Demand fluctuations, precarious incomes, and employee turnover*

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Abstract

Millions of employees face work schedules and wages that change frequently as firms try to match labor to demand. Here, we use personnel records from the retail industry to examine whether workers' income precariousness impacts firm performance. We find that lower income levels and higher income volatility increase employee turnover, without improving revenues. These effects are not driven by employee ability. Using exogenous changes in customer traffic as instruments for employees' income level and volatility, we show that these results have a causal nature. Hence, firm efforts to optimally deploy labor need to account for employees' response to precarious wages.

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1 Introduction

An increasing number of households face precarious labor incomes due to changes in the demand faced by firms. Traditionally, the literature in economics and finance has suggested that firms offer insurance to their workers against temporary fluctuations in demand, through wages that do not depend on these fluctuations. Baily (1974) and Azariadis (1975) are some of the early papers that provide theoretical motivation that firms insure workers against risk by providing them with a stable income. Empirical evidence on full-time and long-tenure workers in Europe and the U.S. indicates that for these types of workers employers indeed provide wages that do not depend on temporary firm shocks (Guiso et al. (2005), Juhn et al. (2017)).[1]

However, many workers nowadays are employed in positions that are neither full-time, nor long-tenured. This is particularly true in the services sector, including the retail industry, where most workers are part-timers and are paid by the hour. Firms in this industry also face demand that varies significantly over time, and as a result their employees face large variation in terms of when they must be at work, how many hours they work, and thus how much income they will realize. Here, we investigate empirically whether the precarious incomes faced by employees have effects on firm outcomes.

Using rich data linking personnel records and firm performance from a large employer in the retail industry, we find that income levels and income volatility are important for employee retention. Lower or more volatile incomes lead to higher employee turnover. Importantly, we document that these effects are not driven by employee ability, as our data allow the estimation of employee productivity fixed effects. Based on instrumental variable analysis, we show that the relationships between income level and volatility, and employee turnover are causal, rather than capturing omitted employee time-varying characteristics.

[1] Guiso et al. (2005) test for wage insurance using matched employer-employee data from Italy and find that firms insure full-time workers against temporary shocks but not permanent shocks to firm output. Juhn et al. (2017) document using US data that firm revenue shocks have a small impact on the earnings of employees with multi-year tenure in the firm.

We instrument for both the income level and income volatility for an employee in a given time period by using customer traffic levels and variability of customer traffic, for the specific part of the day (morning vs. afternoon) that ex-ante seem to be preferred by the employee, based on their schedule prior to the window when we measure their income precariousness. We also find that the increase in turnover driven by low income and high income volatility is not accompanied by an increase in revenues, which might make up for the increase in turnover costs for the firm. To the contrary, low income levels correspond to a decline in temporary worker productivity as inferred from the sales the employees generate. Thus, our findings suggest that firms' attempts to optimize their labor force schedule to account for temporary fluctuations in demand may backfire because they can lead to large increases in turnover, which is costly for firms.

Our data were obtained through collaboration with a large U.S.-based retailer with approximately 100 stores across 22 states. The firm provided us with hourly sales information for each department in each of their stores over a 46-week period during 2012-2013, customer traffic information for each store and each hour, as well as with the complete schedule of all their employees during this time period. Therefore, in this setting, we can measure for how long an employee stays with the firm and when they separate from the firm. Moreover, we can quantify how many hours they work and how much this changes over time, and thus we can obtain measures of income levels and income volatility for each person. Notably in our setting, the vast majority of employees are paid a wage determined solely by the number of hours worked times a flat hourly amount of approximately \$10. Importantly, we have clean measures of customer demand, since we know customer traffic in each store in any given hour. We can thus parse out employee productivity measures from the data on hourly sales in each department, as we know where each employee is assigned to work at any point in time, the customer demand in the store at that time, and the revenues realized by the department where the employee is assigned during that hour.

The retail setting we study here is not unusual, in terms of the degree to which workers face precarious incomes. Gottschalk and Moffit (2009) document significant levels of instability of earnings in the US labor force, and argue that this is particularly troubling for low-wage and unskilled workers, where liquidity constraints are likely to be present and can increase the households' risk of financial difficulties. Dynan et al. (2012) present further evidence that U.S. households' labor earnings have become more volatile over time, in part due to volatility in hours worked. Comin et al. (2009) document that rising turbulence in sales among U.S. firms over the past three decades has raised their workers' wage volatility, across all industry sectors. Unsurprisingly, employees prefer to avoid precarious wages. According to a report on households' well-being issued by the U.S. Federal Reserve in 2015, 49% of workers, especially part-time ones, would like to work more hours.[2] Employees also dislike having volatile schedules, especially when the hours they need to work are determined with short notice by their managers. For example, Mas and Pallais (2016) find that the average worker is willing to give up 20% of their wages to avoid having their schedule set by an employer on a week's notice.

The precarious nature of employees' schedules and income is an emerging topic of debate in academic and policy circles (Enchautegui (2013), Henly and Lambert (2014)), as well as among the public at large (Morduch and Schneider (2017)). Local, state and federal governments are contemplating legislation that would add protection to employees faced with unstable schedules and pay that is promised but not delivered (Andersen et al. (2015)). For example, such legislation was enforced by San Francisco in 2015, and was proposed in the state of Minnesota also in 2015. The U.S. Congress has considered the "Flexibility for Working Families Act" and the "Schedules that Work Act", which were introduced in 2013, and 2014, respectively. Importantly for our study, workers in the retail sector are particularly exposed to precarious incomes, as many firms in this sector match labor supply with customer demand by using computerized scheduling tools that assign labor at 15-minute intervals.

Our paper contributes to the literature on the role of management practices on firm

[2] The report is available at https://www.federalreserve.gov/econresdata/2014-report-economic-well-being-us-households-201505.pdf.

performance, an area in economics and finance where data limitations have slowed progress (Syverson (2011)). The literature has documented that characteristics of managers at various levels in organizations drive firm outcomes (e.g., Bertrand and Schoar (2003), Malmendier and Tate (2005), Gibbons and Henderson (2012)). Firm-wide managerial practices such as use of incentive pay or skills training, whose adoption depends on the competitive environment faced by the firm, also can help explain variation across firms in terms of profitability or growth (Bloom and Van Reenen (2007)). Better management practices are positively related to the quality of employees' work-life balance (Bloom and Van Reenen (2006)). To the extent that some management practices cause better employee morale, that can lead to an increase in the quality of the firm's output (Mas (2008)). Prior work has also analyzed differences in policies across firms regarding wage insurance. Specifically, firms have been shown to vary in their supply of insurance to workers, and workers to vary in their demand for such insurance, as found by work on the behavior of family firms (Sraer and Thesmar (2007), Ellul et al. (2016)), or on the effects of unemployment insurance benefits on firm financing decisions (Agrawal and Matsa (2013)). Bernstein et al. (2017) find that employees facing more economic insecurity due to a negative shock to their housing wealth pursue less risky and less innovative projects. We add to this literature by providing novel empirical evidence on the effects of the precarious nature of workers' incomes on firm outcomes, namely employee turnover and revenues.

