31.

———. 2000. Performance pay and productivity. *American Economic Review* 90, no. 5:1346–61.

Lazear, Edward P., Kathryn L. Shaw, and Christopher Stanton. 2016. Making do with less: Working harder during recessions. *Journal of Labor Economics* 34, no. S1:S333–S360.

Leung, Justin H. 2021. Minimum wage and real wage inequality: Evidence from pass-through to retail prices. *Review of Economics and Statistics* 103, no. 4:754–69.

Machin, Stephen, Alan Manning, and Lupin Rahman. 2003. Where the minimum wage bites hard: Introduction of minimum wages to a low wage sector. *Journal of the European Economic Association* 1, no. 1:154–80.

Mas, Alexandre, and Enrico Moretti. 2009. Peers at work. *American Economic Review* 99, no. 1:112–45.

Mayneris, Florian, Sandra Poncet, and Tao Zhang. 2018. Improving or disappearing: Firm-level adjustments to minimum wages in China. *Journal of Development Economics* 135:20–42.

Neumark, David, J. M. Ian Salas, and William Wascher. 2014. Revisiting the minimum wage-employment debate: Throwing out the baby with the bathwater? *ILR Review* 67, suppl. 3:608–48.

Obenauer, Marie Louise, and Bertha Marie von der Nienburg. 1915. Effect of minimum-wage determinations in Oregon. *Bulletin of the US Bureau of Labor Statistics*, July 1915, no. 176.

Portugal, Pedro, and Ana Rute Cardoso. 2006. Disentangling the minimum wage puzzle: An analysis of worker accessions and separations. *Journal of the European Economic Association* 4, no. 5:988–1013.

Rebitzer, James B. 1987. Unemployment, long-term employment relations, and productivity growth. *Review of Economics and Statistics* 69, no. 4:627–35.

Rebitzer, James B., and Lowell J. Taylor. 1995. The consequences of minimum wage laws: Some new theoretical ideas. *Journal of Public Economics* 56, no. 2:245–55.

Shapiro, Carl, and Joseph E. Stiglitz. 1984. Equilibrium unemployment as a worker discipline device. *American Economic Review* 74, no. 3:433–44.

Stigler, George J. 1946. The economics of minimum wage legislation. *American Economic Review* 36, no. 3:358–65.