A Structural Estimation Approach to Agent Attrition

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Abstract

Worker attrition is a costly and operationally disruptive challenge throughout the world. Although large bodies of research have documented drivers of attrition and its operational consequences, managers still lack an integrated approach to understanding attrition and making decisions to address it on a forward-going basis. To fill this need we build and then estimate a structural model that captures both the firm's decision to terminate a workers' employment (involuntary attrition) and uses an optimal stopping problem process to model a workers' decision to leave the firm (voluntary attrition). We then estimate the parameters of the model and conduct counterfactual analyses on the population of 3,680 agents serving one client over five years for an Indian business process management (BPM) company. Our model reveals a number of interesting findings as we see that agents focus little on the future and are relatively insensitive to salary. These factors only increase with time spent at the firm. We find that supervisors have a strong impact on whether employees stay as they reshape the way that agents make their decisions. If all employees were managed by the best supervisor in our data then voluntary attrition would reduce by over 30%. Altogether our paper contributes to the burgeoning literature on people operations, as well as to managerial practice.

Keywords: Attrition, Empirical Operations, People Operations, Structural Estimation

1 Introduction

The departure of existing employees from a firm, employee attrition, is a costly and consistent operational challenge. For example, industry estimates suggest that attrition costs a firm as much as two times an individual's salary (WSJ (2017)). However, as noted by Heskett et al. (2008), "the real cost of turnover is the loss of productivity and decreased customer satisfaction (p. 168)." Research in operations supports this view finding that attrition leads to slower delivery of products and services and worse quality of the output (Oliva and Sterman (2001); Ton and Huckman (2008); Narayanan et al. (2009)). All told this suggests that attrition can lead to billions of dollars in lost profits for firms (Glebbeek and Bax (2004)).

Given that the cost of attrition is clear, what then is a manager to do? A reasonable first step is to examine drivers of attrition. A long line of research has done just that identifying a myriad of factors from compensation to work structure to one's manager that may lead to increases in attrition (see Griffeth et al. (2000) for a review of the literature). The next step would then be to use research to identify rigorous approaches to decrease turnover. Although prior research has found correlates with worker attrition that could help in this regard, two significant and related challenges remain. First, little of this work has been done with methods to identify causal relationships. Second, even when causal methods are used (e.g., Cable et al. (2013)) they tend to examine one possible driver, rather than taking a more holistic approach. In this paper we aim to address these difficulties by building and then estimating a structural model of worker attrition. With this approach we not only are able to gain insight into the relative impact of different drivers of attrition, but also through the use of counterfactual analysis we can make recommendations on how managers should most effectively address the attrition challenge.

As a context to examine attrition we choose the Indian business process management (BPM) industry. In this industry workers complete back office processes such as data entry or customer support through voice or text. This is an important industry to study as it is estimated that India accounted for 38% of the $186 billion global market in 2015 (NASSCOM (2016)). Moreover, attrition is a constant challenge, with reported industry attrition rates hovering anywhere from 50% - 75% annually (Mukherjee et al. (2009)). Therefore, we collected detailed data from one contact center account within a leading Indian BPM firm. Combining individual demographic information with salary data, and macroeconomic data we study 3,680 individuals working in one customer account at the firm over five years.

To examine the agent attrition decision we build a structural model of the attrition process. An individual can leave a firm either unwillingly (involuntary attrition) or willingly (voluntary attrition). To incorporate this duality we first characterize the firm's decision for involuntary attrition to terminate or not terminate an agent's employment. We then model agents' decision to stay or leave the firm as an optimal stopping process in a dynamic programming context. After evaluating our findings we then conduct a Monte-Carlo based counterfactual analysis to understand how a firm could address the attrition challenge.

Our model reveals a number of interesting findings. First, we find that, although there is variability, in general, agents forward looking behavior is low. In other words, agents discount the expected future utility heavily and are myopic, or short-term focused, rather than being more strategic, or long-term focused. Consequently, agents may not delay their decision to leave the firm for the hope of obtaining a higher utility (e.g. salary) in the future. As a result, employees' time focus has important implications for how to structure interventions meant to reduce attrition. Second, we find that sensitivity to salary is generally low in our sample. This suggests that agents are unwilling to change their attrition behavior dramatically with increases in salary. Our counterfactual analysis supports this view finding that a 30% increase in salary is only related to a 2.5% decrease in voluntary attrition. Third, we find that work experience at the firm changes agents' behavior in important ways. Over time agents' sensitivity to salary increases but their willingness to stay for non-monetary utility goes down. Moreover, the level of forward looking behavior goes down even more. This is consistent with a view that employee relationships with a firm grow more transactional over time. Finally, we find important differences in employee behavior under different supervisors as supervisors terminate agents' employment at different rates and also employees choose to leave supervisors at varying rates. Our counterfactual analysis shows that if all supervisors were to achieve results like the most successful supervisor in the firm then voluntary attrition would decrease by over 30%. Somewhat surprisingly we find that this supervisor actually separates employees at a higher rate than normal, however, this link is consistent throughout our model as we see that an increasing chance of termination is related to increasing forward looking behavior which decreases voluntary attrition.

