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Volume Flexibility in Services: The Costs and Benefits of Flexible Labor Resources

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Organizations can create volume flexibility—the ability to increase capacity up or down to meet demand for a single service—through the use of flexible labor resources (e.g., part-time and temporary workers, as compared to full-time workers). Although organizations are increasingly using these resources, the relationship between flexible labor resources and financial performance has not been examined empirically in the service setting. We use two years of archival data from 445 stores of a large retailer to study this relationship. We hypothesize and find that increasing the labor mix of temporary or part-time workers shows an inverted U-shaped relationship with sales and profit while temporary labor mix has a U-shaped relationship with expenses. Thus, although flexible labor resources can create volume flexibility for a firm along multiple dimensions, it is possible to have too much of a good thing.

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1. Introduction

The last 40 years have seen significant changes in how jobs are structured. Although nontraditional labor structures have existed for some time, factors such as increased competition, higher uncertainty, and poor macroeconomic conditions have led to a significant rise in the use of alternative or flexible employment approaches such as part-time workers (permanent, but fewer hours compared to full time) and temporary workers (limited length of employment with variable time; Pfeffer and Baron 1988, Kalleberg 2000). Estimates on the prevalence of part-time and temporary workers find that over 70% of U.S. organizations use part-time workers, whereas almost 40% use temporary workers, and that approximately one in five U.S. workers are part-time workers (Houseman 2001, Bureau of Labor Statistics 2013). If anything, this use of alternative labor structures is likely to be increasing as data from the Bureau of Labor Statistics shows that since 2006 the retail and wholesale sector has added more than half a million part-time jobs while cutting over one million full-time positions (with a total of 18.6 million jobs; Greenhouse 2012).

One of the primary justifications for using part-time and temporary positions in service settings is that these labor resources may offer a firm volume flexibility—the ability to increase capacity up or down to meet service demand (Goyal and Netessine 2011). A long line of research in operations management has shown that different types of flexibility are key to many organizations competitive success (e.g., Sethi and Sethi 1990, Suarez et al. 1996, Upton 1997) because flexible operations allow a firm to adjust its capacity to match supply to the realized demand. To date, the literature on flexibility has considered primarily manufacturing contexts, as compared to service settings. It is important to study volume flexibility in service settings because not only is the service sector a large part of the global economy (roughly 63% of the world's gross domestic product (GDP) and nearly 80% of GDP in developed economies such as France, the United States, and the United Kingdom in 2011; Central Intelligence Agency 2012), but there are key differences from the manufacturing context.

These differences arise because in services the customer interacts with a service provider to jointly produce the outcome, a process known as customer coproduction. Coproduction has two important implications for studying operational flexibility. First, given the real-time involvement of the customer in service delivery, it is typically not possible to produce more of a service in advance in anticipation of future demand (Abernathy et al. 1973). Because it is not possible to meet variation in temporal demands for a service through production smoothing, service firms must find ways to adjust the number of workers available to serve customers across the week and the day. The limited existing work on flexibility in services has traditionally focused on product flexibility—the ability to move capacity between different services, depending on demand, as well as the ability to deliver multiple services using the same capacity (Goyal and Netessine 2011), as realized through cross-training (Gans et al. 2003, Aksin et al. 2007). By training workers to complete multiple tasks, it may be possible to reallocate workers across services to match supply with demand. However, not all organizations offer multiple services. Furthermore, although cross-training permits changes on the margins, demand spikes, such as the holiday season in retailing or the agricultural picking season, may exceed the capacity of even a fully cross-trained workforce. Both of these reasons highlight the need for volume flexibility in services.

The second significant difference between services and manufacturing is that flexible labor resources, such as temporary and part-time workers, affect not only the costs of an organization, but also its sales. In a manufacturing setting, different classes of labor may produce output with different productivity, wages, and yields, which will affect the final cost. However, assuming that an organization has quality processes in place to identify defects, customers receive the same output, regardless of the type of labor that produces it. On the other hand, in services, because of the interaction between the service provider and the customer, different labor types may see differential performance with respect to customer conversion, upselling, and overall sales. To address each of these points, we examine the context of retail services, and in so doing we undertake, to the best of our knowledge, the first empirical study of volume flexibility in services. Thus, in this paper we seek to answer the following question: How do flexible labor resources affect financial performance in retail services?

To answer this overall research question, we first examine how increasing the flexible labor resources available at the store level may affect retail store sales. Although flexible labor resources may be individually less productive than their full-time counterparts, they offer potential benefits for sales. First, these workers may have unutilized capacity, which can be tapped when high demand is experienced. For example, a part-time worker who only works 20 hours may be able to increase her hours to 30 hours in a period of high demand. The additional hours that they can provide to a store creates *upside flexibility* that may result in greater sales. Furthermore, even holding the number of hours constant, the availability of flexible labor resources may be related to greater sales. This is because flexible labor resources may offer greater *temporal flexibility*—defined as the ability to adjust resources within a fixed window of time. For example, instead of staffing one full time worker for 39 hours spread across the entire week, two temporary or part-time workers may be staffed for 19½ hours each, and those hours can occur when demand is highest (possibly at the same time). Mani et al. (2012) estimate understaffing during peak hours results in 5% lost sales in their retail setting.

Although flexible labor resources may provide advantages, when used in low numbers, we also explore whether flexible labor resources can be increased too far such that the relationship with sales may turn negative eventually. This potential inverted U-shaped[1] relationship between flexible labor resources and sales may be driven by two factors. First, with a greater percentage of flexible labor resources in a store, the effort necessary for coordination may increase nonlinearly, resulting in distractions that lead to a decrease in sales (Heath and Staudenmayer 2000, Staats et al. 2012). Second, operational execution within the store may suffer with increasing number of flexible labor resources, and these effects may increase nonlinearly leading to a negative effect on sales (Raman et al. 2001, Ton 2010).

Second, we examine how increasing flexible labor resource availability may affect retail store expenses. Labor costs are typically a majority of a service organization's variable, or at times even total cost (Hawkes et al. 2011). Because of lower compensation, the increasing use of flexible labor resources may be related to lower costs, compared to using the same number of hours from full-time workers. As was the case with sales, using too large a percentage of flexible labor resources may also lead to nonlinear effects. For example, challenges in coordinating workers may result in difficulties in monitoring, yielding increased shrink or ineffective inventory management. Also, higher levels of flexible labor resources may create safety risks. Each of these factors may increase nonlinearly with an increase in the use of flexible labor resources within a store. Finally, given the hypothesized inverted U-shaped relationship between a flexible labor mix and sales and the U-shaped relationship between a flexible labor mix and expenses, we examine whether a flexible labor mix shows an inverted U-shaped relationship with profitability.

To examine our research questions, we assembled a unique data set from a large, U.S.-based retailer. Our research setting provides several advantages. First, seasonality has a large impact on the sales of most retailers and many use volume flexibility, through the deployment of flexible labor resources to respond to the demand spikes. For example, Home

[1] We use the terms *U-shaped curve* and *inverted U-shaped curve* to be consistent with prior literature (e.g., Lapré and Tsikriktsis 2006, Staats and Gino 2012). By a U-shaped curve, we are referring to a convex, unimodal curve, and by an inverted U-shaped curve, we are referring to a concave, unimodal curve.

Depot planned to hire 70,000 seasonal workers in its stores for the 2012 spring selling season to augment its 320,000 regular employees to meet seasonal demand (Isidore 2012). The retailer in our study also experienced large seasonality in sales and its labor mix changes considerably during these time periods. Thus, the research questions in our study were of significant managerial interest to this company. Second, we possess detailed data on store financial performance, flexible labor, resources used, and additional control variables for 26 months for each store in our sample. With longitudinal data for many stores in a chain, it is possible to control for factors that may affect store performance and so make valid inferences across the sample. Third, although the need to meet demand spikes using flexible resources is universal, different managers may have different ability to do so. Thus, our sample of 445 stores provides substantial heterogeneity in our key variables of interest useful for our estimation. Finally, we supplemented these archival data with interviews with managers from store operations, finance, and human resources (HR).

Our analyses support our hypotheses. First, both part-time and temporary labor mixes show an inverted U-shaped relationship with sales. Second, the temporary labor mix has a U-shaped relationship with expenses, whereas the part-time labor mix has a decreasing, convex relationship with expenses. Finally, we identify an inverted U-shaped relationship between temporary and part-time labor mixes and profitability.

This study makes several contributions to the academic literature on flexibility, service operations, and human resource management. First, we undertake, to our knowledge, the first empirical examination of volume flexibility in services.[2] In so doing, we quantify and demonstrate the large impact of flexible labor resources on store performance for a major retailer. For example, our analysis shows that temporary and part-time workers can increase store sales by 13% over the monthly average during the peak demand period. Furthermore, the volume flexibility offered by these flexible labor resources can increase profitability by 32% over the monthly average during the same period. Second, by examining volume flexibility in services, we identify a previously unexamined relationship—flexible labor resources and sales. Because of customer coproduction, different types of labor can meaningfully change an organization's sales. Our results show that flexible labor resources provide volume flexibility for sales and that one underlying mechanism is upside flexibility in the form of more hours. Additionally, our results show that flexible labor resources do more than just provide additional hours for stores. Holding the total hours constant, we find that both temporary and part-time workers are related to greater sales in a store. We posit that this effect is driven by temporal flexibility, the ability to better match the supply of workers to the within-day or within-week demand of customers. Our findings on the impact of flexible labor resources on sales and the importance of temporal flexibility on store profitability highlight the differences between manufacturing and service settings. Third, we find that flexible labor resources are not an unalloyed good. Although our research shows that both temporary and part-time labor can create volume flexibility for a firm, it is possible to have too much of the labor resource. Surprisingly, by reducing flexible labor resources, a firm may be able to increase sales and profitability. This does not suggest that flexibility is a bad thing, but rather that the means by which flexibility is implemented is an important consideration for management. In the next section we motivate our study's three hypotheses.

2. Labor Mix and Volume Flexibility

Within operations management, two literatures have explored contingent work relationships. The first builds off of research in contract theory (Bolton and Dewatripont 2004) and explores the contractual relationships between employers and temporary employee agencies (e.g., Milner and Pinker 2001). The second is a subset of a broader line of work that looks at the problem of minimizing production labor costs (Holt et al. 1956, Lippman et al. 1967, Sobel 1970). This research examines how to minimize costs when multiple types of workers are available—typically full-time workers and temporary workers (Pinker and Larson 2003, Bhandari et al. 2008). For example, prior analytical work in operations management investigates volume flexibility in call centers, finding that the use of on-call operators who can respond to spikes in demand allows a firm to meet its realized demand at a lower cost (Whitt 1999, Bhandari et al. 2008). Drawing on this second line of work, we turn to the question of how flexible labor resources create volume flexibility.

2.1. Flexible Labor Resources and Sales

Flexible labor resources, in the form of part-time or temporary workers, create volume flexibility that can affect profitability through either sales or expenses. We first consider the effect on sales.