2 Data and Empirical Strategy

2.1 Research Setting

Our data are obtained from a large U.S.-based retailer with annual revenues of about $500 million during the time we study here, which is July 2012 to June 2013. At the time, the company was a pure brick-and-mortar retailer, with close to 100 stores in 22 states, and approximately 5 million square feet of selling space. As a discount department store, this retailer sells primarily women's, men's, and children's apparel, along with accessories, fragrances, and home furnishing goods. Its target customers are 35- to 54-year-old working mothers.

The firm employs over 8,000 year-round employees in its stores. Full-time (FT) employees work on average 37 hours a week whereas part-time (PT) employees work on average 18 hours a week. Store managers are salaried employees, while all other employees (PT and FT) are paid an hourly rate, which is fixed and independent of any performance measure, multiplied by the number of hours worked. The work schedule for PT and FT employees is determined by store managers and announced a week in advance, whereas store managers set their own schedule.

Importantly for our analysis, the retailer has hourly data regarding customer traffic in and out of each store, obtained by video technology through RetailNext, which is an analytics provider to retailers, shopping centers, and manufacturers. It collects traffic information from video cameras in retail stores to codify customer arrival patterns as well as customer pathways in the stores, to assess demand.

2.2 Data

We obtained POS scanner data that provide us with the dollar amount of sales in each department of each store, every hour during every day from July 2012 to June 2013. The six departments found in the retailer's store are men's apparel, women's apparel, junior's and seasonal apparel, children's apparel, accessories and fragrances, and home decor and home essentials. The average hourly amount of sales in a department of a store in the sample is \$285, with a standard deviation of \$343. The median value for hourly department sales is \$185.

Moreover, we obtained detailed work history records for 8,479 employees working at this retailer at any point during our sample period. For each of these employees, we know the number of hours they were scheduled to work each day (if any), as well as the start time and end time for each working day, the department the employee is assigned to work each hour, and whether the employee has full time or part time status.[3]

On any given day in a typical store, about half the employees are assigned to departments for which we have POS scanner data regarding hourly sales volume and transactions completed, based on which we will be able to measure workers' fixed and transitory levels of productivity. The rest of the workers are assigned to support departments, such as cashiering, guest service desks, fitting rooms, stock rooms, for which we do not have separate productivity-related measures. Of the 8,479 employees in the sample, 86.18% are classified as part-time employees, with the rest being full-time employees and salaried store managers.

Finally, we have access to detailed customer traffic data, which provide an accurate measure of the demand faced at any point in time by each of the retailer's establishments. The retailer installed video cameras at store entrances to count the number of visitors. From about 70 million time-stamp records for individuals who pass the store entrance during the sample period, we obtained aggregated time-stamp data at the hourly level. Traffic cameras used in this study were able to differentiate between incoming and outgoing traffic by tracking the direction of customers movements. Each camera has two sensors, and if a customer goes through both, she is counted. The camera captures the direction of movement by determining the order in which a customers motion is detected by the two sensors. If a customer goes through the outside sensor (i.e., farther from the entrance) and then the inside sensor (i.e., closer to the entrance), in that order, then she is categorized as an "out-count", otherwise as an "in-count". RetailNext also audited the data regularly by manually counting the number of visitors and comparing that count to the numbers from the automated sensors, ensuring that the accuracy was at least 95%. Our measure of hourly traffic, or customer demand, faced by the store in any given hour is the average of the in- and out-counts for the store during that window of time.

[3]During the 12 months for which we have data, we do not observe employees experiencing changes in their status, from part-time to full-time or viceversa.

3 Results

3.1 Main results

Our main findings are illustrated in the simple univariate analyses presented in Figures 1 and 2. Figure 1 documents that the frequency of employees leaving the firm is highest for those workers have have received the least amount of work hours, and thus income, over the prior four weeks, for the category of workers that constitute the vast majority of the firm's employee, namely, those with a part-time contract. We split workers each week based on the tertile of the income they have obtained (i.e., the number of hours worked) in the prior four weeks. The tertile assignment is done by week, and by category of worker, that is, separately for full-timers and part-timers. Among part-time workers, the probability of an employee leaving the firm after a given week is 3%, 2.6% and 2.1%, respectively, for workers in the lowest, the middle and the highest income tertile. These estimates are significantly different from each other at $p < 0.01$. Among full-time workers, however, income levels and the turnover probability do not relate in a linear manner.

Figure 2 shows that the frequency of employees leaving the firm is the highest for those workers who have have experienced the highest volatility in the number of weekly work hours, and thus the highest income volatility, over the prior four weeks, and this effect is also driven by part-time workers. Among these, the probability of employee turnover is 2%, 2.5% and 3.1% among workers in the lowest, middle, and highest income volatility tertiles, and these difference are significant at $p < 0.01$. As in the case of income levels, we do not see a linear relationship between income volatility and the turnover probability for full-time workers.

In Table 1 we estimate probit models where the dependent variable $EmployeeDeparture_{it}$ is an indicator equal to one if the current week t is the last week when worker i is still employed with the firm.[4] In line with the results in Figures 1 and 2, we find that higher levels

[4]To determine whether this is the last week when a worker is employed by the firm, we check whether the person is scheduled to work at any later point in time during our sample, as long as we can look ahead

of income and lower levels of income volatility over the prior four weeks reduce significantly the probability of employee turnover. In the first two columns in the table we measure the person's income level and volatility as the average number of hours worked per week over the past four weeks, and respectively, as the standard deviation of the number of weekly hours worked over the prior four weeks. In the specification in the first column of the table we find that an increase in an employee's average weekly income over the prior four weeks of one additional paid hour corresponds to a decline of 0.03% ($p < 0.01$) in the probability that this person will leave the firm after the current week. If the standard deviation of the weekly number of hours worked in the prior four weeks increases by 1, this corresponds to an increase of 0.09% ($p < 0.01$) in the probability that the employee will leave the firm after the current week. Interpreting the economic significance of these marginal coefficients is somewhat cumbersome. In the case of income levels for example, an increase of one hour per week represents around one twentieth or one fortieth, roughly, of a person's weekly income, depending on whether they are a part-time or a full-time worker. To ease the interpretation of the effects we estimate, for the rest of the analysis we will instead assign each person in each week to a tertile in terms of their income levels, and income volatility, depending on how high in the distribution of income, or income volatility, that person is relative to all the workers at the firm that particular week.

Interpreting the economic significance of the marginal coefficients reported in columns three and four of Table 1 is straightforward, since these coefficients represent changes in the percentage chance of there being an employee departure, given a move from one tertile to the next in terms of the person's income level (column 3) and income volatility (column 4). We find that changing the income level from the lowest to the medium tertile leads to a 0.37% ($p < 0.01$) drop in the probability that the employee will leave the firm after the current week, and a change from the lowest to the highest income tertile leads to a drop of

at least four weeks. Therefore, for employees observed during the last four weeks of the dataset (June 2013) we can not determine whether a particular week in that span is their last week at work in this firm, and hence those observations are not used in the analysis of the determinants of employee turnover.

0.66% ($p < 0.01$) in this probability. An increase in income volatility has the opposite effects: moving from the lowest to the medium volatility tertile increases the turnover probability by 0.4%, and moving from the lowest to the highest volatility tertile increases this probability by 0.87%. Both effects are significant at $p < 0.01$.