Altogether our paper contributes to literature on attrition in operations as we introduce a powerful tool to consider the systemic nature of attrition and to make decisions going forward. In addition, our findings help managers to address one of their most significant problems - managing attrition.

In the remainder of the paper, Section 2 presents the literature review. Section 3 describes our data set. Section 4 presents the model for the involuntary and voluntary attrition decisions. Section 5 lays out the estimation framework. Section 6 illustrates the estimation results and insights, and Section 7 provides the interpretation of the demographics and supervisor effects. Section 8 presents the results of our counterfactual analyses. And finally, Section 9 provides a discussion of our results and offers concluding remarks.

2 Literature Review

In this paper we draw on three streams of literature. The first, largely within the management literature, looks at predictors of attrition. A number of thorough reviews have been conducted on this literature (e.g., Griffeth et al. (2000); Holtom et al. (2008)). These studies highlight a number of important correlates with worker attrition. These include demographic characteristics, such as age, monetary factors, such as salary, non-monetary factors, such as the work in the job or the work environment, supervisor interaction, and the external environment, such as alternative job opportunities. A thorough consideration of a worker's decision to leave a firm must consider each of these elements independently, but also together as a system, something that has rarely been done (Griffeth et al. (2000)). In addition, although the reviews point out that theory on attrition/turnover has grown more dynamic with time, there is a need for more development as can be seen when Holtom et al. (2008) call out that "We believe that the increase in temporal theorizing in turnover study is promising and clearly one of the most fertile areas for future research (p. 255)." In this paper we believe that we are the first to not only examine demographic, monetary, non-monetary, supervisor, and external characteristics together, but also do so in a dynamic model.

The second area of related research is in the work that examines the relationship between attrition and operational performance. Park and Shaw (2013) review this literature across the management, economics', and operations' domains. The operations literature has typically focused on one of two areas in this tradition. In one line of work attrition has served as an input to decision models. For example, models looking at employee planning problems explicitly incorporate attrition (Dill et al. (1966); Sohoni et al. (2004)). In a related line of work, Green et al. (2013) show that overwork leads to absenteeism and then offer a staffing model that incorporates the impact of overwork.

In the second line of work the focus is on how attrition changes operational performance. For example, Oliva and Sterman (2001) use a systems dynamics model to show how attrition can lead to an erosion of service quality. Ton and Huckman (2008) show that worker attrition leads to lower profits and worse customer service, although they find that increased process conformance can offset the negative effect. Narayanan et al. (2009) use software teams to show that not only does worker attrition lead to longer task completion times, but also that teams are hurt more when more knowledgeable team members leave. A meta-analysis of this line of work highlights the importance of breaking attrition down into voluntary attrition, when workers leave by choice, and involuntary attrition, when workers are forced to leave, as the paper finds that voluntary attrition is related to negative operational performance, but involuntary attrition is not negatively related to performance (Park and Shaw (2013)). This body of work motivates our study of worker attrition since it highlights the importance of attrition as an input to successful operational systems. Moreover, we are guided by the insight of two types of attrition and so model both the firm's involuntary attrition decision and the worker's voluntary attrition decision.

Finally, we build on prior work that use a structural estimation approach. The structural estimation approach has recently become popular in the Operations Management literature. Olivares et al. (2008) use a structural estimation approach to impute the parameters of a newsvendor model for operating room scheduling. Li et al. (2014) model customers as strategic decision makers in the airline industry context. Aksin et al. (2013), Aksin et al. (2016) and Yu et al. (2016) use an optimal stopping model, similar to that of the seminal work by Rust (1987), to model customers' decision between waiting and abandoning in the call center context. We use a similar stopping model for agents' voluntary attrition decision. Some of the most relevant work for this paper are those that use the structural estimation approach to model workers' decision making processes. In Daula and

Moffitt (1995) the authors use a dynamic model to estimate the impact of financial incentives on the re-enlistment decisions of military personnel. Chung et al. (2013) and Misra and Nair (2011) estimate a dynamic model of sale force compensation to find the impact of financial incentives, such as bonuses, on sale force productivity. Our framework is focused on attrition rather than productivity. We not only implement the involuntary attrition decisions of the firm (employment termination decisions) but also use a dynamic model for agents' voluntary attrition decisions, and take into account the impact of agents' level of forward looking behavior and their non-monetary utility on top of their sensitivity to monetary compensations (salary). One similarity between our work and Chung et al. (2013) is that we are able to estimate agents' discount factors as a proxy for their level of forward looking behavior. We give more details about this in Section 5.

3 Data

Our data contains human resources information (including the attrition decisions) for agents working in a contact center for a BPM service provider in India. We call this contact center service provider "the firm" for the remainder of the paper. The firm provides contact center services for different clients/companies in firm facilities throughout India. However, our data shows the information for agents providing service to only one of the clients working across two firm centers. We can observe agent demographics, their annual salaries and their attrition status. We do not observe agents' operational performance measures in the data. To be more specific, our cleaned data set includes information for the complete population of 3,680 agents from January of 2011 to February of 2016 working for the client with the following entries:[1]

- Year and Month of joining the firm
- Status of the agent:
  - Current (C): the agent is still working for the firm
  - Involuntary attrition (IA): the agent's employment was terminated by the firm
  - Voluntary attrition (VA): the agent left the firm voluntarily
- Year and month of leaving the firm if the agent is not currently working for the firm (IA and VA status)
- Annual salary for every year (we do not observe the actual numbers. The salaries were scaled for confidentiality.)
- Gender
- Age when joined the firm

[1] We have removed rare observations and outliers, which consist of less than 5% of our data set. The following observations were removed from our data: 37 agents with location in Saritavihar, 25 agents with shift defined as general and 117 agents with missing position.