Prior work indicates that flexible labor resources may be less productive than their full-time counterparts (Stratman et al. 2004). First, in many settings, flexible labor resources may have less capability than

[2] Such an empirical examination is absent in industry reports also. The *New York Times* reports, "*No one has collected detailed data on part-time workers at the nation's major retailers*" (Greenhouse 2012, italics added).

permanent, full-time workers because of lower initial qualifications. Stores may have lower requirements for flexible labor resources or may attract less-qualified workers to take flexible positions. Second, part-time and temporary workers may not have the same opportunity to engage in learning by doing as full-time laborers. Research finds that increasing cumulative experience improves performance (Lapré and Nembhard 2010) and that learning is dependent on the context in which the work occurs (Edmondson 2002, Staats et al. 2011). Since full-time workers spend more hours working each week, often over longer periods of time (the latter as compared to temporary workers), full-time workers may grow more productive than their flexible counterparts. Finally, labor productivity differences may result from differences in employees' long-term incentives.[3] With aligned incentives, full-time employees may be more likely than their flexible counterparts to engage in activities that benefit the organization.

Despite these differences that indicate an individual flexible labor resource may be less productive than a full-time worker when working the same hour on the same day, there are two primary reasons why in aggregate that flexible labor resources may increase sales. First, flexible labor resources offer upside flexibility, the ability to increase production beyond normal capacity, and thus create the possibility to better match the supply of labor to the demand of customers on an absolute basis (Bhandari et al. 2008). Although increasing overtime of permanent, full-time workers is one way to expand the total labor hours, there may be times when such an increase is insufficient to meet spikes in demand or management is unwilling to incur the cost of overtime. For example, in a seasonal business, such as a toy store, even with all full-time staff working as many hours as possible, there may be unmet demand during the peak season. Thus, a temporary employee can join during the peak season and leave when the season ends. In the same way, if a part-time worker typically works 15 hours per week, it may be possible to expand that worker's staffing to 39 hours when demand is high. Both part-time and temporary workers offer a valuable buffer in terms of hours so that an organization can respond to changes in demand.

In addition to benefitting from a potential increase in total hours, flexible labor resources offer temporal flexibility. In service settings, customer demand is not typically uniform in its arrival rate. Rather, demand spikes on certain days (e.g., on weekends when customers have free time) or certain hours (e.g., lunch hour at a quick service restaurant). Flexible labor resources may increase sales because they provide firms with a dynamic adjustment option—they offer a greater ability to adjust staffing to match demand within a day or within a week (Pinker and Shumsky 2000, Milner and Pinker 2001, Pinker and Larson 2003, Bhandari et al. 2008). For example, if a firm has 39 hours to allocate within a week, it could staff one full-time worker or staff two part-time workers for 19.5 hours, perhaps even the same 19.5 hours. Assuming that the marginal sales benefit is not equal across all hours during the week—a reasonable assumption in many contexts—then the use of flexible resources may lead to higher sales.

Given these different benefits and costs, the question is what relationship would one expect to observe between flexible labor resources and sales. At low levels, we posit that the benefits likely outweigh the costs. Despite the potential lower level of productivity of individual workers, we predict that flexible resources are beneficial because of the upside and temporal flexibility they provide.

Although initially increasing flexible labor resources may show a positive relationship with sales, there are two reasons why this relationship may eventually turn negative. First, a significant and nonlinear cost of flexible labor resources arises from the coordination costs necessary to support part-time and temporary workers' efforts. Many of the activities within a store have multiple touch points with other employees and require workers to coordinate their tasks. Work on coordination finds that either when group size grows or when inexperienced members join a group, group effectiveness may suffer (Brooks 1975, Heath and Staudenmayer 2000, Staats et al. 2012). This could affect expenses (as detailed below), but also may affect sales. Rather than focusing on selling to customers as they arrive, a full-time worker could be occupied with training or helping a flexible labor resource. In the same way, if a flexible labor resource were to interrupt a full-time worker in the midst of working with a customer, then the full-time worker might lose her customer while also failing to convert the customer with the flexible worker.

As a related point, increasing flexible labor resources may introduce challenges around fit. As noted earlier, flexible labor resources may have lower labor productivity than full-time resources. At least initially this may be acceptable. For example, some store activities, such as stocking shelves and receiving merchandise may not require significant ex ante knowledge and may well suit the background of flexible resources. Although flexible labor resources may initially be placed in non-customer-facing tasks, with their increasing use this grows more difficult. If flexible resources are placed in selling tasks and then are unable to interact well with customers, a company could find itself in a negative spiral. The temporary or

[3] We thank an anonymous reviewer for suggesting this point.

part-time workers might distract the full-time workers on the selling floor, thus lowering overall sales. As more flexible labor resources are added to the selling floor, to help meet the uncaptured demand, the productive resources could grow even more distracted, resulting in lower sales still.

Second, increasing use of flexible labor resources may lead to poor store execution. In many of the same ways that flexible labor resources have lower sales productivity, part-time and temporary workers may be less likely to execute to the same standard as full-time workers. The lack of knowledge and/or commitment could lead to flexible labor resources failing to follow operating procedures. This lack of process could negatively affect sales because products may not be on the right shelf or the shopping environment may be less clean and inviting, leading to lower purchase rates (Raman et al. 2001, Ton 2010). Furthermore, Fisher et al. (2007) find that when customers perceive that inventory is not in stock, customer dissatisfaction increases, and this could decrease sales due to lower conversion rates or basket values. These challenges may grow nonlinearly in the increase of flexible labor resources, because not only does it become more difficult to execute properly when others have made mistakes, but also individuals may be less likely to follow operating procedures when others are not. Thus, we hypothesize the following:

Hypothesis 1. *Flexible labor mix has an inverted U-shaped relationship with store sales.*

2.2. Flexible Labor Resources and Expenses

We now turn our attention to expenses. Expenses in a services setting may include labor-related charges such as salaries and commissions, administrative expenses due to accidents and insurance, and inventory-related costs due to insurance, shrink, and damages. With respect to flexible labor resources and expenses, we again see potential benefits and costs from the use of temporary or part-time workers, as compared to full-time staff, to achieve a given level of sales. Starting with the benefits, flexible labor resources may cost less than permanent, full-time labor (Kalleberg 2000).[4] National legislation often mandates different required benefits (e.g., healthcare) for permanent, full-time workers compared to part-time or temporary workers. Furthermore, in the case of unexpected demand, the part-time worker's hours can be increased without paying overtime (up to 40 hours per week in the United States, over which workers receive 150% of their traditional rate).[5] Typically companies cannot increase a part-time workers' hours to the "full-time" standard for an extended time period or the worker may be redefined as full time, but a worker can reach 40 for a small number of pay periods and can go up to a lower standard (e.g., 30) without consequence. A temporary worker may have variable hours each week.

In addition, compared to full-time labor, temporary and part-time workers create an option of staffing fewer workers in the store when expected demand is low. Not only may the initial staffing plan be lower, but also when realized demand is lower, temporary or part-time workers may be sent home if a worker will still perform the promised hours for the week. Thus, temporary and part-time workers create the ability to lower idle labor expenses. It is also possible that greater use of flexible labor resources may lead to higher expenses since a store could add labor hours to meet demand. To address this possibility, we control for hours of labor in our examination of the flexible labor mix and expense relationship.

Although the arguments above highlight how, when controlling for the hours of labor, increasing flexible labor resources may be related to lower expenses, there are costs that may lead to an increase in expenses with the increasing use of flexible labor. The idea of a convex cost function is captured in the literature on aggregate production planning (Holt et al. 1956, 1955). For example, Holt et al. (1956) note that the cost function may be convex due to factors such as the hiring and firing of workers to match supply of labor to demand (see Graves 1981 for a review of the literature).

In addition to this factor, there are two additional drivers that may yield a convex cost function in a services environment.[6] First, if increasing use of flexible labor resources leads to poor store execution, as detailed above, then costs may suffer. For example, if flexible labor resources are less likely to follow standard operating procedures, and once some workers don't follow standard operating procedures, then more will do the same, there is a risk for a nonlinear increase in costs with increasing flexible labor resources. This could be seen in increasing inventory costs due to factors such as shrinkage, phantom stockouts, or inventory record inaccuracy (Raman et al. 2001, Ton 2010). Additionally, if flexible labor resources do not follow standard operating procedures then they could be more likely to experience

[4] Although flexible labor resources typically receive lower wages and benefits in settings such as retail, in other service industries (e.g., nursing), flexible labor may be more expensive (Green et al. 2013).

[5] The hours that qualify as full and part time as well as overtime pay vary by country (Kalleberg 2000).

[6] In our empirical analyses we will control for hiring and firing costs to examine whether additional factors may yield a convex cost function.

accidents, potentially even severe ones, which could increase safety and insurance expenses.

Second, as noted previously, coordination costs increase nonlinearly with an increasing number of workers (Levine and Moreland 1998). In our study that suggests that with a higher percentage of flexible labor resources, coordination costs will escalate due to the increased attention paid to the flexible resources for training, mentoring, and recovering from mistakes. The increasing coordination costs incurred by full-time workers and management may lead to a lack of monitoring. This lack of monitoring may heighten the store execution costs noted previously. As a result, we hypothesize the following:

Hypothesis 2. *Flexible labor mix has a U-shaped relationship with store expenses.*

Finally, if flexible labor resources show a concave relationship with store sales and a convex relationship with store expenses, then there will be a concave relationship with store profitability since the sum of two concave functions is concave. For our final hypothesis, we test this proposition:

Hypothesis 3. *Flexible labor mix has an inverted U-shaped relationship with store profitability.*

3. Data and Empirical Strategy

3.1. Research Setting

Our research setting is RetailCo (a pseudonym), a Fortune 500 big box retailer with annual revenues exceeding $10 billion. RetailCo has over 1,000 stores in the United States that represent more than 100 million square feet of selling space. The typical store carries over 40,000 items that include both national brands and RetailCo's private brands. Stores offer similar products and services with limited variations based on local market characteristics. RetailCo offers an ideal setting to examine coproduction in services because a large portion of its sales involve the collaborative interaction of salesperson and customer as the customer attempts to determine what product is right for her needs. In addition, customers often come to RetailCo with projects in mind, and RetailCo employees work with customers to make the project a reality.

RetailCo employs over 100,000 year-round employees in its stores. Of these, roughly 40% were part time. Full-time employees typically work 39 hours a week and can be employed up to 49 hours with overtime pay. Full-time employees are salaried and are eligible for sick pay, vacation pay, and healthcare benefits. Some departments within the store may also offer commissions. Their overtime compensation is 1.5 times the wage rate. Part-time employees are guaranteed 10 hours a week and can be employed up to 30 hours a week. Part-time workers may be employed for more than 30 hours, but if they do so for too many weeks, then they are reclassified as full-time employees. Part-time employees are paid on an hourly basis and are eligible for all benefits for which full-time employees are eligible. Temporary employees, also known as seasonal employees, have a shorter period of employment. They can be employed up to 39 hours a week. They are paid an hourly wage and commissions if they are employed in a sales role in certain departments within the store. They are not eligible for any of the benefits that are available to full-time and part-time employees. The labor planning process is explained in detail in §3.3.

3.2. Data

Our sample includes data from 451 RetailCo stores. These stores were selected randomly by RetailCo after dividing the store population by sales volume and geography. After removing stores with missing observations and outliers, we are left with 445 stores for our analysis. We collected data from three departments (finance, HR, and store operations) within the company. These data were then merged together for analysis. Along with these data, we supplemented our analysis with data collected from telephone interviews, store visits, and interviews with RetailCo managers.