In column 5 of the table we document that income levels and income volatility together help predict employee departures, and the effect sizes are similar to those documented separately in columns 3 and 4.

In column 6 of the table we include a control for whether the person is a full-time or a part-time employee. In line with the patterns shown in Figures 1 and 2, full-time workers have a lower probability of turnover relative to part-time worker, by about 1.53%. We also include store fixed effects, to capture across-store differences in employee turnover rates. Finally, in column 7 we include fixed effects for each of the calendar weeks in our sample period, as the retail industry is a setting with significant seasonality in terms of both employment levels, customer demand, and likely, hours of work offered to employees. As expected, these calendar week fixed effects are important drivers of employee departures, given the increase in the model explanatory power from column 6 to column 7. Importantly, while store and calendar week fixed effects certainly drive employee turnover decisions, the results in Table 1 show that our main findings regarding the effect of workers' income levels and income volatility on the probability of departures are not affected by including these controls into the model. In other words, independent of the time of the year, and of the store location, it is the case that employees with the lowest income and the highest income volatility, hence those with precarious incomes, are the people most likely to leave the firm.

3.2 Can employee productivity explain our main results?

It is possible that the connection we find between precarious incomes and employee turnover is simply driven by employee ability or productivity. Specifically, workers who are the least productive might receive the fewest work hours and have the most volatile schedules week to week. At the same time, these low productivity workers might be the most likely to be fired, or to leave on their own to find an employment situation that is a better match.

We can investigate this alternative explanation using our data, given the rich information we have about exactly which department in the store a person works in at any given hour, and the exact volume of sales and customer transactions that occur in that department and hour. Moreover, we have a precise measure of customer traffic in the store that hour, which therefore allows us to measure customer demand at that point in time. Hence, in a procedure similar to that used in Mas and Moretti (2009) and Lazear et al. (2015), we can obtain estimates as to how much on average, per hour, an employee contributes to the department sales, after controlling for customer traffic, date fixed effects, store-department fixed effects, and fixed effects for the day of the week interacted with the hour in the day.

Our data therefore allows us to infer the productivity of each worker, as a person fixed effect, for all employees who during the sample period are assigned to work in store departments for which there exists sales information, that is, for 4634 individuals. For those workers who always are assigned to non-POS departments, such as fitting rooms or stock rooms, we do not have measures of productivity or ability.

We obtain worker fixed effects in productivity by estimating the following regression model, using hourly-level data on sales in each department in each of the stores of the retailer during the 12 months of our sample, and data regarding where each employee i was assigned to work at that specific point in time:

$$\begin{aligned} Sales_{sdth} = \sum_{i=1} \Theta_i \mathbb{1}_{isdth} + \beta_0 Traffic_{sth} + \beta_{\mathbf{1}} \mathbf{Date} + \beta_{\mathbf{2}} \mathbf{Store\ x\ Department} \\ + \beta_{\mathbf{3}} \mathbf{DayofWeek\ x\ Hour} + \varepsilon_{sdth} \end{aligned} \tag{1}$$

where i refers to the worker, s indexes the store, d refers to the department (e.g., women's apparel), t refers to the calendar date, and h refers to the hour when the sales are measured.

The indicator $\mathbb{1}_{isdth}$ is equal to 1 if employee i was assigned to work in store s in department d on date t during hour h. The worker fixed effect for work i is measured by parameter estimate Θ_i. Typically, either one or two workers are present in each department at any given hour, but during busy times this number can be higher. $Traffic_{ish}$ captures the number of customers who are in store s during hour h of date t. **Date** is a vector of indicators for each calendar date in our sample, **Store x Department** is a vector of indicators for all combinations of stores and departments, and **DayofWeek x Hour** is a vector of indicators for all combinations of day of the week and hour in the day. Lastly, ε_{sdth} is the error term.

This regression model allows for hourly sales in a department to depend on the calendar day, given the seasonality in sales faced by retailers. Moreover, sales are also allowed to differ across departments of the same type (e.g., women's apparel) which are located in different stores, for example due to differences in customer disposable income in the areas where the stores are located. The model also allows for within-week and within-day of the week variation in sales. For example, afternoon hours on Tuesdays may be characterized by lower sales than the corresponding afternoon hours on Saturdays, but by higher sales than morning hours on Tuesdays, due to differences in the clientele present in the store at those different times, in terms of spending capacity per person. Importantly, in the model we also control for the actual customer traffic in the store at that point in time, to account for the demand faced by the store and thus by its employees during that hour. Clearly, there is a large correlation between customer traffic and sales at a point in time, and we need to estimate the workers' contribution to sales after accounting for traffic, since employees do not control the number of customers who enter the store.

From this model we obtain worker productivity fixed effects for 4634 individuals. For each person, their productivity fixed effect indicates how much higher or lower hourly department sales are if the person is working there, controlling for customer demand, seasonality in sales across calendar days, or within a day, and for any fixed effects in sales driven by the type of department or by the identity of the store.

Figure 3 presents the distribution of the estimated worker fixed effects in productivity. The distribution is relatively narrow, with 50% of the workers fixed effects being between -$19 per hour to $63 per hour, but outliers in each direction do exist. The figure shows that there are differences across workers in their ability, and thus, it is important to check whether these differences are the omitted factor the drives the relationship between precariousness of a worker's income, and their departure probability.

We observe that the probability of employee departure is in fact related to worker productivity, but in a non-linear fashion, as can be seen in Figure 4. For either part-time or full-time workers we find that those with the lowest productivity and those with the highest productivity are the most likely to leave in any given week. The differences are economically and statistically significant. Among part-time workers, the probability of turnover in any given week is 2.63% for individuals in the highest ability tertile and 2.42% for those in the lowest ability tertile, significantly higher ($p < 0.01$) than the probability of turnover among people in the middle ability tertile, which is 1.51%. Among full-time workers, those in the middle ability tertile have a probability of leaving the firm each week of 0.54%, which is significantly lower ($p < 0.05$) than the probability of turnover of employees in the lowest or highest ability tertile, namely, 0.89% and 0.84%, respectively. The same pattern would hold if instead of using productivity tertiles we use quintiles, for instance. That is, employees most likely to leave the firm are those with the lowest and the highest estimated productivity. It is possible that low ability workers are let go by the firm, and high ability workers leave due to better employment options elsewhere, but our data do not allow us to track employees as they switch firms.

We then re-estimate our employee turnover model including worker productivity as a control variable. Given the non-linear relationship we documented between worker ability and turnover, we include indicators for whether the employee's productivity is low, medium or high, or it is not measured (for those workers without sales information). The results are shown in Table 2 and are in line with those documented in Table 1, in terms of effect size and statistical significance. People in higher income tertiles have a lower probability of leaving the firm after the current week. This drop is of 0.4% ($p < 0.01$) when income changes from the lowest to the medium tertile, and of 0.76% ($p < 0.01$) when it changes from the lowest to the highest tertile. When income volatility increases from the lowest to the medium tertile, the probability of employee turnover increases by 0.39% ($p < 0.01$), and when it increases from the lowest to the highest tertile, the corresponding increase in the chance of the employee leaving is 0.77% ($p < 0.01$).