- Location of the center: Airoli, Noida (two Indian cities)
- Education level prior to joining the firm: Engineering, Graduate, Undergraduate, others
- Position: Associate, Senior Associate, Analyst
- Shift of work: Day or ND (Not determined)
- ID of agents' supervisor

The following table shows the summary statistics of agent demographics.

Table 1: Summary statistics of agent demographics.

Education	**Location**	**Tenure (years)**
Graduate - 26.93%	Noida -70.95%	Mean = 0.71
Under graduate - 33.97%	Airoli - 29.05%	St. Dev.= 0.66
Engineering - 12.47%	**Gender**	**Age (years)**
Others - 26.63%	Male - 70.68%	Mean=25.85
Position	Female - 29.32%	St. Dev.=4.51
Associate - 75.92%	**Shift**	
Senior associate - 16.90%	Day - 45.41%	
Analyst - 7.17%	ND - 54.59%	

Figure 1 shows the number of agents joining the firm in different years.

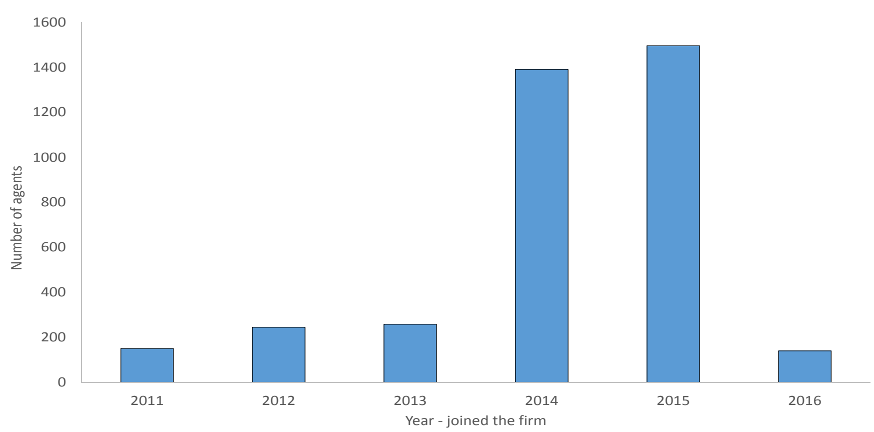

Figure 1: The number of agents joining the firm in different years.

As can be seen in Figure 1, as a result of a larger share of business from the client, the firm started to hire a relatively higher number of agents from 2014 onwards. The number in 2016 is low, which is a result of having data until February of 2016 and not observing all hires in 2016.

The following table shows the number of agents, the percentage of the total agents and the average tenure depending on agents' status.

Status of the agent	Number of agents	% of total	Average tenure (years)
Voluntary Attrition	1823	49.54%	0.88
Involuntary Attrition	561	15.24%	0.60
Current	1296	35.22%	0.62

Table 2: The number of agents, the percentage of the total number of agents and the average tenure depending on agents' status.

As can be seen in Table 2 around 65% of the agents in the population leave the firm either voluntarily or involuntarily. Moreover, the average tenures of the agents who left the firm are less than a year.

Figure 2 illustrates the histogram of agents' tenure durations depending on their status. As can be seen in Figure 2, most of the agents currently working in this account have been working for less than two years. In addition, Figure 2 shows that most of the agents who left the firm irrespective of it being voluntarily or involuntarily worked for less than a year. In the next section, we explain the model for the attrition decisions.

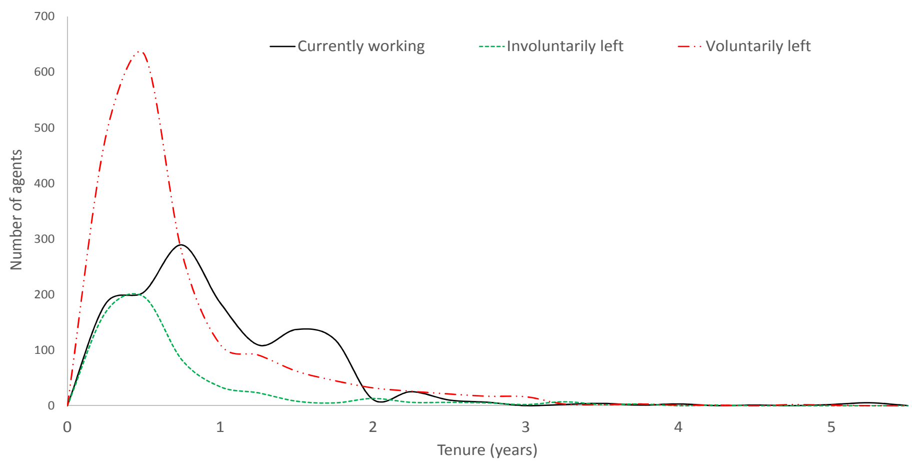

Figure 2: The histogram of agents' tenure duration depending on status.