The study period is from July 2009 to August 2011. For this period, we obtained monthly financial statement data for each of the 445 stores. The stores' financial statements contained the stores' revenues and detailed information about expenses (e.g., fleet expenses, administrative expense, occupancy expenses, etc.). The HR data provided us with information on each employee who worked in the store for each of the 26 months. This information included whether the employee was full time, part time, or temporary. The store operations data included weekly information on the actual hours each employee worked. There were over 6.5 million records across the 445 stores and 26 months. We aggregated the weekly data to the monthly level, to match the financial statement data.

Summary statistics and correlations among all variables used in our analysis are provided in Tables 1 and 2, respectively. We note that some of the variables are normalized as explained in the next section. The summary statistics and correlations are reported for these normalized variables. Below, we describe our measures and then introduce our empirical strategy.

3.2.1. Dependent Variable. We measure store performance for store i and month t using sales ($Sales_{it}$), expenses ($Expenses_{it}$), and profit ($Profit_{it}$). Monthly store sales are calculated as the total revenue net of returns. Monthly store expenses include labor costs related to salaries and commissions paid, employee

Table 1 Summary Statistics (Sample of 445 Stores)

Variable	Nonpeak/peak period	*N*	Mean	Median	Std. dev.	Min	Max
$Sales_{it}$	Nonpeak	7,216	17.54	16.73	5.94	4.75	54.29
	Peak	4,270	23.23	22.19	7.42	6.81	57.86
$Expenses_{it}$	Nonpeak	7,216	3.88	3.78	0.86	1.66	10.41
	Peak	4,270	4.38	4.29	0.96	1.89	10.48
$Profit_{it}$	Nonpeak	7,216	1.52	1.35	1.99	−12.09	10.27
	Peak	4,270	3.00	2.75	1.55	−1.71	13.53
$SalesForecast_{it}$	Nonpeak	7,216	0.89	0.88	0.16	0.49	1.44
	Peak	4,270	1.19	1.20	0.17	0.62	1.81
$LaborHours_{it}$	Nonpeak	5,863	7.37	7.15	1.541	4.24	16.77
	Peak	4,270	8.49	8.53	1.568	4.69	16.29
$TempMix_{it}$	Nonpeak	7,216	0.01%	0%	0.02%	0%	36.86%
	Peak	4,270	7.69%	7.00%	5.72%	0%	40.86%
$PTMix_{it}$	Nonpeak	7,216	33.75%	33.61%	9.29%	16.03%	57.57%
	Peak	4,270	33.87%	32.32%	9.62%	16.03%	57.57%
# $Temp\ Workers_{it}$	Nonpeak	7,216	0.38	0	0.93	0	13.69
	Peak	4,270	3.38	3.06	2.52	0	16.08
# $PT\ Workers_{it}$	Nonpeak	7,216	14.16	13.76	4.48	2.06	39.08
	Peak	4,270	14.96	14.37	4.94	2.36	43.23
# $FT\ Workers_{it}$	Nonpeak	7,216	42.13	41.28	6.89	25.30	69.05
	Peak	4,270	44.39	43.68	6.96	26.05	70.34
$Turnover_{it}$	Nonpeak	7,216	8.72%	2.89%	5.31%	0%	9.03%
	Peak	4,270	4.11%	3.75%	4.11%	0%	17.44%

Notes. Sales, expenses, and profit are divided by a constant to ensure confidentiality of data. All independent variables except the ratios $TempMix_{it}$, $PTMix_{it}$, and $Turnover_{it}$ are normalized by average monthly store sales in millions ($\overline{Sales}_i = \sum_{t=1}^{T} Sales_{it}/(1{,}000{,}000T)$). FT, full time; PT, part time.

costs related to relocation and training, administrative expenses related to accidents and insurance, and inventory-related costs including insurance, shrink, and damages. We do not include occupancy costs because they are fixed costs for a store. On average, the labor-related costs account for over half of the total expenses in the store. The store profit represents the before-tax profit for each individual store in that month. It is a function of sales, expenses, and cost of materials. We divide each of these metrics by a constant to preserve the confidentiality of our data.

3.2.2. Key Variables of Interest. To test our hypotheses, we analyze two types of flexible labor resources: part-time and temporary workers. We operationalize labor mix as either part-time (temporary) workers divided by full-time workers or part-time (temporary) hours worked divided by full-time hours worked. We normalize each variable by the full-time workers (or hours) to enable comparison across stores. We use the former operationalization (workers) in our main models and return to the hour-based operationalization in the robustness section (both show the same pattern of results). Therefore, our primary independent variables are $PTMix_{it}$ and $TempMix_{it}$, which capture the ratio of part-time to full-time employees and temporary to full-time employees working in the store in a given time period, respectively. The means and standard deviations of the number of hours per month worked by temporary, part-time, and full-time workers for the entire sample period are (80, 35), (90, 17), and (156, 19), respectively.

As shown in Table 1, there is considerable heterogeneity in $PTMix_{it}$ and $TempMix_{it}$ across and within stores. The latter is typically much higher during the peak period, indicating that store managers hire

Table 2 Pearson Correlation

	$Sales_{it}$	$Expenses_{it}$	$Profit_{it}$	$SalesForecast_{it}$	$LaborHours_{it}$	$TempMix_{it}$	$PTMix_{it}$	$Turnover_{it}$
$Sales_{it}$	1							
$Expenses_{it}$	0.72**	1						
$Profit_{it}$	0.89**	0.36**	1					
$SalesForecast_{it}$	0.90**	0.67**	0.79**	1				
$LaborHours_{it}$	0.73**	0.73**	0.53**	0.74**	1			
$TempMix_{it}$	0.55**	0.29**	0.58**	0.59**	0.43**	1		
$PTMix_{it}$	0.04**	0.05**	0.02**	0.04**	0.02**	−0.05**	1	
$Turnover_{it}$	0.33**	0.17**	0.33**	0.35**	0.23**	0.39**	−0.02**	1

**Significant at the 0.05 level.

temporary workers during the peak period. In fact, the median value of $TempMix_{it}$ during the nonpeak period is zero, suggesting that temporary workers are exclusively recruited during the peak period in most stores. The summary statistics for $PTMix_{it}$ suggests that the proportion of part-time workers does not change between peak and nonpeak periods. However, when we measure the hours allocated to part-time workers in the peak and nonpeak periods, we find that the mean hours worked per month by part-time workers in the peak period is 96 hours, whereas during the nonpeak period it is 83 hours.

3.2.3. Controls. We include the following control variables in our model. The variable $SalesForecast_{it}$ refers to the 30-day-ahead sales forecast that is generated for store i for month t. This control variable is valuable because store performance is affected by several events such as promotion, local events, and entry/exit of competitors. These events contribute to the unobservable heterogeneity problem in many settings. Since store managers would be aware of many of these factors and account for them in their sales forecast, we are able to mitigate the effects of unobservable heterogeneity. As a validity check, we regress sales forecast against actual sales and obtain an R^2 value of 0.80. This adds further validity to our expectation that the 30 day sales forecast would control for unobservable heterogeneity in our setting. In addition, we control for employee turnover among full-time and part-time workers, $Turnover_{it}$, in all of our regressions, because this variable was found to affect profitability in prior literature (Ton and Huckman 2008).

Finally, we control for store fixed effects to account for location-specific, time-invariant factors. These stores are clustered into 25 different geographical regions within the United States. Each region for RetailCo has a similar number of stores, and the stores are located in close geographical proximity. Large states like California might fall under two regions, whereas smaller states like Vermont, Rhode Island, and New Hampshire may be grouped into one region. Since stores in the same geographical region have similar seasonality and trends, we use region-specific monthly indicator variables in our regression and region-specific time trend to control for seasonality and trend in our regressions. Other control variables used in robustness checks are explained in §4.3.

3.3. Labor Planning and Onboarding Process at RetailCo

The labor planning approach at RetailCo mirrors the hierarchical planning strategies used in manufacturing. In the first stage, called the labor planning stage, store managers determine the number of temporary, part-time, and full-time employees to have in the store. In the second stage, they match the store's labor requirement at an hourly level to the available labor. The second stage is typically called the labor scheduling stage. We seek to understand how first stage labor decisions affect store performance.

The labor planning process at RetailCo begins with a sales forecast for each store in each month. RetailCo generates sales forecasts through a collaborative process involving inputs from their finance division and store managers. This process includes both quantitative techniques as well as judgments of different participants. Once the sales forecasts are determined, the labor planning unit in the corporate office forecasts labor hours for each store using a regression model. The regression model is built based on the stores' historical sales and labor hours. In addition, the stores are divided into six sales tiers and each sales tier has a minimum number of managers, cashiers, and backroom staff that all stores in that sales tier need to have at all times, irrespective of the labor requirement generated by its sales forecast.

Store managers allocate the aggregate forecasted hours across full-time and part-time workers. If they are unable to allocate the hours to the existing workers based on past workload, then they either (1) allocate additional hours to existing staff or (2) recruit new staff. To meet their staffing need, managers may turn to their existing part-time and full-time workers to determine if they are willing to work extra hours. Since full-time workers are usually working for their full 39 hours already, any extra hours would require the manager to pay one-and-half times the wage rate for those hours. Managers may also turn to part-time workers to work extra hours. Alternatively, they may consider recruiting additional employees. Typically, the store manager recruits temporary employees when they need additional hours for a short time period, such as the peak period. However, if the store manager believes that they need additional employees on an ongoing basis, then they may recruit additional part-time or full-time employees. Once recruited, full-time and part-time employees undergo an orientation program at the start of employment and then receive several weeks of Web-based and on-the-floor training. Temporary employees often have much shorter training programs, and they need to learn on the job.

In our context, each store manager is responsible for allocating labor hours. The corporate office offers little guidance on how to split hours among the three types of labor. We utilize the heterogeneity in store manager decisions across the 445 stores to examine the impact of labor mix on store performance.

3.4. Model Specification and Estimation

We begin by considering an appropriate specification to study our research question. Store performance in a given time period may be partitioned into time-invariant store fixed effects, region-specific time effects, and time-varying store factors, as shown below:

$$\begin{aligned} \mathit{Sales}_{it} &= \alpha_i + \alpha_1(\mathit{TempMix}_{it}) + \alpha_2(\mathit{TempMix}_{it})^2 \\ &\quad + \alpha_3(\mathit{PTMix}_{it}) + \alpha_4(\mathit{PTMix}_{it})^2 \\ &\quad + \alpha_5(\mathit{SalesForecast}_{it}) + X_{it}\alpha + \epsilon_{it}, \qquad (1) \\ \mathit{Expenses}_{it} &= \beta_i + \beta_1(\mathit{TempMix}_{it}) + \beta_2(\mathit{TempMix}_{it})^2 \\ &\quad + \beta_3(\mathit{PTMix}_{it}) + \beta_4(\mathit{PTMix}_{it})^2 + \beta_5(\mathit{Sales}_{it}) \\ &\quad + \beta_6(\mathit{LaborHours}_{it}) + \beta_7(\mathit{LaborHours}_{it})^2 \\ &\quad + X_{it}\beta + \vartheta_{it}, \qquad (2) \\ \mathit{Profit}_{it} &= \partial_i + \partial_1(\mathit{TempMix}_{it}) + \partial_2(\mathit{TempMix}_{it})^2 \\ &\quad + \partial_3(\mathit{PTMix}_{it}) + \partial_4(\mathit{PTMix}_{it})^2 \\ &\quad + \partial_5(\mathit{SalesForecast}_{it}) + X_{it}\partial + \varphi_{it}. \qquad (3) \end{aligned}$$

Here α_i, β_i, and ∂_i capture time-invariant store fixed effects; α, β, and ∂ are vectors of slope coefficients for the control variables, X_{it}. We estimate the model during the five month peak period when stores most actively use temporary workers, but conduct a robustness check over the entire year.