The regression model in Table 2 also shows that, relative to workers for whom we could not calculate an ability measure, as they never worked in a department that generates sales, the probability of turnover in any given week is lower by 0.58%, 1.08%, and 0.41%, respectively, for workers in the low, middle and high productivity tertile. All effects are significant at $p < 0.01$. These results imply that among those employees whose ability we can estimate, people most likely to leave the firm are the lowest and highest productivity workers, rather than those with medium levels of productivity fixed effects, in line with the pattern documented in Figure 4.

3.3 Are our main results indicative of a causal mechanism?

The results in Tables 1 and 2 show that the workers' income level and volatility are related to their likelihood of leaving the firm. Is is important to understand whether these relationships are causal, in the sense that workers subjected to schedules that lead to low and volatile incomes, due to reasons unrelated to the workers themselves, then decide to separate from the firm. An alternative hypothesis is that some workers have low or volatile incomes because they face certain issues in the background, either related to their personal life, or perhaps to a second job, and because of these issues they leave the firm. Here we have a natural way to test whether exogenous changes in schedules and thus in income patterns drive employee turnover, rather than endogenous factors, ommitted in the analysis.

In the retail setting, expectations of customer demand are important drivers of the number of man-hours scheduled by store managers for any window of time. In other words, expected customer traffic, which is exogenous to the personal situation of store employees, is a critical variable that determines how workers are scheduled. The regression models in Table 3 provides clear evidence for this. The dependent variable in each of the models estimated there is the number of employees scheduled to work in each store, in each day in our sample, during each hour when the store is open. The independent variables of interest are proxies for store managers' expectations regarding customer demand during that specific hour. Workers' schedules at this firm are created a week in advance. The managers, in part helped by the scheduling software used by this retailer, have quite accurate expectations for the number of customers who will be in the store in a given hour in the future, and for the dollar amount of sales to be realized that hour. Our first measure of these expectations, used in the first three specifications, is the actual traffic observed that hour. The second measure of customer demand expectations is the value of sales forecasted for that hour using sales data for the same hour and same store in the two weeks prior to the time when the workers are scheduled. Either measure of customer demand expectations is a very strong and positive predictor of the number of workers assigned to the store in that specific hour.

Without any other control variables, we find that customer traffic or forecasted sales explain 30% of variation in the number of workers assigned to be in the store in any given hour during our sample period. Adding store fixed effects, and calendar week fixed effects, each improves the R^2 of the model by 10%. Hence, the number of employees scheduled to work during a specific day and hour can be predicted well using time and location indicators, but the strongest predictor of schedules is customer traffic, or expectations of demand.

Now that we have evidence the expected traffic drives worker schedules, we can proceed to the instrumental variables estimation of the effects of worker income level and income volatility on the likelihood of employee turnover in a given week. In our setting we have two endogenous variables, hence we need at least two instruments. Here we use three instruments: the mean weekly store traffic over the prior four weeks (i.e., weeks $t-4$ to $t-1$), during hours that are preferred by the employee; the standard deviation of the weekly store traffic over the prior four weeks, during hours that are preferred by the employee; and an indicator for whether the employee's preferred work hours are in the morning or in the afternoon. This is based on the schedule observed for this employee over weeks $t-6$ to $t-5$. If during those two weeks the employee works more days when their shift starts before 12pm, compared to days when their shift starts after 12pm, then we infer that over weeks $t-4$ to $t-1$ the employee prefers morning shifts. Otherwise, they prefer afternoon shifts. We attempt to capture employee's preference towards morning or afternoon hours because this will induce variation across employees in a store in a given week with respect to how much traffic patterns will impact their work schedules. For example, if morning traffic is volatile from one week to the next, but afternoon traffic is not, then the workers whose schedules and thus incomes will be more volatile across the two weeks will be those who normally work morning shifts.

In Table 4 we present the first stage results of our instrumental variables estimation. As expected, the three instruments together with the other control variables (worker full-time vs. part-time status, store fixed effects and week fixed effects) are significant determinants of the income level and income volatility of a worker in a given week. In this table we use tertiles to measure these two quantities, to be consistent with the earlier part of the analysis, but the results will be similar if instead we used continuous measures of income level and volatility. We conduct a test for weak instruments based on the Cragg-Donald eigenvalue statistic, as in Waldinger (2010). The value we obtain for this statistic, as shown in Table 4 is 73.30, which is well above the critical value for our setting. Hence, weak instruments are not likely to be a concern.

The OLS and IV estimates of the effect of income precariousness on the probability of an employee's turnover in any given week are shown in Table 5. The direction of the effects is similar across the OLS and IV specifications, but the IV coefficients are larger in magnitude, indicating that endogeneity is indeed present in the OLS specification, which is formally confirmed by Durbin and Wu-Hausman tests. The IV estimates indicate that the probability of an employee leaving the firm is 0.82% lower if their income is one tertile higher (e.g., it moves from the lowest to the medium tertile), and 5.82% higher if the volatility of their income increases by one tertile.

3.4 Are there worker productivity gains that can offset employee turnover costs?

The results so far show that schedules that offer low and volatile incomes to workers increase employee turnover. It is natural to ask whether the firm benefits somehow from these schedules, in terms of gains in the productivity of workers. That is, it might be the case that lower employee incomes or more volatile ones lead to higher employee productivity, which in our setting would translate into higher sales. The evidence in Table 6 indicates that this is not the case.

In the analysis in Table 6 we examine whether sales are predicted by the level and variability of income of the people working at that point in time. The dependent variable in the regression models in the table measures sales in each department and store on each day in the sample, during every hour when the store is open. We restrict the sample to hourly sales data from departments that at that point in time had only one worker assigned to them, as in these situations the productivity (i.e., revenues) of the department at that point in time can be attributed to a specific worker, rather than to a team. This subsample represents approximately 80% of the department-hour observations. The independent variables of interest are measures of the employees average and standard deviation of the weekly (i.e., 7-day) income, over the prior four weeks (i.e., the prior 28 days relative to day d). In the specifications in the table, these measures of income level and income volatility are expressed as continuous variables, or as tertile indicators, i.e., high, medium or low in the distribution of these variable for workers actively employed with the firm at that point in time. Similar to our earlier analysis where we estimated worker fixed effects based on the regression model in (1), we include as control variables fixed effects for the calendar date, interactions of store and department indicators, interactions of indicators for day of the week and hour, and worker fixed effects. We also control for customer traffic in the store during the hour when the department sales are measured, to account for demand.

We find that the average weekly income level over the prior four weeks (i.e., the 28 days prior to the day when sales are measured) of the employee assigned to a department at a particular hour is positively and significantly correlated with the department sales that hour, while income variability has no significant effect on sales. Specifically, if the employee's average income per week in the prior four weeks was higher by the equivalent of one additional hour of pay, revenues per hour in the department they are assigned to currently increase by \$0.51 ($p < 0.01$). If instead we examine the effect of moving an employee's prior weekly income level from the lowest to the highest tertile, we find that this corresponds to an increase in hourly department sales of \$6.41 ($p < 0.01$), which is about 4% of the median hourly department sales (\$163) for observations when only one person is assigned to work in a department in a given hour. Since we control for worker fixed effects, these results indicate the effects of employees' income precariousness on the temporary deviation in their productivity from its average. If anything, the results in Table 6 show that lower incomes reduce worker productivity, and thus the firm does not benefit in this regard by adopting scheduling policies that lead to precarious wages.