4 The Model

In this section, we lay out a structural estimation model for agent attrition. We first characterize the firm's decision between terminating or not terminating an agent's employment (Involuntary attrition). Then we model agents' decision of leaving the firm or continuing to work at the firm (voluntary attrition) as an optimal stopping process.

Preliminaries. Suppose that agents are indexed by $i \in \{1, ..., N\}$. Let t denote the time passed since an agent joined the firm and let $d(t)$ denote the actual calendar month of t. For example, if agent i joins in October of 2008 and continues to work until December of 2008, in December we have: $t = 2$ months and $d(t) =$ December, 2008. We denote the vector of macro economic conditions at time t since joining the firm by $E_{d(t)}$. In our setting, we assume the vector $E_{d(t)}$ contains two variables: Indian GDP (in 10 Trillion) and inflation rate (in percentage).

Denote by W_i the duration of time the agent worked or has been working for the firm, and denote by O_i the status of the agent. The variable O_i is equal to 1, 2 and 3 if the agent is currently working for the firm, was terminated by the firm and voluntary left the firm, respectively. Furthermore, suppose that s_{it} denotes the salary of agent i in period t since joining the firm. Moreover, let x_i denote the vector of demographics of agent i. The vector x_i contains the following variables for agent i: age when joined the firm, indicator variables for location, shift assignment, gender, position, supervisor, and education level. And finally, denote by y_{it} the vector of state variables observable by agent i in period t since joining the firm. This vector is observable by the firm as well. We have $y_{it} = (t, s_{it}, E_{d(t)})$. In other words, the vector of state variables includes how long the agent has been working for the firm, the current salary and the vector of economic conditions in the current period. Next we explain the model for involuntary attrition. In the remainder of the paper, the term "IA" and "VA" stand for "involuntary attrition" and "voluntary attrition," respectively.

4.1 The Model for Involuntary Attrition

As mentioned in Section 3 around 15% of the agents in our data set involuntarily leave the company. In other words, the firm chooses to terminate their employment. We do not observe the reason for employment termination. However, we want to find out the impact of agents' tenure, salary and demographics on their chances of involuntary attrition.

Let f_{it} denote the decision of the firm with respect to agent i in period t since the agent joined the firm, where $f_{it} = 1$ corresponds to terminating the agent's employment and $f_{it} = 0$ corresponds to keeping the agent. The utility of the firm from taking action f_{it} is given by

$$u_{fit}^{IA}(f_{it}, y_{it}, \epsilon_{fit}) = v_{fit}^{IA}(f_{it}, y_{it}) + \epsilon_{fit}(f_{it}), \tag{1}$$

where ϵ_{fit} is the random shock (unobserved to the econometricians) that may shift the utility of the firm. The term $v_{fit}^{IA}(f_{it}, y_{it})$ is the nominal utility of the firm that is independent of the random shock. The error term ϵ_{fit} captures the impact of factors unobserved in the data that may contribute to the decision of the firm with respect to the involuntary attrition decision such as unsatisfactory performance of an agent that may trigger termination.[2] We assume that the error terms $\epsilon_{fit}(f_{it})$ are independent across agents and time periods.

Following the standard practice in the marketing and industrial organization literature (Nevo (2000)), for identification purposes we need to normalize one of the nominal utilities. We assume

[2]Recall that we do not observe the agents' operational performance in the data.

that the nominal utility of the firm from keeping the agents (not-separating) is zero.[3] That is:

$$v_{fit}^{IA}(0, y_{it}) = 0. \tag{2}$$

The nominal utility of the firm from terminating the agent's employment depends on the agent's salary, tenure, demographics, and the economic conditions in the following fashion:

$$v_{fit}^{IA}(1, y_{it}) = \lambda_0 + \lambda_t t + \lambda_s s_{it} + \lambda_x^T x_i + \lambda_e^T E_{d(t)}. \tag{3}$$

We assume the firm makes the decision between terminating and not terminating the agent's employment at the end of period t. If the firm decides to keep the agent, the agent may work in period $t+1$ and the firm makes the decision between terminating and not terminating again at the end of period $t+1$. The optimal decision of the firm denoted by $f_{it}^{optimal}$ is given by

$$f_{it}^{optimal} = \max_{f_{it} \in \{0,1\}} u_{fit}^{IA}(f_{it}, y_{it}, \epsilon_{fit}(f_{it})). \tag{4}$$

Moreover, we assume that the random shocks ϵ_{fit} have type-I extreme value distribution with the scale parameter equal to 1 and the location parameter $-\gamma$, where γ is Euler's constant. This ensures that the mean of the extreme value distribution is zero (see Nair (2007)). Following this assumption the probability of involuntary attrition for agent i in period t since joining the firm has the Logit form and is given by

$$P_{fit}^{IA}(1, y_{it}) = \frac{\exp(\lambda_0 + \lambda_t t + \lambda_s s_{it} + \lambda_x^T x_i + \lambda_E^T E_{d(t)})}{1 + \exp(\lambda_0 + \lambda_t t + \lambda_s s_{it} + \lambda_x^T x_i + \lambda_E^T E_{d(t)})}. \tag{5}$$

The next section lays out the model for agents' voluntary attrition decisions.