Equation (1) is used to test Hypothesis 1, which predicts the impact of flexible workers on store sales. Recall that this hypothesis predicts that sales will be impacted due to upside flexibility (more hours) and temporal flexibility. In addition to testing Hypothesis 1, we may also use Equation (1) to decouple the effects due to the two types of flexibility by adding linear and quadratic terms of labor hours ($\mathit{LaborHours}_{it}$) as controls to separately analyze the effect of temporal flexibility only. Consistent with Hypothesis 2, which argues that flexible resources will allow stores to achieve sales by using labor hours at lower expenses, up to a point, and then face increasing expenses, we control for actual sales and labor hours in (2). Finally, we use Equation (3) to test Hypothesis 3.

We use the coefficients of the linear and quadratic terms of the temporary and part-time labor-mix variables to test for an inverted U-shaped relationship for sales. To distinguish an increasing concave relationship from an inverted U-shaped relationship, we compute the stationary points for temporary and part-time labor mixes as $-\alpha_1/2\alpha_2$ and $-\alpha_3/2\alpha_4$, respectively, for the sales equation and check if they lie within the sample. We repeat the process for the expense and profitability equations to test for U-shaped and inverted U-shaped relationships, respectively.

3.4.1. Endogeneity Concerns and the Selection of Instruments. An important concern in labor regressions is that of endogeneity. This concern arises because store managers could change labor based on store performance.

To account for endogeneity bias, we estimate our main models using instrumental variable regression. We instrument linear and quadratic terms of temporary labor mix and part-time labor mix with two sets of instruments. The first instrument is the monthly unemployment rate of the county in which the store is located. The unemployment data are obtained from the Bureau of Labor Statistics website. Assuming that monthly unemployment rate is not correlated with store performance, unemployment rate would be a valid instrument because it serves as a cost-based labor-supply shifter for our endogenous variables. We use the three-month rolling average of monthly unemployment rate as an instrument. In the event that unemployment rate affects contemporaneous store performance directly, this variable would fail the exclusion condition. Therefore, we repeated the analysis by dropping this instrument and by using lagged values of this instrument, and we obtained similar conclusions in both cases.

The second set of instruments includes linear and quadratic terms of lagged temporary and part-time labor mix. Since we require four time- and store-varying instruments, an easily available set of instruments for labor mix is the previous month's labor mix. For lagged labor-mix variables to be valid instruments, they must be correlated with contemporaneous labor mix and independent of the errors in each equation. If these two conditions are met, then lagged labor mix will generate consistent estimates of labor mix on sales, expenses, and profit, conditional on those equations being correctly specified.

We argue that lagged labor-mix variables are valid instruments for the following reasons. First, they are correlated with contemporaneous labor mix because labor is sticky due to hiring and training costs. Store managers cannot drastically change the number of workers from month to month without incurring high hiring and training costs. The R^2 values of the first stage regressions are high (as reported below). Second, lagged labor-mix variables satisfy the exclusion condition since they do not impact current period's sales, expenses, and profit. Finally, we note that lagged values of labor have been commonly used as instruments in many settings (Bloom and Van Reenen 2007, Siebert and Zubanov 2010, Tan and Netessine 2012). For example, Tan and Netessine (2012) use linear and quadratic terms of the lagged ratio of diners to number of workers as instruments for contemporaneous values of the same variables.

To assess the validity of the instruments, we perform several statistical tests to examine whether they meet the relevance criteria. First, we note that the R^2 values from the first stage regressions of the four endogenous variables lie between 0.55 and 0.70, indicating that the instruments have significant explanatory power. Second, the F-statistics of the excluded instruments in the first stage regressions are well over 10 in all of our regressions, indicating that the instruments are not "weak" in the sense of Staiger and Stock (1997). Although not conclusive, these test statistics build our confidence that our instruments are valid.

One concern with using lagged endogenous variables as instruments is that they can be problematic in the presence of serial correlation. Using the test for serial correlation (Wooldridge 2002), we find that serial correlation is an issue only in the sales equation. We undertook several measures to address this concern. First, we follow Tan and Netessine (2012) and include trend as a control variable. Since we have stores in different regions of the United States, and each region could have a different trend, we include region-specific trends in our model. Second, as described in §4.1, we perform robustness checks where we eliminate serial correlation in the sales model through transformation of the dependent variable without changing the interpretation of the coefficients of the independent variables. Third, we identify market-based instruments (Nevo and Wolfram 2002) that are not impacted by serial correlation in the underlying model and use these instruments as robustness check for sales, expenses, and profit equation. These results are also reported in §4.1.

With the instruments identified, we estimate Equations (1), (2), and (3) using two different methodologies. The introduction of sales as an independent variable implies that we can treat these equations as a system of simultaneous equations model. However, this is a special case of the simultaneous equations model since the simultaneity between sales and expenses exists in only one equation. Greene (2003) calls this case a triangular system and shows that it is possible to estimate each equation separately using two-stage least squares (2SLS) when the errors across the two equations are uncorrelated. If the errors are correlated, then three-stage least squares (3SLS) technique produces consistent estimates (Zellner and Theil 1962). For the main analysis, we assume the errors are uncorrelated and use the 2SLS technique for the individual equations. We confirm our results with 3SLS estimation (not reported).

4. Results

First, we run (1)–(3) using ordinary least squares (OLS) methodology, which does not correct for endogeneity (columns (1), (4), and (6) of Table 3). The coefficients of the linear and quadratic terms of temporary labor-mix variables and part-time labor-mix variables are both jointly significant ($p < 0.01$) in all three models. Although the signs of both labor-mix variables are consistent with Hypotheses 1–3, the statistical significance of the quadratic terms are marginal in some cases. Since these coefficient estimates are biased due to endogeneity, we discuss the coefficient estimates obtained after accounting for endogeneity next.

In column (2) of Table 3 we report the results for Hypothesis 1, which posits an inverted U-shaped relationship between labor mix and sales, using our instrumental variable regression. The coefficients of the linear and quadratic terms of the temporary labor-mix variable are individually and jointly significant ($p < 0.01$). The stationary point of 0.13 lies well within the support of the data, indicating an inverted U-shaped relationship between temporary labor mix and sales. In other words, for low levels of temporary labor mix, sales increase with increasing temporary labor mix; however, beyond the stationary point, we find that an increase in temporary labor mix is associated with lower sales. Thus, our results support Hypothesis 1 for temporary labor mix. Furthermore, we find that the linear and quadratic terms of part-time labor mix are both individually and jointly significant ($p < 0.01$). The stationary point is 0.45 and lies within the sample. Thus, Hypothesis 1 is supported for part-time labor mix as well.

In Hypothesis 1, we argued that the sales benefits from flexible resources arise due to upside flexibility and temporal flexibility. Recall that upside flexibility is the ability of stores to increase labor hours to meet demand, and temporal flexibility is defined as the ability to adjust resources within a fixed window of time. In the results reported in column (2) of Table 3, we capture the impact of upside flexibility and temporal flexibility together. To determine the impact of temporal flexibility alone, we add actual labor hours, both linear and quadratic terms, in the model in column (3) so the coefficients of the labor-mix variables only capture the incremental impact on sales provided by labor mix beyond the benefit from increased hours. In other words, those coefficients capture only the benefits due to temporal flexibility offered by flexible resources. Examining column (3), first, we note that the linear and quadratic terms of actual labor hours are jointly significant ($p < 0.01$), and their coefficients indicate an increasing concave relationship as expected (Fisher et al. 2007, Perdikaki et al. 2012). We find that the linear and quadratic terms of both temporary and part-time labor-mix variables are jointly significant ($p < 0.05$). The stationary points of temporary and part-time labor-mix variables are 0.08 and 0.37 and lie well within the sample. We note that the stationary point shifts to the left once we add actual labor hours as a control since

Table 3 Regressions Testing the Impact of Temporary Labor Mix and Part-Time Labor Mix on Store Performance

	Sales			Expenses		Profit		
	(1) OLS	(2) Main model	(3) Temporal flexibility	(4) OLS	(5) Main model	(6) OLS	(7) Main model	(8) Temporal flexibility
Temporary labor mix	7.89***	22.29***	8.38*	−0.88***	−2.55***	2.22***	7.09***	5.82***
	(2.34)	(4.92)	(4.54)	(0.326)	(0.780)	(0.82)	(1.72)	(1.71)
(*Temporary labor mix*)^2	−5.32	−82.63***	−52.21**	3.03*	10.52***	−5.64	−32.81***	−30.16***
	(11.53)	(26.12)	(23.41)	(1.58)	(4.10)	(4.07)	(9.09)	(8.84)
Part-time labor mix	8.89***	14.89***	13.64***	−1.01**	−2.44***	2.41**	5.45***	5.32***
	(3.07)	(3.98)	(3.49)	(0.48)	(0.67)	(1.09)	(1.41)	(1.37)
(*Part-time labor mix*)^2	−9.30**	−16.49***	−18.296***	0.85	2.32**	−2.57*	−6.10***	−6.25***
	(3.96)	(5.16)	(4.46)	(0.60)	(0.85)	(1.39)	(1.81)	(1.76)
Sales forecast	5.06***	4.97***	3.79***			1.63***	1.58***	1.46***
	(0.55)	(0.34)	(0.30)			(0.17)	(0.12)	(0.11)
Sales				0.03***	0.03***			
				(0.004)	(0.00)			
Actual labor hours			5.48***	0.73***	0.75***			0.93***
			(0.23)	(0.05)	(0.04)			(0.08)
(*Actual labor hours*)^2			−0.21***	−0.02***	−0.03***			−0.04***
			(0.01)	(0.00)	(0.00)			(0.00)
Turnover of FT and PT workers	−3.67***	−4.84***	−0.49	0.24	0.42**	−1.02**	−1.43***	−1.07**
	(1.16)	(1.26)	(1.19)	(0.19)	(0.21)	(0.41)	(0.46)	(0.45)
R^2	0.83	0.83	0.89	0.85	0.86	0.71	0.68	0.70
Joint significance Wald test of $TempMix_{it}$ and $TempMix^2_{it}$ (p-value)	0.000	0.000	0.037	0.003	0.000	0.0001	0.000	0.001
Joint significance Wald test of $PTMix_{it}$ and $PTMix^2_{it}$ (p-value)	0.001	0.000	0.002	0.000	0.000	0.001	0.000	0.001

Notes. $n = 4{,}270$ in all cases. All models, other than those indicated as OLS, were estimated by 2SLS methodology. Standard errors, reported in parentheses, are clustered by region. All regressions were run with store fixed effects, trend, and region-specific monthly dummies as additional controls. FT, full time; PT, part time.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the positive impact of temporary and part-time labor due to upside flexibility is now accounted for in the coefficient of labor-mix variables. These results show that flexible resources appear to offer both upside and temporal flexibility that impact sales positively.