3.5 Impact on firm profit

The US Bureau of Labor Statistics (BLS) documented that, as of 2016, the quit rate in the retail industry, defined as voluntary separations initiated by employee, was about 3.0% per month, while the quit rate for all of the private industries in the U.S. was 2.3% per month.[5] While the BLS does not breakdown the turnover rate for part-time workers, industry estimates[6] show that it can be much higher than 3.0%. Employee turnover is costly for firms, and can run anywhere from a month's salary to several years' salary per turnover event,

[5] See https://www.bls.gov/news.release/jolts.htm.
[6] See http://www.haygroup.com/us/press/details.aspx?id=33807.

depending on the complexity of the job (Mitchell et al. (2001)). While many retail tasks are not complex, industry estimates of cost of turnover of an employee earning $8 per hour are between $3,500 and $25,000 (Ton and Huckman (2008)). These costs are driven by factors such as advertising for the new position, screening costs of all candidates that typically includes background verification and drug testing, interviewing-related costs such as travel reimbursement, documentation, and time of store managers, and finally on-boarding costs once the candidate has accepted the offer.

Apart from these tangible costs involved in recruiting replacements, there are several hidden costs to employee turnover. Losing an employee may cause disruption, which can affect the productivity of the entire team. The new employees will have lower productivity until they learn how to best perform their tasks. Turnover could result in losing clients with whom employees have built relationships, and lower customer satisfaction (Ton and Huckman (2008)). As many of the new employees are assigned to mentors, it is possible that the productivity of the mentors could decline initially when the new recruits need more attention. For example, many retail organizations lack a formal training program and usually expect the department manager where the new employee is assigned to train them. As these department managers are already responsible for many tasks, the new employees may either end up with less attention or could cause the department manager to divert attention from other tasks that may affect store performance. Also, when employees quit, they burden the remaining workforce with a higher workload, which could lead to lower quality of work and lower employee morale. At the extreme, this might prompt more employees to quit, creating a vicious cycle in the organization.

We can do a back of the envelope calculation to examine the economic significance of the increase in employee turnover that stems from an increase in income precariousness for a firm such as that providing the data for this study. This retailer has about 45 part-time employees per store. The average turnover rate for workers with the least precarious incomes (i.e., those in the highest tertile of income level or in the lowest tertile of income volatility) is 2% per week or about 104% per year, and the turnover rate for those with the most precarious incomes (i.e., those in the lowest tertile of income level or in the highest tertile of income volatility) is 3% per week or about 156% per year. This implies that turnover for a store increases from 48 (i.e., 45 x 104%) per year to 70 (i.e., 45 x 156%) per year if workers' schedules are shifted to the most precarious category, and thus such a store will need to recruit 22 more part-timers. Assuming the cost of turnover per person to be $3500, which is the lowest amount imputed by Ton and Huckman (2008), this will lead to an increase of $77,000 in labor costs, which represents more than 20% of the total payroll cost for the average store in this chain. Hence, changes in employee turnover related to worker scheduling practices will likely have a significant impact on the profit margin of firms similar to that in our study.

4 Caveats and limitations

An important concern regarding our findings is that they may have limited external validity. Given that we use data from a firm representative of the retail industry as a whole, we expect that our results generalize to most firms in this sector. However, it is difficult to assess whether the effects of income precariousness on turnover, and worker productivity, that we document here would be more or less pronounced in firms in other industries.

That being said, our empirical approach provides the benefit of very detailed data on control variables, dependent and independent variables of interest, which are difficult to obtain in studies that examine a large cross-section of firms to analyze the connections between firm managerial practices and outcomes. Thus, we believe that these rich data, used in what Gibbons and Henderson (2012) referred to as "focused-sample work", can provide important novel insights regarding the inner workings of firms.

Another issue is that we do not have direct measures of the firm's profits, but rather, we only know its revenues at any point in time. Our results show that low incomes and high income volatility lead to more employee turnover, without a gain in employees' productivity, and based on these findings we infer that the firm's profitability is impacted. We make this inference based on prior work that shows that turnover costs are substantial contributors to the overall performance of a firm. For example, Boushey and Glynn (2012) estimate across a wide range of industries and job functions that it costs businesses about 20% of a workers salary to replace that worker. For jobs paying $50,000 or less, that cost is 19.7% of an employee's annual salary, and for jobs paying $30,000 or less the turnover cost is 16.1%. Thus, even in our setting, where employees' wages are at the low end of the scale, turnover-related costs are substantial, and thus understanding what drives employee turnover can help us better assess the factors impacting firm profitability.

5 Conclusion

Non-standard work arrangements have become increasingly more prevalent, particularly in the services sector. The retail industry is one of the industries where the traditional idea that firms insure workers against demand fluctuations does not describe the reality of hiring agreements. Specifically, in this setting, worker wages for a vast majority of the firms' employees depend on the demand faces by these firms, which the workers have little or no control over. Because firms try to save on labor costs by matching the right number of workers to expected customer demand, this induces uncertainty in the income of the workers. Here, we investigate whether the precariousness of employees' incomes in turn has effects on firm outcomes.

Using a rich dataset from the retail industry, we examine whether firm outcomes are impacted by managerial policies that regulate the scheduling of employees. In this setting, where employees' incomes are solely driven by the number of hours they work, we document that low income levels and high income volatility are factors that increase the rate of employee turnover in the firm. We show that these results are not driven by employee ability, and that they are causal in nature, using an instrumental variables approach by building on the observation that employees schedules are affected exogenously by changes in customer demand. Moreover, we find that precarious incomes hinder worker productivity, as measured by the revenues generated by employees.

An increasing number of workers are faced with unstable work schedules and as a result, with precarious incomes. Hence it is important for future work to further investigate how firm outcomes are impacted by the characteristics of their labor force and by the managerial practices that govern how labor is deployed.