4.2 The Model for Voluntary Attrition

We model agents' voluntary attrition decisions using an optimal stopping framework in the dynamic programming context. The dynamic optimal stopping models have been used extensively in the literature in different areas from the seminal work of Rust (1987) to more recent applications in the OM literature such as Aksin et al. (2013).

Agents are forward looking and take expected future utility into account when making decision about leaving the firm or continuing to work. The motivation for including the forward looking behavior of the agents using a dynamic model is that agents when making the voluntary attrition decision not only take their current condition into account but also may take the expectation about their future utility into consideration. For example, not only the current salary of an agent, but also her expectation about the amount of its increase in future years would impact her voluntary

[3]The results would be the same if we assume the nominal utility from terminating the agent's employment is zero and characterize the nominal utility for keeping the agent.

attrition decisions.

We assume that an agent makes her voluntary attrition decision at the beginning of each time period (in contrast to the involuntary attrition decision made by the firm at the end of the period). If she decides to continue working at the firm, she works for the current period; and if her employment is not terminated by the end of the period, she makes another decision between working and quitting at the beginning of the next period.

Denote the action of agent i in period t after joining the firm by a_{it}, where $a_{it} = 1$ indicates quitting and $a_{it} = 0$ indicates continuing to work. The utility of agent i from taking action a_{it} in period t is given by

$$u_{it}^{VA}(a_{it}, y_{it}, \epsilon_{it}(a_{it})) = v_{it}^{V}(a_{it}, y_{it}) + \epsilon_{it}(a_{it}), \tag{6}$$

where $\epsilon_{it}(a_{it})$ denotes the random shocks and $v_{it}^{V}(a_{it}, y_{it})$ denotes the nominal utility. Similar to the error term in the involuntary attrition model ϵ_{fit}, the error term in the voluntary attrition process $\epsilon_{it}(a_{it})$ captures the impact of unobserved effects that may encourage an agent to quit or continue working such as a new job opportunity or moving to a different city. If the agent quits, she will get utility from outside options that depends on the economic condition. Consequently, we assume that the nominal utility from quitting has the following linear form

$$v_{it}^{VA}(1, y_{it}) = \omega^T E_{d(t)}, \tag{7}$$

where the vector ω captures the impact of the economic condition on an agent's outside option.[4] The nominal utility of continuing to work for the firm is given by

$$v_{it}^{VA}(0, y_{it}) = \alpha_{it} s_{it} + \eta_{it} + \delta_{it}(1 - P_{fit}^{IA}(1, y_{it}))V_{it}(y_{it}) + \delta_{it} P_{fit}^{IA}(1, y_{it})\ (\omega^T \mathbb{E}[E_{d(t+1)}|E_{d(t)}]). \tag{8}$$

As can be seen in (8) agent i's per period utility of working for the firm is $\alpha_{it} s_{it} + \eta_{it}$, where α_{it} is the sensitivity of the agent to her salary, and η_{it} captures all factors other than salary that encourage the agent to stay with the firm such as satisfaction with the job or the position. We call η_{it} the non-monetary utility. The parameter δ_{it} is the discount factor of the agent for the expected utility of the next period. For example, $\delta_{it} = 0.8$ indicates that the agent attaches 20% less value to the utility in the next period compared to that of the current period. As illustrated in the fourth term on the right hand side of (8), the agent's employment will be terminated by the end of the period with the probability $P_{fit}^{IA}(1, y_{it})$, and consequently, she will get the expected utility of the outside option for the next period. In addition as illustrated in the third term on the right hand side of (8), with the probability $(1 - P_{fit}^{IA}(1, y_{it}))$ the agent's employment will not be terminated and she will get the expected future utility of staying with the firm and making the optimal decision in the next period denoted by $V_{it}(y_{it})$. The function $V_{it}(y_{it})$ is the value function in the dynamic programming context. We assume that the probability of termination by the end of the period $P_{fit}^{IA}(1, y_{it})$ is known by the agents, and that the agents acquire this knowledge based

[4]Note that adding a constant to the utility of the discrete choice models would not change the choice probabilities (Rust (1996)). Hence, for identification purposes, we need to fix the intercept to zero.

on their experience with the firm and observing the involuntary attrition of other coworkers. This assumption is similar to the rational expectation assumption in the industrial organization context where it is assumed that consumers make rational forecasts about future prices and their forecasts matches the actual values (see Nair (2007)).