Next consider the results for Hypothesis 2. Recall that this hypothesis argued that the use of flexible resources will be associated with a U-shaped relationship with expenses, after controlling for actual sales and actual labor hours. We control for actual labor hours since stores with more flexible resources may increase sales by using additional labor hours. Thus, it is necessary to control for sales and labor hours to ensure an apples-to-apples comparison. In column (5), we report the results for Hypothesis 2. Both the linear and quadratic terms of temporary labor mix are individually and jointly significant ($p < 0.01$). We find that an increase in temporary labor mix is associated with a decrease in store expenses up to a point, and a further increase in temporary labor mix is associated with an increase in store expenses. The stationary point is 0.12 and lies well within our sample. The linear and quadratic terms of part-time labor mix are individually and jointly significant ($p < 0.01$). However, even though the stationary point, 0.52, lies within the sample, only 5% of the sample lies above the stationary point, raising a concern that this relationship may be a decreasing convex one rather than a U-shaped relationship as hypothesized. We examine if this relationship is decreasing convex or U-shaped with additional robustness tests. Thus, we find strong support for Hypothesis 2 only for temporary labor mix.

Finally, in column (7) we present the results of Hypothesis 3, where we examine the impact of labor mix on store profit. We observe inverted U-shaped relationships between both temporary labor mix and part-time labor mix with store profitability. The stationary points for temporary and part-time labor-mix variables are 0.11 and 0.45, respectively, and they lie within the sample. Thus, Hypothesis 3 is supported for temporary and part-time labor-mix variables.

Next we examine the impact of temporal flexibility on store profits by additionally controlling for linear and quadratic terms of actual labor hours in the profit Equation (3). As reported in column (8) of Table 3, we find that the linear and quadratic terms of both labor-mix variables are both jointly and independently significance ($p < 0.01$). Interestingly, we find that the coefficients of the linear and quadratic terms of both labor-mix variables are statistically similar to those in the case where we had not controlled for labor hours. This suggests that the benefit of labor mix on profitability is largely driven by temporal flexibility.

In the models of temporal flexibility (columns (3) and (8)), where we control for total labor hours, we use one control variable rather than a separate variable for each type of labor hours because of issues with multicollinearity. Further studies with a larger sample or an experimental design should examine if there are any biases as a result of this restriction.

4.1. Robustness Checks

4.1.1. Tests for Inverted U-Shaped and U-Shaped Relationships. Up to this point, our conclusion for the presence of inverted U-shaped and U-shaped relationships was based on the criterion that the stationary point should lie within the range of the variable in our sample. Lind and Mehlum (2010) argue that a quadratic approximation of a convex unimodal relationship could be misleading in the presence of extreme observations. Similar concerns have been raised by other researchers, and so a commonly used approach is Aiken and West's (1991) procedure for testing curvilinear relationships. This method is similar to the Sasabuchi test proposed in Lind and Mehlum (2010). Aiken and West (1991) state that to identify a nonmonotonic relationship, the stationary point should lie within the meaningful range of the variable. To test if the stationary point lies in a meaningful range, they suggest computing the slope of the curve for different points of the variable and ensuring that the slope is significantly different from zero and of different signs on either side of the stationary point. For example, in the sales equation, the slope of the curve is given by $\alpha_1 + 2\alpha_2 TempMix_{it}$, and the standard error is calculated as $\sqrt{\sigma_{11} + 4TempMix_{it}\sigma_{12} + 4\sigma_{22}(TempMix_{it})^2}$. Here σ_{11} and σ_{22} are the variance of α_1 and α_2, respectively, and σ_{12} is the covariance between α_1 and α_2. Table 4(a) shows the tests of the simple slopes for temporary and part-time labor-mix variables at the stationary point, and ± 1 SD, minimum, and maximum values in the sample. Since the simple slopes on either side of the stationary point are statistically significant and are of different signs for both temporary and part-time labor-mix variables, we can conclude that the inverted U-shaped relationship is supported within the sample for the sales equation. We repeat the similar analysis for the expense equation, and the results are reported in Table 4(b). We find that our statistical tests confirm the U-shaped relationship for temporary labor-mix variable. Since the stationary point for the part-time labor-mix variable lies close to the maximum value, we cannot statistically validate the presence of the U-shaped relationship between part-time labor mix and expenses in our sample. We also perform the simple slope tests for the profit equation and confirm the inverted U-shaped relationships between the labor-mix variables and profit as shown in Table 4(c).

In addition, Lind and Mehlum (2010) suggest computing the confidence interval of the stationary point and ensuring that it lies within the sample. Although it is common to employ the delta method (Muggeo 2003) to obtain the confidence intervals of ratios, Staiger et al. (1997) recommend the Fieller (1954) method over the delta method, because the latter is biased in small samples. We perform our analysis using both methods, finding the same pattern of results for each, and so we report the results from the Fieller (1954) method. The 95% confidence interval of

Table 4(a) *t*-Tests for Simple Slopes in Sales Equation

	Temporary labor mix			Part-time labor mix		
	Value	Slope	*p*-value	Value	Slope	*p*-value
Minimum value	0	22.29	0.000	0.16	9.62	0.000
Stationary point −1 SD	0.07	10.74	0.000	0.34	3.68	0.000
Stationary point	0.13	0	0.99	0.44	0	0.99
Stationary point +1 SD	0.18	−7.42	0.06	0.54	−2.91	0.05
Maximum value	0.41	−45.37	0.003	0.58	−4.23	0.03

Note. The *p*-values are based on one-tailed test on whether the slope is >0 or <0.

Table 4(b) *t*-Tests for Simple Slopes in Expense Equation

	Temporary labor mix			Part-time labor mix		
	Value	Slope	*p*-value	Value	Slope	*p*-value
Minimum value	0	−2.55	0.000	0.16	−1.69	0.000
Stationary point −1 SD	0.07	−1.08	0.000	0.41	−0.53	0.000
Stationary point	0.12	0	0.99	0.51	0	0.99
Stationary point +1 SD	0.18	1.23	0.04	<Outside of range>		
Maximum value	0.41	6.07	0.01	0.58	0.26	0.24

Note. The *p*-values are based on one-tailed test on whether the slope is >0 or <0.

Table 4(c) *t*-Tests for Simple Slopes in Profit Equation

	Temporary labor mix			Part-time labor mix		
	Value	Slope	*p*-value	Value	Slope	*p*-value
Minimum value	0	7.09	0.000	0.16	3.50	0.000
Stationary point −1 SD	0.04	4.46	0.000	0.35	1.18	0.000
Stationary point	0.11	0	0.99	0.45	0	0.99
Stationary point +1 SD	0.16	−3.41	0.005	0.55	−1.26	0.029
Maximum value	0.41	−19.81	0.000	0.58	−1.62	0.017

Note. The *p*-values are based on one-tailed test on whether the slope is >0 or <0.

θ from the Fieller (1954) method is obtained using the following equation:

$$\theta + \left(\frac{k}{1-k}\right)\left(\theta + \frac{\sigma_{12}}{\sigma_{22}}\right) \pm \frac{Z_{\alpha/2}}{\gamma(1-k)} \cdot \left[\sigma_{11} + 2\theta\sigma_{12} + \theta^2\sigma_{22} - k\left(\sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}}\right)\right]^{1/2},$$

where $\theta = -\alpha_1/\alpha_2$. We obtain the 95% confidence interval of the stationary point $(-\alpha_1/2\alpha_2)$ by cutting the interval in half. In the sales equation, the 95% confidence interval from the Fieller (1954) method for the stationary point for temporary labor mix is $[0.11, 0.21]$, and for part-time labor mix is $[0.40, 0.57]$. We find that the 95% confidence interval lies within the range of the sample for both variables, confirming Hypothesis 1 for both variables. In the expense equation, the 95% confidence interval from the Fieller (1954) method for the stationary point for temporary labor mix is $[0.09, 0.21]$, and for part-time labor mix is $[0.46, 0.81]$. We find that the 95% confidence interval lies within the range of the sample for temporary labor mix, but not for part-time labor-mix variable. So, we conclude that the U-shaped relationship is supported for temporary labor mix, but not for part-time labor mix. Analysis of the profit equation shows that the 95% confidence intervals for temporary labor mix, $[0.09, 0.14]$, and part-time labor mix, $[0.40, 0.55]$, lie within the sample, confirming the inverted U-shaped relationship for both labor-mix variables.

In summary, we find statistical support for Hypotheses 1 and 3 for both the temporary and part-time labor-mix variables. We only observe partial support for Hypothesis 2 since the U-shaped relationship is statistically validated for the temporary labor-mix variable, but not the part-time labor-mix variable. We posit that reasons for a decreasing convex relationship, rather than a U-shaped relationship, between part-time labor mix and expenses could be because coordination costs and execution errors associated with part-time employees are lower compared to temporary employees, because the former are employed year-round. Future research can confirm whether this is the case.

4.1.2. Alternate Model Specifications. Our main model used labor-mix variables, which are ratios of the number of temporary or part-time workers divided by the number full-time workers. We retest our hypotheses using the number of workers in each class—full time, part time, and temporary—directly. We divide the number of workers in each class by the average store sales to normalize for scale differences across stores. We report the results of the OLS regression in columns (1), (4), and (6) in Table 5. Because we expect labor to be endogenous, we use lagged values of full time, part time, and temporary as instruments and estimate the regressions using 2SLS methodology. We use unemployment rate, as we did earlier, as an additional instrument.

The results of Hypotheses 1–3 are reported in columns (2), (5), and (7) of Table 5, respectively. Since we cannot report the average store sales and the scaling factor used for each of the dependent variables to preserve RetailCo's anonymity, the coefficient estimates are harder to explain meaningfully. However, we note that the coefficients of the linear and quadratic terms of both the temporary and part-time labor variables are consistent with an inverted U-shaped relationship with sales. In addition, the stationary points for temporary and part-time labor variables are 5.31 and 20.96, respectively, and they lie within the sample of the data. Furthermore, the 95% confidence interval based on Fieller's (1954) method indicates that the interval lies within the sample. We repeat the analysis for the expenses regression based on coefficient estimates reported in column (5). We find that using Fieller's (1954) method, the 95% confidence interval of the stationary points supports U-shaped relationships between temporary workers and expenses as well as between part-time workers and expenses. Finally, we observe inverted U-shaped relationships between temporary workers and profits as well as part-time workers and profits. Using Fieller's (1954) method, the 95% confidence interval lies completely within the sample for both temporary and part-time workers.

In summary, we find that our results with the alternate model specification are stronger with support for all three hypotheses for both temporary and part-time workers. We note that even though similar inverted U-shaped and U-shaped relationships are observed with full-time employees, additional robustness checks find strong support for an increasing concave relationship between full-time employees and sales, but not an inverted U-shaped relationship. It is also worth mentioning that an important difference between flexible resources and full-time resources is that full-time workers do not appear to provide temporal flexibility, as the full-time coefficients in columns (3) and (8) are not jointly significant. This is presumably because full-time workers need to be deployed for the full 39 hours every week at this retailer.