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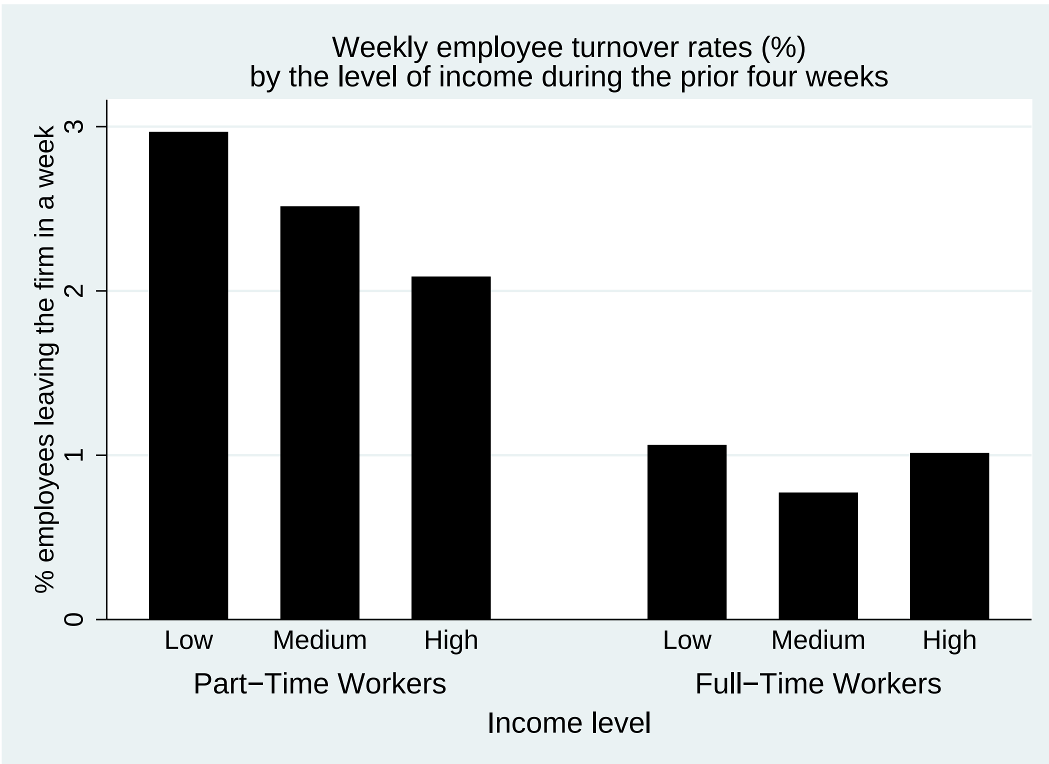

Figure 1: The incidence of employee departures in a given week, as a function of the tertile of the employees' income level over the prior four weeks. Separately for PT and FT workers, each week we assign each of the individuals employed by the retailer at that point in time to a tertile (low, medium, and high) based on the number of weekly hours of work they had been scheduled for over the prior four weeks. Since the hourly pay is fixed and independent of hourly sales or other performance measure, and is also very similar across employees, the number of work hours tracks closely the income received by each person from the employer during this time. Categorizing people in the three tertiles of income levels was done controlling for calendar week effects to account for any seasonal patterns in hours worked.

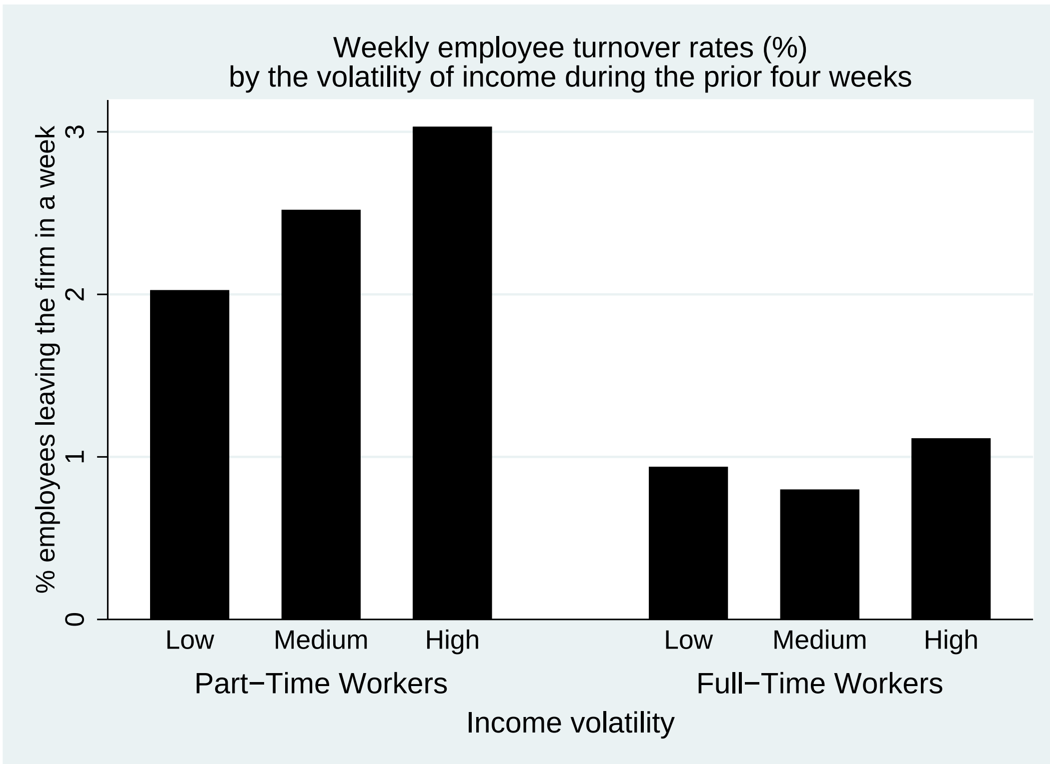

Figure 2: The incidence of employee departures in a given week, as a function of the tertile of the employees' income volatility over the prior four weeks. Separately for PT and FT workers, each week we assign each of the individuals employed by the retailer at that point in time to a tertile (low, medium, and high) based on the standard deviation of the weekly hours of work they had been scheduled for over the prior four weeks. Since the hourly pay is fixed and independent of hourly sales or other performance measure, and is also very similar across employees, the number of work hours tracks closely the income received by each person from the employer during this time. Categorizing people in the three tertiles of income volatility was done controlling for calendar week effects to account for any seasonal patterns in hours worked.