To account for the impact of agents' tenure and demographics on their sensitivity to salary, non-monetary utility and their discount factor, we assume that the parameters α_{it}, η_{it} and δ_{it} are given by:

$$\begin{aligned} \alpha_{it} &= \alpha_0 + \alpha^T x_i + \lambda_\alpha t, \\ \eta_{it} &= \eta_0 + \eta^T x_i + \lambda_\eta t, \\ \delta_{it} &= \frac{\exp(\delta_0 + \delta^T x_i + \lambda_\delta t)}{1 + \exp(\delta_0 + \delta^T x_i + \lambda_\delta t)}. \end{aligned} \tag{9}$$

Note that the functional form of (9) ensures that the discount factor δ_{it} would be a value between 0 and 1.

Following Rust (1987), by assuming type-I extreme value distribution for the error terms $\epsilon_{it}(a_{it})$, we can find a closed form solution for the integrated value function $V_{it}(y_{it})$ as follows

$$\begin{aligned} V_{it}(y_{it}) = \int \log \Big(\exp(\omega^T E_{d(t+1)}) + \exp \Big(& \alpha_{it+1} s_{it+1} + \eta_{it+1} \\ & + \delta_{it+1}(1 - P^{IA}_{fit+1}(1, y_{it+1}) V_{it+1}(y_{it+1}) \\ & + \delta_{it+1} P^{IA}_{fit+1}(1, y_{it+1}) \ (\omega^T \mathbb{E}(E_{d(t+2)} | E_{d(t)})) \Big) \Big) dF(y_{it+1} | y_{it+1}), \end{aligned} \tag{10}$$

where $F(y_{it+1}|y_{it})$ denotes the distribution of future state variables conditional on the current state variables observed by the agent. We assume that an agent does not work more than T periods in the firm. Hence the terminal condition for the value function is given by

$$V_{iT}(y_{it}) = \mathbb{E}[E_{d(T)} | E_{d(t)}]. \tag{11}$$

The agent would take the action that maximizes her utility in period t. The optimal action of the agent i in period t since joining the firm denoted by $a^{optimal}_{it}$ is given by

$$a^{optimal}_{it} = \max_{a_{it} \in \{0,1\}} u^{VA}_{it}(a_{it}, y_{it}, \epsilon_{it}(a_{it})). \tag{12}$$

Given our assumption about the type-I extreme value distribution for the error term, the probability of choosing action a_{it} in period t for agent i denoted by $P^{VA}_{it}(a_{it}, y_{it})$ is given by

$$P^{VA}_{it}(a_{it}, y_{it}) = \frac{\exp\left(v^{VA}_{it}(a_{it}, y_{it})\right)}{\exp\left(v^{VA}_{it}(0, y_{it})\right) + \exp\left(v^{VA}_{it}(0, y_{it})\right)}, \tag{13}$$

where $v^{VA}_{it}(1, y_{it})$ and $v^{VA}_{it}(0, y_{it})$ are given by (7) and (8), respectively.

5 Estimation Strategy

In this section we lay out the estimation strategy to estimate the parameters of the involuntary and voluntary attrition models. We use a two-stage approach to estimate the parameters of the model. We first estimate the parameters of the involuntary attrition model. Next, we estimate the parameters of the voluntary attrition model assuming that agents know their chances of involuntary attrition (employment termination). The two-stage estimation approach has been used extensively in the industrial organizations and marketing literature. For example, Rust (1987) estimates the transition probabilities of the state variables first. Then, he estimates the parameters of the decision maker assuming that the decision maker knows the transition probabilities based on past experiences. Similarly, in Nair (2007) the author estimates the parameters of the demand model assuming that the consumers make rational (and perfect) forecasts about the evolution of prices. Then, the author uses the parameters of the demand model to find the optimal pricing policy.

5.1 Estimation of the Parameters of the Involuntary Attrition Model

We use the maximum likelihood estimation method to estimate the parameters of the involuntary attrition model denoted by $\Theta_f = (\lambda_0, \lambda_t, \lambda_x, \lambda_E)$. Recall that W_i signifies the duration of time the agent worked or has been working for the firm and O_i denotes the status of the agent in the data. Hence, if agent i is currently working for the firm ($O_i = 1$), the sequence of actions of the firm (termination vs. not-termination) with respect to agent i are ($f_{i1} = 0, f_{i2} = 0, ..., f_{iW_i} = 0$). If the agent was terminated ($O_i = 2$), the sequence of actions are ($f_{i1} = 0, f_{i2} = 0, ..., f_{iW_i} = 1$). However, if the agent voluntarily left the firm ($O_i = 3$), given that we assume agents make their voluntary decision at the beginning of the period and the firm makes their involuntary attrition decisions at the end of the period, the sequence of action of the firm would be ($f_{i1} = 0, f_{i2} = 0, ..., f_{iW_i-1} = 0$). Note that in this case, the agent leaves at the beginning of period W_i.

The likelihood of the involuntary attrition decisions of the firm with respect to agent i denoted by $L^{IA}_{fi}(\Theta_f)$ is the product of the firm's decisions and is given by

$$L^{IA}_{fi}(\Theta_f) = \prod_{t=1}^{\mathbb{I}_{\{O_i=1,2\}} W_i + \mathbb{I}_{\{O_i=3\}}(W_i - 1)} P^{IA}_{fit}(f_{it}, y_{it}). \tag{14}$$

The log-likelihood of the actions of the firm with respect to all agents denoted by $\log -L^{IA}_{f}(\Theta_f)$ is given by

$$\log -L^{IA}_{f}(\Theta_f) = \sum_{i=1}^{N} \log\left(L^{IA}_{fi}(\Theta_f)\right). \tag{15}$$

To estimate the vector of the parameters of the involuntary attrition model, we maximize (15) with respect to Θ_f.