4.1.3. Serial Correlation. The use of lagged endogeneous variables can be problematic when errors are serially correlated. In the sales model, our test for serial correlation (Wooldridge 2002) indicates that the errors are autocorrelated, with the correlation estimate of the AR(1) errors being 0.13 ($p < 0.001$). Serial correlation is not a problem in the expenses and

Table 5 Alternate Model Specification

	Sales			Expenses		Profit		
	(1) OLS	(2) Main model	(3) Temporal flexibility	(4) OLS	(5) Main model	(6) OLS	(7) Main Model	(8) Temporal flexibility
# of temp workers	0.244***	0.648***	0.259**	−0.017***	−0.06***	0.071***	0.213***	0.151***
	(0.062)	(0.112)	(0.108)	(0.006)	(0.017)	(0.022)	(0.04)	(0.041)
(*# of temp workers*)^2	−0.011**	−0.061***	−0.054***	0.001	0.005**	−0.006**	−0.024***	−0.024***
	(0.005)	(0.013)	(0.012)	(0.0007)	(0.0002)	(0.002)	(0.005)	(0.005)
# of part-time workers	0.362***	0.503***	0.148	−0.023**	−0.087***	0.067**	0.153***	0.094***
	(0.082)	(0.098)	(0.094)	(0.009)	(0.015)	(0.029)	(0.032)	(0.035)
(*# of part-time workers*)^2	−0.007***	−0.012***	−0.008***	0.0004	0.002***	−0.002*	−0.004***	−0.003***
	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0004)	(0.0008)	(0.0009)	(0.0009)
# of full-time workers	0.663***	0.488***	−0.119	−0.001	−0.06***	0.147***	0.108***	0.012
	(0.132)	(0.135)	(0.138)	(0.012)	(0.019)	(0.036)	(0.040)	(0.047)
(*# of full-time workers*)^2	−0.006***	−0.0048***	−0.0008	0.00005	0.0006***	−0.002***	−0.001***	−0.0008*
	(0.0013)	(0.001)	(0.001)	(0.0001)	(0.0002)	(0.0004)	(0.0004)	(0.0005)
Sales forecast	4.743***	4.746***	4.028***			1.647***	1.672***	1.521***
	(1.274)	(0.346)	(0.307)			(0.384)	(0.107)	(0.113)
Sales				0.033***	0.034***			
				(0.003)	(0.004)			
Actual labor hours			6.467***	0.746***	0.855***			1.172***
			(0.327)	(0.039)	(0.056)			(0.114)
(*Actual labor hours*)^2			−0.233***	−0.026***	−0.030***			−0.045***
			(0.013)	(0.002)	(0.002)			(0.004)
Turnover of FT and PT workers	−4.699***	−5.731***	4.151***	0.243	0.632***	−0.945**	−1.195***	0.275
	(1.028)	(1.297)	(1.469)	(0.200)	(0.249)	(0.382)	(0.463)	(0.543)
R^2	0.83	0.83	0.86	0.86	0.86	0.69	0.68	0.69
Joint significance Wald test for linear and quadratic terms of temporary labor (p-value)	0.000	0.000	0.000	0.009	0.000	0.0119	0.000	0.000
Joint significance Wald test for linear and quadratic terms of part-time labor (p-value)	0.000	0.000	0.000	0.006	0.000	0.0625	0.000	0.000

Notes. All models, other than those indicated as OLS, were estimated by 2SLS methodology. Standard errors, reported in parentheses, are clustered by region. All regressions were run with store fixed effects, trend, and region-specific monthly dummies as additional controls. FT, full time; PT, part time.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

profit equations ($p > 0.1$ in both cases). If store managers take the serial correlation into account in their sales forecasts, then forecast errors may not be serially correlated. Therefore, to examine the robustness of our results in the sales equation, we transform the dependent variable from sales to forecast error (sales minus forecast) and find that this transformation eliminates the serial correlation in our sample ($p = 0.39$). We rerun the sales model with forecast error as the dependent variable with both labor-mix variables (similar to column (2) in Table 3) and labor variables (similar to column (2) in Table 5), and the results are reported in column (1) of Tables 6 and 7, respectively. This new model is similar to the earlier sales model with the exception that the slope of forecast is constrained to 1. So, the interpretation of the coefficients in this new model is similar to the earlier sales models. As reported in column (1) of Table 6, we find that this model also supports the inverted U-shaped relationship between the labor-mix variables and sales. In addition, the inverted U-shaped relationship is preserved with the alternate model specification, using labor variables, as shown in column (1) of Table 7. While this mitigates our concern that our earlier results were affected by the use of lagged endogenous variables as instruments due to the presence of serial correlation in the sales equation, we conduct further robustness checks with a different set of instruments as explained next.

4.1.4. Market-Based Instruments. Next we use market-based instruments to handle endogeneity in our setting. This approach is similar to that of Nevo and Wolfram (2002), who examined the impact of manufacturer's coupons on retailers' shelf price in a city. To account for endogeneity bias, the authors used a regional average of the couponing variable of all cities in a focal region after excluding the city that was being instrumented. Similarly, we use the average values of the linear and quadratic terms of our labor variables from other stores in the same state as instruments. There was one state with only one store, and it was dropped for this analysis. The rest

Table 6 Robustness Checks with Labor-Mix Variables

		Market-based instruments		
	(1) Forecast error	(2) Sales	(3) Expenses	(4) Profit
Temporary labor mix	23.56***	112.14***	−12.12***	19.76***
	(5.85)	(13.64)	(2.88)	(3.60)
(*Temporary labor mix*)^2	−111.82***	−455.43***	45.44***	−100.12***
	(31.97)	(107.86)	(13.49)	(0.92)
Part-time labor mix	12.89***	433.10***	−61.89***	18.89**
	(4.56)	(52.41)	(15.31)	(9.19)
(*Part-time labor mix*)^2	−11.48**	−523.33***	75.52***	−21.88*
	(5.79)	(59.95)	(18.23)	(11.70)
Observations	4,270	4,244	4,244	4,244
R^2	0.23	0.84	0.85	0.69
Joint significance Wald test for linear and quadratic terms of temporary labor mix (p-value)	0.000	0.000	0.000	0.000
Joint significance Wald test for linear and quadratic terms of part-time labor mix (p-value)	0.000	0.000	0.000	0.000

Notes. All regressions were run with store fixed effects, region-specific trend, and state-specific monthly dummies as additional controls. In addition the sales and profit regressions control for sales forecast and monthly turnover; expense regression controls for sales and linear and quadratic terms of total labor hours. All regressions were estimated using 2SLS methodology.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

of the sample had between 3 and 44 stores in the different states. These instruments serve as exogenous cost-based labor-supply shifters since the labor cost within a state would be correlated. We chose state-level averages, as opposed to a higher level of aggregation (region level) or lower level of aggregation

Table 7 Robustness Checks for Alternate Model Specification with Labor Variables

		Market-based instruments		
	(1) Forecast error	(2) Sales	(3) Expenses	(4) Profit
# of temp workers	0.024***	1.965***	−0.171**	0.022***
	(0.007)	(0.367)	(0.065)	(0.002)
(*# of temp workers*)^2	−0.003***	−0.141**	0.018*	−0.002**
	(0.0008)	(0.060)	(0.010)	(0.001)
# of part-time workers	0.014**	6.152***	−0.640***	0.091***
	(0.005)	(0.794)	(0.183)	(0.014)
(*# of part-time workers*)^2	−0.0003**	−0.179***	0.018***	−0.002***
	(0.000154)	(0.019)	(0.0049)	(0.0004)
# of full-time workers	0.006	0.549***	0.008	0.004***
	(0.005)	(0.098)	(0.009)	(0.001)
(*# of full-time workers*)^2	−0.0001	−0.005***	−0.000	−0.0001***
	(0.0000)	(0.001)	(0.0001)	(0.00001)
Observations	4,270	4,244	4,244	4,244
R^2	0.22	0.89	0.85	0.74
Joint significance Wald test for linear and quadratic terms of temporary labor mix (p-value)	0.000	0.000	0.034	0.000
Joint significance Wald test for linear and quadratic terms of part-time labor mix (p-value)	0.000	0.000	0.000	0.000
Joint significance Wald test for linear and quadratic terms of full-time labor mix (p-value)	0.14	0.000	0.06	0.000

Notes. All regressions were run with store fixed effects, region-specific trend, and state-specific monthly dummies as additional controls. In addition the sales and profit regressions control for sales forecast and monthly turnover; expense regression controls for sales and linear and quadratic terms of total labor hours. All regressions were estimated using 2SLS methodology.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(county level) for the following reasons. Higher levels of aggregation would produce weak instruments since labor costs would be different across stores in different states. We avoided county-level aggregation because most of the stores in our sample were present in different counties, so we could not obtain sufficient instruments with our approach.

Like prior research that used market-based instruments, our instruments also have the weakness that they could be problematic when there are nationwide demand shocks. In addition, our instrument can also suffer when there are state-specific demand shocks. Nevo and Wolfram (2002) state that this approach will work as long as there are sufficient fixed effects so that the errors across stores in a state will be uncorrelated. We undertake the following measure to mitigate the impact of such unobservable shocks. We include state-specific monthly dummies that should capture unobserved state-specific demand shocks that are correlated with seasonality. Since the shocks themselves are not observable, it is not possible to test for their presence directly.

We use these instruments with both model specifications: the one with labor-mix variables and the one with labor variables. The results of the analysis with labor mix are presented in columns (2)–(4) of Table 6, and the results of the analysis with the labor variables are presented in columns (2)–(4) of Table 7. We also calculate the 95% confidence interval for the stationary point in each of the cases to ensure that they lie within the sample (Fieller's (1954) method). Overall, we find that the results are stronger compared to our other instruments, as we find support for all three hypotheses for both temporary and part-time labor variables. The fact that two different sets of instruments generate similar patterns of results increases our confidence in our findings.

4.1.5. Hour-Based Labor Mix. One potential drawback of measuring labor participation in the store based on the number of workers is that it ignores the number of hours spent by workers in the store. For example, 10 part-time workers spending 30 hours per week would have a different impact from those workers spending 15 hours per week. To address this concern, we redefine the temporary and part-time labor-mix variables using the number of hours worked by each class of employees in a given month. For example, temporary labor mix is now defined as the ratio of number of hours worked by temporary workers to that of full-time employees. An advantage of these new measures is that they do not count employee participation when the employee is on vacation or absent. We estimate the model using 2SLS, where the instruments include lagged values of the newly defined labor-mix variables and unemployment rate, as defined earlier. As shown in

Table 8 Robustness Checks: Labor mix Based on Hours

	Labor mix based on hours		
	(1) Sales	(2) Expenses	(3) Profit
Temporary labor mix	47.86***	−3.75***	12.74***
	(8.16)	(1.28)	(2.75)
(*Temporary labor mix*)^2	−292.58***	24.43**	−93.20***
	(67.32)	(10.35)	(22.67)
Part-time labor mix	17.49***	−3.66***	7.17***
	(5.58)	(0.91)	(1.99)
(*Part-time labor mix*)^2	−26.83**	5.85***	−12.99***
	(11.31)	(1.88)	(4.09)
Observations	4,270	4,270	4,270
R^2	0.87	0.86	0.68
Joint significance Wald test for linear and quad. terms of temp labor mix (*p*-value)	0.000	0.000	0.000
Joint significance Wald test for linear and quad. terms of part-time labor mix (*p*-value)	0.000	0.002	0.000

Notes. The following control variables were included in all of the regressions: store fixed effects, region-specific trend, region-specific monthly dummies, sales forecast in sales and profit models, and sales and linear and quadratic terms of actual labor hours in expense models. All regressions were estimated using 2SLS methodology.