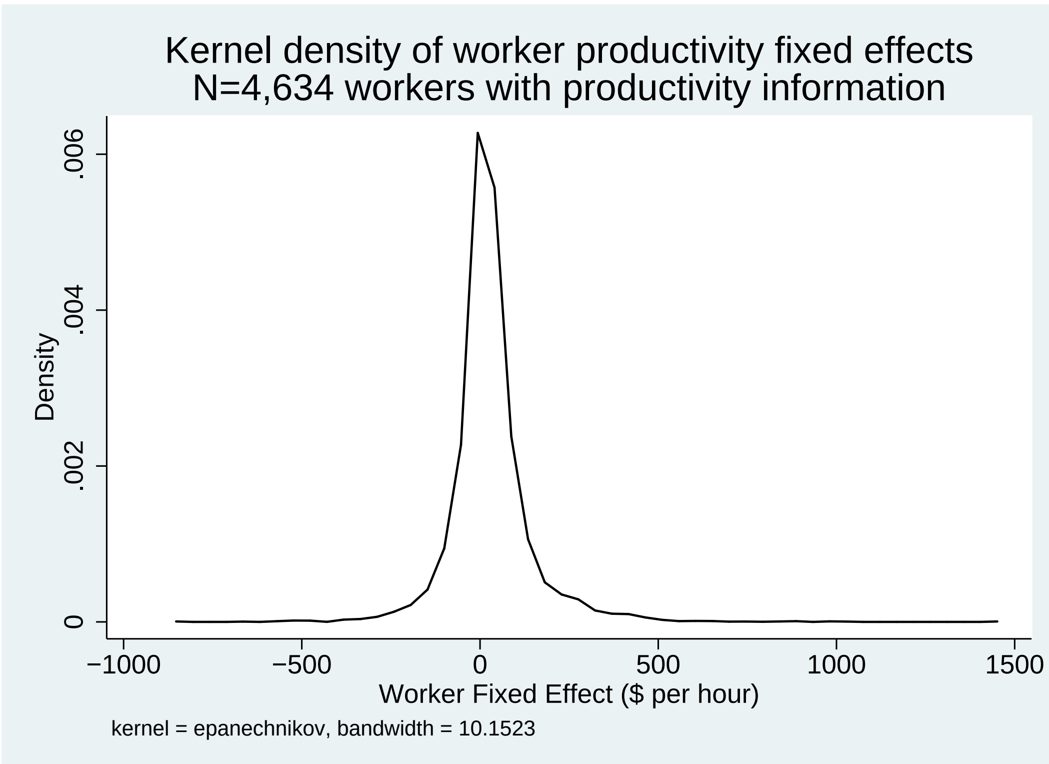

Figure 3: The distribution of worker fixed effects in productivity, estimated using regression model 1 in the main text, for the 4634 employees with assignments to store departments that generate sales (our measure of productivity). For 50% of the workers, these fixed effects are between -$19 per hour and $63 per hour. The average value of hourly department sales in our data is $285, with a standard deviation of $343. The median value for hourly department sales is $185.

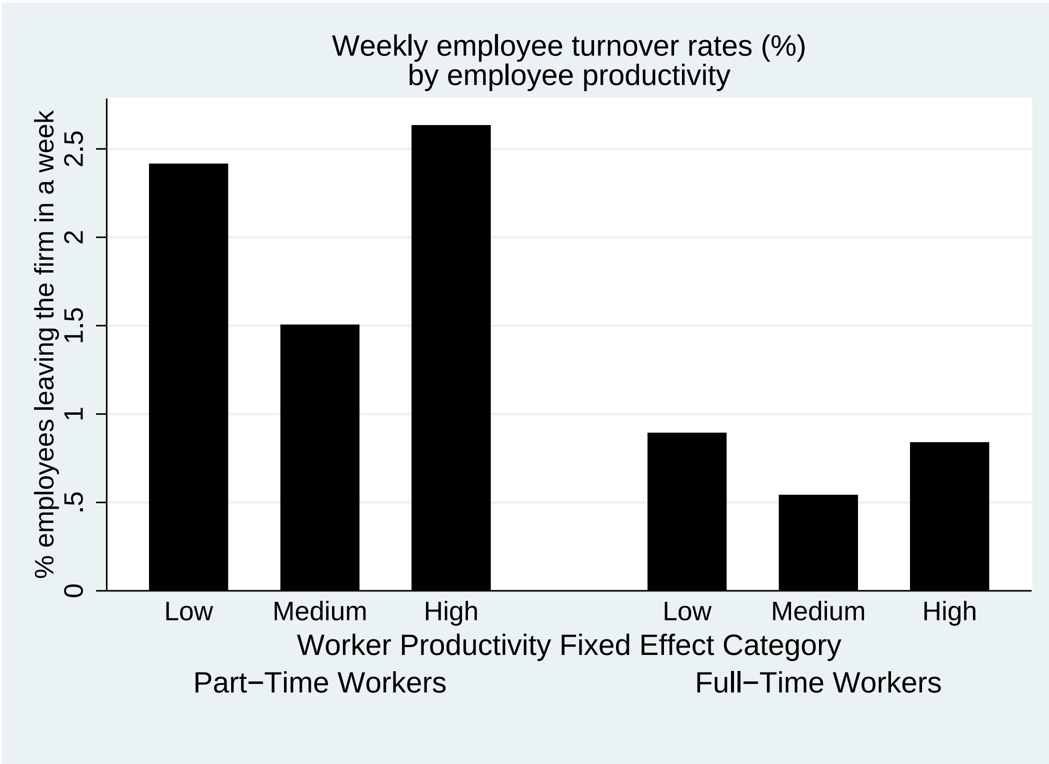

Figure 4: Employee departure probability depends on the employees' productivity. Each worker is assigned to a tercile of productivity (low, medium or high), based on the estimate of their worker fixed effect from regression model 1 in the main text. The figure shows the average weekly turnover frequency among employees with different productivity levels, separately for part-time and full-time workers.

Table 1: Employee departure probability and income precariousness. The dependent variable in the probit models below, $EmployeeDeparture_{it}$, is an indicator equal to 1 if week t is the last week when worker i was employed by the firm. The independent variables of interest are the average weekly income earned by the person over the prior four weeks, and the standard deviation of their weekly income over the same period of time. We measure income as the number of hours scheduled to work over a period of time, since hourly pay is a fixed amount (close to $10). In the models in the first two columns we include continuous measures of these two variables. In the last five columns we replace them with indicators for whether the income, or the income volatility, were in the lowest, middle, or highest tertile of the distribution of these variables among employees who are with the firm in week t. In the last two columns we add as control variables an indicator for whether the person is a full-time or a part-time worker, as well as fixed effects for the store where employee i works, and for calendar week, to account for seasonality in the firms' operations. The table presents marginal effects, expressed in percentage points. Standard errors are robust to heteroskedasticity and are clustered by employee, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

Dependent variable	$EmployeeDeparture_{it}$						
$Income\ level_{t-4,t-1}$	–0.03						
	(–8.73)***						
$Income\ volatility_{t-4,t-1}$		0.09					
		(11.78)***					
$Medium\ income\ level_{t-4,t-1}$			–0.37		–0.44	–0.54	–0.48
			(–4.15)***		(–5.00)***	(–6.55)***	(–6.59)***
$High\ income\ level_{t-4,t-1}$			–0.66		–0.74	–0.93	–0.81
			(–7.22)***		(–8.29)***	(–11.25)***	(–11.09)***
$Medium\ income\ volatility_{t-4,t-1}$				0.40	0.47	0.43	0.36
				(3.87)***	(4.49)***	(4.40)***	(4.07)***
$High\ income\ volatility_{t-4,t-1}$				0.87	0.96	0.86	0.75
				(8.14)***	(8.93)***	(8.37)***	(8.21)***
$FT\ worker_i$						–1.53	–1.23
						(–21.31)***	(–19.15)***
Store FEs	No	No	No	No	No	Yes	Yes
Week FEs	No	No	No	No	No	No	Yes
R^2	0.003	0.004	0.002	0.003	0.005	0.027	0.086
Observations	144391	144391	144391	144391	144391	144391	144391

Table 2: Worker ability, income precariousness and employee turnover. The dependent variable in the probit model below, $EmployeeDeparture_{it}$, is an indicator equal to 1 if week t is the last week when worker i was employed by the firm. The independent variables of interest are indicators for whether the level and volatility of the person's income over the prior four weeks were in the lowest, middle, or highest tertile of the distribution of these variables among employees who are with the firm in week t. Control variables include an indicator for whether the person is a full-time or part-time employee, and indicators for whether their productivity fixed effect is in the lowest, middle, or highest tertile of the estimated worker ability distribution. The omitted category in terms of worker productivity refers to employees for whom a productivity fixed effect could not be estimated, because those individuals were never assigned to work in a department that directly generates sales. The table presents marginal effects, expressed in percentage points. Standard errors are robust to heteroskedasticity and are clustered by employee, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