5.2 Estimation of the Parameters of the Voluntary Attrition Model

Denote the vector of parameters of the voluntary attrition model by $\Theta_a = (\{\alpha_0, \alpha, \lambda_\alpha\}, \{\eta_0, \eta, \lambda_\eta\}, \{\delta_0, \delta, \lambda_\delta\})$. Moreover, denote the sequence of actions of agent i with respect to her voluntary attrition decision by $\{a_{it} : t = 1, ..., W_i\}$. The likelihood of actions of agent i denoted by $L_i^{VA}(\Theta_a)$ is given by

$$L_i^{VA}(\Theta_a) = \prod_{t=1}^{W_i} P_{it}^{VA}(a_{it}, y_{it}). \tag{16}$$

The log-likelihood of actions of all agents with respect to their voluntary attrition decisions denoted by $\log -L_a^{VA}(\Theta_a)$ is given by

$$\log -L_a^{VA}(\Theta_a) = \sum_{i=1}^{N} \log \Big(L_i^{VA}(\Theta_a) \Big). \tag{17}$$

To estimate the parameters of the voluntary attrition model we maximize $\log -L_a^{VA}(\Theta_a)$ subject to the agent choice probability in Equation (13), the integrated value function in Equation (11), the nominal utilities in Equations (7)-(8), and agent heterogeneity in Equation (9). The estimation problem is as follows:

$$\underset{\Theta_a}{\text{maximize}} \log -L_a^{VA}(\Theta_a)$$

$$\begin{aligned}
\text{subject to} \quad & \text{for all } i = 1, ..., N, \ t = 1, ..., W_i : \\
& P_{it}^{VA}(a_{it}, y_{it}) = \frac{\exp\Big(v_{it}^V(a_{it}, y_{it})\Big)}{\exp\Big(v_{it}^V(0, y_{it})\Big) + \exp\Big(v_{it}^V(0, y_{it})\Big)}, \\
& V_{it}(y_{it}) = \int \log\Big(\exp(\omega^T E_{d(t+1)}) + \exp\Big(\alpha_{it+1} s_{it+1} + \eta_{it+1} + \delta_{it+1}(1 - P_{fit+1}^{IA}(1, y_{it+1}) V_{it+1}(y_{it+1}) \\
& + \delta_{it+1} P_{fit+1}^{IA}(1, y_{it+1}) \ (\omega^T \mathbb{E}(E_{d(t+2)} | E_{d(t)}))\Big)\Big) dF(y_{it+1} | y_{it+1}), \\
& v_{it}^V(1, y_{it}) = \omega^T E_{d(t)}, \\
& v_{it}^V(0, y_{it}) = \alpha_{it} s_{it} + \eta_{it} + \delta_{it}(1 - P_{fit}^{IA}(1, y_{it})) V_{it}(y_{it}) + \delta_{it} P_{fit}^{IA}(1, y_{it}) \ (\omega^T \mathbb{E}[E_{d(t+1)} | E_{d(t)}]), \\
& \alpha_{it} = \alpha_0 + \alpha^T x_i + \lambda_\alpha t, \\
& \eta_{it} = \eta_0 + \eta^T x_i + \lambda_\eta t, \\
& \delta_{it} = \tfrac{\exp(\delta_0 + \delta^T x_i + \lambda_\delta t)}{1 + \exp(\delta_0 + \delta^T x_i + \lambda_\delta t)}.
\end{aligned} \tag{18}$$

To solve this maximum likelihood problem we use the FMINCON package in MATLAB. We solved the maximization problem for 300 random starting points to make sure that we find the actual maximizer.

To simplify the estimation procedure we decrease the number of decision epochs and assume the firm and the agents make their decisions every quarter (3 months). Given that the data is more granular and that the agents make their voluntary attrition decisions at the beginning of the period while the firm makes the involuntary attrition decision at the end of the period, we round the tenure time for agents with the current status and involuntary attrition status upward, and for the agents with the voluntary attrition status downward.

Furthermore, as mentioned in Section 4 the vector of demographics for agents x_i include the indicator variables for supervisors. There are 164 supervisors in total in the data set. Considering an indicator variable for all of them would increase the number of variables in our model significantly, which makes calculation of the integrated value functions and solving the estimation problem cumbersome. Consequently, we create indicator variables only for supervisors who have more than or equal to 50 agents under their supervision. The number of agents with this characteristics is 12.[5]