** and *** denote statistical significance at the 5% and 1% levels, respectively.

columns (1)–(3) of Table 8, the linear and quadratic terms of labor-mix variables are jointly significant ($p < 0.01$) in all cases. We compute the 95% confidence interval using the Fieller (1954) method and find support for Hypotheses 1–3. These results are stronger since Hypothesis 2, which was only supported for temporary labor, is also supported for part-time labor, as we observe a U-shaped relationship between part-time labor mix and expenses.

4.1.6. Quantile Regressions. Next we perform quantile regressions to test the robustness of the inverted U-shaped and U-shaped relationships using Equations (1)–(3). Quantile regressions are valuable since they provide robust estimates in the presence of misspecification errors due to heteroskedasticity and error-term misspecification, and also due to measurement errors. In addition, quantile regressions enable us to understand if the relationships hold across the entire distribution of the variables or they are specific to different parts of the distribution. Since our key variables of interest are endogenous, we follow Amemiya (1982) and perform a two-stage regression with OLS in the first stage and bootstrapped quantile regression in the second. The quantile regression results at 25%, 50%, and 75% are reported for the labor-mix variables in Table 9. The first three columns are related to the sales regression and the next three to expenses regression, and the last three are for profit regressions. We find that both linear

Table 9 Robustness Checks Using Quantile Regressions

	Sales			Expenses			Profit		
	(1) 25%	(2) 50%	(3) 75%	(4) 25%	(5) 50%	(6) 75%	(7) 25%	(8) 50%	(9) 75%
Temporary labor mix	15.29***	13.99***	13.50**	−3.09***	−2.06***	−1.89***	2.57	4.47**	4.46**
	(4.46)	(4.76)	(4.31)	(0.749)	(0.572)	(0.619)	(1.71)	(2.02)	(2.02)
(*Temporary labor mix*)^2	−57.65***	−49.76**	−42.96**	11.28***	8.13***	7.09**	−8.67	−20.03**	−19.15**
	(21.28)	(22.82)	(20.72)	(3.287)	(2.66)	(2.93)	(7.46)	(9.26)	(8.67)
Part-time labor mix	7.131	15.23***	12.99***	−0.86	−1.34**	−1.08*	5.27***	3.65**	5.36***
	(5.28)	(3.75)	(3.39)	(0.589)	(0.554)	(0.59)	(1.68)	(1.77)	(1.31)
(*Part-time labor mix*)^2	−7.419	−15.23***	−15.07***	0.68	1.46**	0.94	−6.66***	−4.18*	−6.44***
	(6.77)	(3.75)	(4.822)	(0.813)	(0.74)	(0.81)	(2.25)	(2.28)	(1.54)
Observations	4,270	4,270	4,270	4,270	4,270	4,270	4,270	4,270	4,270
Pseudo-R^2	0.60	0.61	0.61	0.68	0.68	0.66	0.42	0.46	0.43

Note. The following control variables were included in all of the regressions: store fixed effects, region-specific trend, region-specific monthly dummies, sales forecast in sales and profit models, and sales and linear and quadratic terms of actual labor hours in expense models.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

and quadratic terms of temporary and labor-mix variables are jointly significant in almost all cases ($p < 0.05$). In addition, we find that the stationary point lies within the sample in all the cases with temporary labor-mix variables providing support for the inverted U-shaped relationships with sales and profit and U-shaped relationships with expenses. In addition, the location of the stationary point within the sample for the part-time labor mix in the sales and profit equations supports the inverted U-shaped relationship between these variables. Although we do not find strong support for the U-shaped relationship between part-time labor mix and expenses, our estimates are consistent with a decreasing convex relationship as found earlier.

4.1.7. Spline Regressions. As further validation of the inverted U-shaped and U-shaped relationships, we run spline regressions. Spline regressions use knots to capture the changes in coefficients for different intervals of the independent variables. Since more knots increase the risk of multicollinearity, we use two and three knots for our analysis. Furthermore, since our interest lies in examining whether the slope of temporary and part-time labor-mix variables change direction in different intervals, we generate marginal splines such that the coefficient of each spline may be interpreted as the change in slope from the preceding interval. The results are reported in Table 10. Consider column (1), where we report the regression of sales equation with two knots. We find that the coefficient of the first spline is positive and significant, whereas the second is negative and significant ($p < 0.01$), supporting the inverted U-shaped relationship between temporary labor mix and sales. Similarly we find that the coefficient of the second knot is negative and significant ($p < 0.1$) for part-time labor mix, supporting the inverted U-shaped relationship between this variable and sales. The conclusions are similar when we consider the case with three knots, as shown in column (2). Next consider the results with two knots in the case of expense regression as shown in column (3). The coefficient of the first spline is negative and significant ($p < 0.05$), and that of the second spline is positive and significant ($p < 0.05$), indicating support the U-shaped relationship between temporary labor mix and expenses. We obtain similar conclusion with three knots as well, as shown in column (4). Finally, columns (5) and (6) support the inverted U-shaped relationship between both labor-mix variables and profit.

4.1.8. Higher Order Effects. Finally, despite the strong theoretical motivation and empirical evidence supporting our U-shaped relationship, we evaluate whether a cubic relationship might better capture the underlying empirical relationship. We estimate Equations (1)–(3) after inserting a cubic term for the part-time and temporary labor-mix variables. As recommended by Greene (2003), we compare the Akaike information criterion and the Bayes information criterion for the two sets of models (quadratic versus cubic for sales, expenses, and profits), and in each case the values for the quadratic models (those without the cubic terms) are lower, suggesting that our chosen model is the preferred approach.

4.2. Alternate Explanations

4.2.1. Workload Effect. First, we examine if the inverted U-shaped relationships between our labor-mix variables and sales are a result of the workload effect identified in prior literature (Tan and Netessine 2012). Ideally, we would need traffic data to measure workload so we can examine its effect on performance. Since we do not possess traffic data, we do the following. We obtain sales per labor hour by dividing

Table 10 Robustness Check Using Spline Regressions

	Sales		Expenses		Profit	
	(1) Two knots	(2) Three knots	(3) Two knots	(4) Three knots	(5) Two knots	(6) Three knots
Temporary labor mix 1	6.42***	7.41***	−0.39**	−0.39**	1.59***	2.23***
	(1.52)	(2.33)	(0.19)	(0.19)	(0.50)	(0.80)
Temporary labor mix 2	−33.29***	−1.35	1.06**	1.07*	−4.58*	−1.69
	(12.39)	(3.22)	(0.49)	(0.59)	(2.48)	(1.17)
Temporary labor mix 3		−26.92***		−0.11		−5.98**
		(10.14)		(2.92)		(2.42)
Part-time labor mix 1	4.97**	4.99***	−0.49*	−0.49*	2.53***	2.21***
	(1.91)	(1.91)	(0.27)	(0.27)	(0.73)	(0.66)
Part-time labor mix 2	−3.95*	−3.77*	0.38	0.41	−2.32***	−1.91**
	(2.18)	(2.21)	(0.31)	(0.37)	(0.81)	(0.77)
Part-time labor mix 3		−14.62		−0.06		−0.92
		(18.57)		(0.31)		(1.78)
Observations	4,156	4,156	4,156	4,156	4,156	4,156
R^2	0.86	0.87	0.85	0.85	0.67	0.68

Note. The following control variables were included in all of the regressions: store fixed effects, region-specific trend, region-specific monthly dummies, sales forecast in sales and profit models, and sales and linear and quadratic terms of actual labor hours in expense models.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

sales by total labor hours for each store-month combination. Our expectation is that sales per labor hour is a proxy for workload with higher values of sales per labor hour being correlated with higher workload. In fact, our conversation with RetailCo revealed that they use sales per labor hour as a measure for work load in the same way. One issue with subsampling based on workload is that stores are likely to have fewer temporary workers when the workload is low. So the coordination costs, which we expect would increase with number of workers, would be lower as well, thereby confounding this analysis. However, part-time workers are year-round employees, so we can examine the impact on these workers to tease out the impact of coordination costs from workload effect.

We divided our sample in two halves based on sales per labor hour and chose the subsample with sales per labor hour in the bottom 50th percentile. We expect the workload effect, if any, to be absent or mitigated in this subsample. As predicted, we find that proportion of temporary workers is lower (median = 5.7%) when workload is in the bottom 50th percentile compared to when workload is higher (median = 8.3%). Column (1) in Table 11 reports the results of the regression of sales against labor-mix variables in this subsample. We find support for the inverted U-shaped relationship between part-time labor-mix variables and sales, indicating that our results are driven by factors beyond just workload. To be clear, our proxy for workload is weak so future work should use traffic data to explore what additional effects workload might have in a retail setting, as well as how workload interacts with flexible operations.

4.2.2. Manager Turnover. Another possible explanation for the observed result may be attributed to manager turnover. Because store managers play an important role in training and managing labor, stores can be subject to considerable disruption when the manager departs. This could result in exacerbation of issues, such as coordination costs and the mismatch between labor and task, that we argue are driving forces behind the inverted U-shaped and U-shaped relationships. Therefore, we examine if stores without turnover also exhibit this phenomenon so we may learn about the generalizability of our results. Of the 445 stores in our sample, we find that 228 stores had manager turnover during the period of study. Our discussions with RetailCo revealed that less than 30% of those stores had their managers terminated. The vacancies created by those openings were filled by managers from other stores, resulting in additional changes. Our results, shown in columns (2)–(4), based on stores that do not experience manager turnover also reveal inverted U-shaped and U-shaped relationships similar to those obtained with the entire sample, indicating that manager turnover did not confound our results.