Dependent variable	$EmployeeDeparture_{it}$
$Medium\ income\ level_{t-4,t-1}$	–0.40
	(–5.59)***
$High\ income\ level_{t-4,t-1}$	–0.76
	(–10.63)***
$Medium\ income\ volatility_{t-4,t-1}$	0.39
	(4.52)***
$High\ income\ volatility_{t-4,t-1}$	0.77
	(8.52)***
$LowProductivity\ FE_i$	–0.58
	(–7.57)***
$MediumProductivity\ FE_i$	–1.08
	(–15.63)***
$HighProductivity\ FE_i$	–0.41
	(–5.21)***
$FT\ worker_i$	–1.20
	(–19.16)***
Store FEs	Yes
Week FEs	Yes
R^2	0.093
Observations	144391

Table 3: Store traffic expectations and employee scheduling. The dependent variable in the table is the number of employees scheduled to work in store s on date t during hour h. The independent variables include measures of expected demand for the store at that time, as well as store and calendar week fixed effects. We use two proxies for the expected demand to be faced by store in a given hour: the actual traffic observed during that hour (first three columns) and the sales forecasted for that store for that exact hour (last three columns). The sales forecast, expressed here in thousands of dollars, is the sum of forecasted sales for each department in the store, estimated using observed sales in the prior two weeks before date t. Standard errors are robust to heteroskedasticity and are clustered by store, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

Dependent variable	*Number of employees in store$_{sth}$*					
$Traffic_{sth}$	0.04	0.04	0.03			
	(8.88)***	(12.00)***	(10.98)***			
$Forecasted$				2.63	2.28	2.16
$Sales_{sth}$				(26.73)***	(32.90)***	(34.19)***
Store FEs	No	Yes	Yes	No	Yes	Yes
Week FEs	No	No	Yes	No	No	Yes
R^2	0.304	0.400	0.502	0.303	0.358	0.502
Observations	328453	328453	328453	328453	328453	328453

Table 4: First stage results for the instrumental variables estimation of the effects of income level and income volatility in the prior four weeks on employees' probability of leaving the firm after the current week t. OLS models are estimated in both columns. We have three instruments for the two endogenous variables (i.e., the employee's income level and volatility in week t). The instruments are the mean weekly traffic in the store the person works in during the prior four weeks ($t-4$ to $t-1$) during hours preferred by the employee, the standard deviation of the weekly traffic in the store the person works in during the prior four weeks ($t-4$ to $t-1$) measured during hours preferred by the employee, and an indicator for which hours the employee prefers – morning hours versus afternoon hours – as indicated by their schedule in weeks $t-5$ to $t-6$. Over those two weeks, which precede the time when we measure the person's income level, volatility and the departure likelihood, we calculate the number of days when the person's shift started before 12pm, which indicate morning shifts, and the number of days when the person's shift started after 12pm, which indicate afternoon shifts. If during weeks $t-5$ to $t-6$ the employee worked more morning shifts than afternoon shifts, the variable $Employee's\ preferred\ hours_{t-6,t-5}$ ($Morning\ vs.\ afternoon\ indicator$) takes the value of 1, otherwise it is 0. Store traffic during each week is measured in thousands of people. Standard errors are robust to heteroskedasticity and are clustered by employee, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

	First stage results	
Dependent variable	$Income\ level\ tertile_{it}$	$Income\ volatility\ tertile_{it}$
$Mean\ weekly\ store\ traffic$ ('000 persons)	0.01	0.02
$during\ employee's\ preferred\ hours_{t-4,t-1}$	(2.54)**	(6.56)**
$Volatility\ of\ weekly\ store\ traffic$ ('000 persons)	0.02	0.02
$during\ employee's\ preferred\ hours_{t-4,t-1}$	(4.02)***	(2.76)***
$Employee's\ preferred\ hours_{t-6,t-5}$	0.5	0.19
($Morning\ vs.\ afternoon\ indicator$)	(18.43)***	(9.50)***
$FT\ worker_i$	-0.24	-0.02
	(-10.78)***	(-1.53)
Store FEs	Yes	Yes
Week FEs	Yes	Yes
R^2	0.096	0.023
Observations	129111	129111
Cragg-Donald eigenvalue statistic	73.30	73.30

Table 5: Instrumental variables estimation of the effects of income level and income volatility in the prior four weeks on employees' probability of leaving the firm after the current week t. Effects are shown in percentage points. The first column presents the results of a linear probability (OLS) model, whereas the second column presents the results of a 2SLS instrumental variable estimation. Standard errors are robust to heteroskedasticity and are clustered by employee, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

Dependent variable	Linear probability model $EmployeeDeparture_{it}$	IV 2SLS model $EmployeeDeparture_{it}$
$Income\ level\ tertile_{t-4,t-1}$	–0.43	–0.82
	(–8.73)***	(–2.15)**
$Income\ volatility\ tertile_{t-4,t-1}$	0.33	5.82
	(7.02)***	(3.56)***
$FT\ worker_i$	–1.17	–1.24
	(–15.41)***	(–11.83)***
Store FEs	Yes	Yes
Week FEs	Yes	Yes
R^2	0.015	.
Observations	129111	129111
Cragg-Donald eigenvalue statistic	73.30	

Table 6: Sales and income precariousness. The dependent variable, $Sales_{sdth}$, represents the sales realized in store s, department d, on date t during hour h. The sample is restricted to hourly sales data from departments that at that point in time had only one worker assigned to them, as in these situations the productivity (i.e., revenues) of the department at that point in time can be attributed to a specific worker, rather than to a team. This subsample represents approximately 80% of the department-hour observations. The independent variables of interest are measures of the employees' average and standard deviation of the weekly (i.e., 7-day) income, over the prior four weeks (i.e., the prior 28 days relative to day d). These measures of income level and income volatility are expressed as continuous variables in column 2, or as tertile indicators (i.e., high, medium or low in the distribution) in column 3. Control variables include customer traffic in the store that hour, fixed effects for the calendar date, interactions of store and department indicators, interactions of indicators for hour in the day and day of the week, as well as worker fixed effects, as in regression model (1) specified in the main text. Standard errors are robust to heteroskedasticity and are clustered by store, and t-statistics are shown in parentheses. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

Dependent Variable	$Sales_{sdth}$	
$Weekly\ income\ level_{prior\ 28\ days}$	0.51	
	(3.62)***	
$Weekly\ income\ volatility_{prior\ 28\ days}$	0.21	
	(1.48)	
$Medium\ weekly\ income\ level_{prior\ 28\ days}$		1.57
		(0.95)
$High\ weekly\ income\ level_{prior\ 28\ days}$		6.41
		(2.75)***
$Medium\ weekly\ income\ volatility_{prior\ 28\ days}$		–0.67
		(–0.43)
$High\ weekly\ income\ volatility_{prior\ 28\ days}$		0.01
		(0.00)
$Traffic_{sdth}$	1.59	1.59
	(6.68)***	(6.67)***
Date FEs	Yes	Yes
Day of the Week X Hour FEs	Yes	Yes
Store X Department FEs	Yes	Yes
Worker FEs	Yes	Yes
R^2	0.623	0.623
Observations	757659	757659