4.2.3. Hiring and Layoff Costs. An alternate explanation for the U-shaped relationship between expenses and temporary labor mix is the presence of hiring and layoff costs. We obtained the line item expense for employee screening and deducted this expense and repeated the analysis and found the U-shaped relationship to persist. However, it is likely that the costs of hiring and layoff are intangible, so we follow Holt et al. (1955) and include a quadratic

Table 11 Alternate Explanations

	Workload effect	Manager turnover			Hiring/firing costs	Experience		
	(1) Sales	(2) Sales	(3) Expenses	(4) Profit	(5) Expenses	(6) Sales	(7) Expenses	(8) Profit
Temporary labor mix	14.69***	23.62***	−4.505***	11.01***	−2.45***	23.42***	−2.34***	6.19***
	(5.57)	(8.21)	(1.208)	(2.68)	(0.81)	(5.18)	(0.85)	(1.77)
(*Temporary labor mix*)^2	−40.25	−77.63*	19.397***	−46.39***	10.42**	−93.14**	10.33***	−30.78***
	(31.22)	(43.79)	(6.252)	(14.32)	(4.22)	(27.01)	(4.45)	(9.35)
Part-time labor mix	12.92***	18.46***	−2.405***	6.60***	−2.48***	13.04***	−2.42***	5.24***
	(4.22)	(5.80)	(0.853)	(1.93)	(0.63)	(4.14)	(0.67)	(1.40)
(*Part-time labor mix*)^2	−13.30**	−18.21**	2.422**	−6.60***	2.38***	−15.69***	2.37***	−6.11***
	(5.39)	(7.36)	(1.078)	(2.46)	(0.82)	(5.60)	(0.76)	(1.80)
Cost of hiring and layoff					685.14			
					(571.39)			
Store associate experience						−0.01***	0.00***	−0.00***
						(0.00)	(0.000)	(0.00)
Observations	2,154	2,107	2,107	2,107	4,270	4,270	4,270	4,270
R^2	0.84	0.83	0.82	0.69	0.89	0.86	0.84	0.68
Joint significance Wald test for linear and quad. terms of temp labor mix (p-value)	0.000	0.000	0.000	0.000	0.016	0.040	0.004	0.000
Joint significance Wald test for linear and quad. terms of part-time labor mix (p-value)	0.004	0.000	0.000	0.000	0.000	0.004	0.000	0.000

Notes. The sales and profit models had sales forecast as a control. The expense models were controlled for sales and linear and quadratic terms of actual labor hours. All regressions were run with store fixed effects, trend, and region-specific monthly dummies as additional controls. All regressions were estimated using 2SLS methodology.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

term of the change in number of temporary employees from one period to the next as a control variable in our analysis, as shown in column (5). We continue to observe the U-shaped relationship between labor mix and expenses, indicating that our results are not driven solely by the hiring and layoff costs of temporary workers.

4.2.4. Store Associate Experience. The average experience of associates in a store is correlated with the labor-mix variables, raising questions about omitted variable bias in our estimates of our key variables. Although we know the start date of temporary workers in our sample, we do not have the start date for part-time and full-time workers unless they joined the store during our study period. We calculate the average experience of the workforce as the average worker tenure beginning from the start of the sample period, weighted by their monthly work hours. As shown in columns (6)–(8), Hypotheses 1–3 are supported with the addition of the new control, indicating that our main results are not driven by omitted variable bias.

5. Discussion and Conclusion

5.1. Economic Significance of Volume Flexibility Offered by Flexible Labor Resources

We now examine the economic significance of the impact of volume flexibility offered by flexible resources on store performance. Specifically, we have two goals. We want to determine, first, the overall economic significance of flexible resources to retail stores and, second, the economic significance of following the optimal labor mix, as found in our research, to RetailCo. Since this is the first study that has examined flexible resources in a service setting, knowledge of the overall value that flexible resources provide to retailers could provide impetus for future work. Addressing the second goal enables us to understand if the potential improvement for RetailCo is substantial and worth acting upon. Recall that the coefficients reported in columns (2) and (7) of Table 3 capture the overall impact of volume flexibility on sales and profitability, so we use these coefficients for our analysis. Because the dependent variables were divided by a constant to preserve the confidentiality of our data, we readjust the economic effects by that same constant before expressing them as a percentage of average store performance.

5.1.1. Economic Significance of Flexible Resources to Retailers. First, consider the impact of volume flexibility offered by the temporary labor mix on sales based on the coefficients reported in column (2) of Table 3. This impact may be quantified by assessing the sales impact of increasing temporary labor mix from zero to its optimal value of 13.48%. For this case, we find that the increase in sales will be 6.78% of average monthly sales (during the peak season) for this retailer. A similar analysis for the part-time workers shows that increasing part-time labor mix from zero to its optimal value, 44.03%, increases sales by 15.04% of average monthly sales. However, we find the minimum part-time labor mix to be 16.03% in our sample. To avoid the risk of extrapolating beyond the sample, we only consider the impact of increasing part-time labor mix from 16.03% to its optimal value and find this value to be 6.21%. Together, we estimate the total impact of volume flexibility offered by flexible resources on sales to be 12.99% of average monthly sales.

Next consider the impact of volume flexibility on store profitability using coefficients reported in column (7) of Table 3. The optimal value of labor mix that maximizes profit is different from that which maximizes sales. Since retailers can either maximize short-term profit or maximize sales that could result in potentially longer-term profit, we allow these optimal values to be different for the purpose of this analysis. We find the increase in store profitability when temporary labor mix increases from zero to the optimal value to be 13.92% of average store profit during peak season. A similar analysis for part-time labor mix shows the increase in store profitability to be 18.22% of average store profit when part-time labor mix increases from 16.03% to the optimal value. Together, our results show that flexible resources can increase profitability by 32.22% of average store profit.

5.1.2. Economic Significance of Having the Optimal Labor Mix for RetailCo. Next consider the impact of following the optimal labor mix for RetailCo. To do so, we consider the average store in the chain. The average store has temporary and part-time labor mix values of 7% and 32.32%. If this store increases its temporary and part-time labor mixes to their respective optimal values that maximize sales, then this store's sales would increase by 2.75%. Since this retailer's annual revenues exceed $10 billion Dollars, with more than 60% of the annual revenue achieved during the five month peak period, an increase in sales by 2.75% translates into well over $100 million of additional sales in the peak period. A similar analysis for profitability shows that this store can increase its profitability by 3.4%.

Our above analysis assumes that retailers would increase the part-time labor mix during the peak season. Since part-time workers are year-round employees, it is possible that this retailer may not want to increase the part-time labor mix only during peak season. So, we repeat the analysis by only considering an increase in the temporary labor mix to its optimal value during peak period. This analysis shows that the average store sales will increase by 1.45% and profitability will increase by 1.72% if retail stores increase only their temporary labor mix during the peak season.

To summarize, our results on the impact of volume flexibility on sales and profitability show a large impact of flexible labor resources on store performance. Our analysis of RetailCo shows that this retailer captures significant value through use of flexible labor resources, but can benefit further by following the optimal labor mix found in our research.

5.2. Limitations and Venues for Future Research

As with all studies, our work has limitations that bear noting and offer opportunities for future work. Although our study benefitted from the access provided to data and personnel from RetailCo, it is still limited to one organization. Thus, it is important to conduct further research in other firms to determine the generalizability of our results. In addition to examining other retail settings, services such as healthcare, call centers, construction, and even software could prove to be interesting venues for exploration of these trade-offs. A second limitation of our study is that, because of space limitations, we are unable to examine potential moderators of our relationships in this paper. For example, how might the observed nonlinear effects between labor mix and store performance vary based on characteristics of the store, the manager, or the workforce. We note that we do not see differences in the nonlinear effects across stores of different sizes. Future work should examine each of these factors. Third, although we have made significant efforts to eliminate endogeneity bias, through the use of instrumental variables in our main model, as well as our additional robustness checks, we cannot guarantee that we have done so. Future work should seek to implement a controlled field experiment to clearly establish causality.

Another limitation of our study is that the aggregate nature of our data set prevents us from studying the behavior of individuals. Combining detailed individual data with traffic information could generate further insight on the mechanisms driving our results. For example, prior work finds that service rates are endogenous to load (KC and Terwiesch 2009, Staats and Gino 2012) and that overloading workers may result in a degradation of performance (Tan and Netessine 2012). It would be useful to understand how effects such as workload might vary across different types of workers. Future work may also utilize field or lab experiments as well as qualitative data collection to investigate potential micromechanisms in more detail. Fourth, although we were predominantly interested in examining the impact of labor mix on short-term financial performance, it is possible that labor mix might have an impact on other dependent variables, such as service quality, employee turnover, worker safety, long-term financial performance, etc. Additionally, if stores shift away from full-time positions to part-time and temporary positions, then there could be negative long-term effects on workers. For example, with less job security, a worker might be unwilling to commit to learn as much over time as a full-time worker would have. These long-term issues are important concerns that are worth future study.

Finally, our study's time frame overlapped with the economic downturn in the United States. The high levels of unemployment during this period would have provided greater access to labor supply for this retailer. Although the shift toward unconventional employment relationships has been underway since at least the 1970s, through both economic downturns and expansions (Kalleberg 2000), investigating the relationships we study under tight labor market conditions could generate additional insights.

5.3. Conclusion

This study makes several contributions to the academic literature. First, we respond to the call to examine flexibility in services (Ettlie and Penner-Hahn 1994) by providing, to our knowledge, the first empirical examination of volume flexibility in services. Second, by studying services, we identify a heretofore unexamined relationship between flexible labor resources and organizational performance—sales. Because of customer coproduction, different types of labor can meaningfully change an organization's sales. Our results show that flexible labor resources provide volume flexibility for sales, and that one underlying mechanism is upside flexibility in the form of more hours. Additionally, holding the total hours constant, we find that both temporary and part-time workers are related to greater sales in a store, at least up to a point. We posit that this effect is driven by temporal flexibility, the ability to better match the supply of workers to the within-day or within-week demand of customers.

Third, we find that flexible labor resources are not an unalloyed good. Our results highlight that although both temporary and part-time labor can yield higher sales, lower expenses, and greater profits, it is possible to have too much of a seemingly good thing. Counterintuitively, we find that, in the case of many stores, reducing the amount of flexible resources in a store may yield higher sales and greater profits. Fourth, whereas prior analytical approaches have investigated two class systems (e.g., permanent workers versus flexible workers; Pinker and Larson 2003, Bhandari et al. 2008), by examining the problem empirically, we find that there are actually two dimensions for flexible resources (part time and temporary). Dimensionalizing flexible resources appropriately is important, because these dimensions have predictable and different effects. Future work in operations management should extend our findings by not only investigating additional moderators of the empirical relationships, but also by expanding analytical models to incorporate these multiple dimensions of flexible labor resources.

Fifth, the role of labor in driving store performance is a topic of emerging interest in the retail operations area (Fisher et al. 2007, Ton and Huckman 2008, Netessine et al. 2010, Ton 2010, Perdikaki et al. 2012). We contribute to this literature by unpacking the differential impacts of various types of labor on store financial performance. Finally, with our field study we heed the call to advance theory at the boundary of operations and human resources management (Boudreau et al. 2003).

Our findings also have important implications for managers. In §5.1 we detail how the increasing use of flexible labor resources may lead to increased sales and profitability. Managers should be mindful of the expansionary capacity that flexible labor resources may offer and avoid underutilizing such resources. However, as noted before, the inverted U-shaped relationships between temporary labor mix and both sales and profitability indicate that it is possible to overuse flexible labor resources. Organizations must carefully evaluate their use of flexible labor resources. With such evaluation it may be possible to either limit the use of such resources or develop ways to extend the amount of temporary or part-time resources that can be used productively. For example, one mechanism to explore in this latter area is the onboarding process for new staff (Cable et al. 2013). In discussing our results at RetailCo a manager noted, "Managing temporary staff in the retail industry is a fundamental challenge. Whoever you are you have a seasonal peak that you have to address. If you can manage that onboarding process more effectively then you can derive significant competitive advantage." Future work should explore how the on-boarding process may moderate the impact of temporary workers on profitability.

Altogether our results highlight that flexible labor resources can create volume flexibility in services; however, such flexibility must be deployed carefully for firms to achieve maximum benefit.

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