Moreover, to calculate the nominal utility of waiting in Equation (8) we need to specify agents' expectation about the economic condition variables in the next period given the observable condition in the current period ($\mathbb{E}[E_{d(t+1)}|E_{d(t)}]$). Similarly, to calculate the recursive formula for the integrated value function in Equation (11) we need to specify agents' belief about the state transition probabilities ($F(y_{it+1}|y_{it})$). Recall that the vector of state variables y_{it} contains the following variables: t, s_{it} and $E_{d(t)}$. The transition of the time variables t is trivial: it will be $t+1$ with 100% probability in the next period. For the salary variable s_{it} we assume that the agents, before the first annual salary increase after joining the firm, believe that the future increases will be equal to the average salary increase in the firm (7.5%). However, after experiencing an increase in the salary at the end of the year, the agents use the amount of experienced increase as their estimate for salary increase in the future. For the economic condition variables we assume that the agents use a moving average as the estimate. To be more specific, suppose that the length of the moving average window is l. Then agents in period t believe that the vector of economic condition in the next period will be $\sum_{k=0}^{l-1} E_{d(t-k)}/l$. In our estimation procedure we considered different values for the length of the moving average window from $t = 1$ to $t = 8$. the best fit (the highest likelihood value) is achieved by $t = 4$.

One of the main differences between the structural estimation procedure in this work and the traditional literature in Marketing and Industrial Organization is that we are able to find agents' discount factors by estimating $(\{\delta_0, \delta, \lambda_\delta\})$. It is well known in the literature on dynamic discrete choice models that discount factors cannot be identified. Hence the standard approach is to assume discount factors (Rust (1994)). However, as illustrated in Chung et al. (2013) discount factors can be identified if two conditions are satisfied: having a finite horizon model, and an exclusion restriction separating the current and future payoffs. Both condition are satisfied in our setting. The agent attrition model is a finite horizon problem and agents do not work for an unlimited time period for the firm and will leave the company eventually without having any forward looking behavior in the last period. In addition, salary increases occur only annually. In other words, in three quarters agents do not expect any salary increase. Consequently, only a forward looking person (with a non-zero discount factor) may change her attrition decision based on proximity to the time of salary increase and her expectation about the salary increase in the future. Next we explain the estimation results and insights.

[5]For robustness check we repeated all analyses for a case that we consider indicator variables for 39 supervisors who supervise more than 30 agents. The results and insights of our analyses do not change.

6 Estimation Results

In this section we lay out our estimation results and insights. We estimate the parameters of the involuntary attrition model using the procedure in 5.1. The maximum log-likelihood value is -1,817.23. Table 3 shows the estimation results along with the standard errors of the estimates. To calculate the standard errors we use the non-parametric bootstrap method (see Heckman (1979)).

Table 3: The estimates for the parameters of the involuntary attrition model.

Parameter	Estimate	Standard Error
λ_0	-71.10	8.04
λ_t	0.22	0.07
λ_s	-0.05	0.02
λ_{age}	0.03	0.01
λ_{Noida}	0.82	0.10
λ_{Male}	0.47	0.09
$\lambda_{Shift\ -\ Day}$	-0.88	0.14
$\lambda_{Graduate}$	-0.12 †	0.10
$\lambda_{Under\ graduate}$	-0.94	0.20
$\lambda_{Other\ degrees}$	-0.35	0.14
$\lambda_{Associate}$	39.98	8.58
$\lambda_{Senior\ Associate}$	37.08	8.53
$\lambda_{Supervisor\ 1}$	2.14	0.20
$\lambda_{Supervisor\ 2}$	1.20	0.20
$\lambda_{Supervisor\ 3}$	0.24 †	0.31
$\lambda_{Supervisor\ 4}$	-0.48 †	0.69
$\lambda_{Supervisor\ 5}$	-0.16 †	0.35
$\lambda_{Supervisor\ 6}$	-0.13 †	0.47
$\lambda_{Supervisor\ 7}$	1.38	0.22
$\lambda_{Supervisor\ 8}$	-0.25 †	0.38
$\lambda_{Supervisor\ 9}$	1.76	0.34
$\lambda_{Supervisor\ 10}$	-1.15	0.56
$\lambda_{Supervisor\ 11}$	0.49 †	0.33
$\lambda_{Supervisor\ 12}$	-0.69	0.29
λ_{GDP}	117.91	17.85
$\lambda_{Inflation}$	57.09	8.81

All parameters except those marked by † are significant at $p < 0.05$.

The estimation results in Table 3 support the following insights with respect to involuntary attrition:

Insight 1 (IA). The chance of employment termination goes up with agents' tenure. As can be seen in the results, the coefficient for tenure (λ_t) is positive and significant.

Insight 2 (IA). Both economic factors (GDP and Inflation) increase the chance of termination. This insight follows from the fact that the coefficients for the economic factors (λ_{GDP} and $\lambda_{Inflation}$) are positive and significant.

Insight 3 (IA). Supervisors exhibit statistically significant differences in their likelihood to terminate workers' employment at the firm. This insight follows from the difference between the magnitudes of the estimates for the supervisor indicator variables in Table 3. We note that these differences are statistically significant.

The parameters of the voluntary attrition model are estimated using the procedure laid out in Section 5.2. The maximum log-likelihood value is -3,448.86. Table 4 shows the estimates and standard errors for the parameters of salary sensitivity (α_{it}), non-monetary utility (η_{it}) and discount factor (δ_{it}) in the voluntary attrition model. Furthermore, Table 5 shows the estimation results for the parameters of the outside option utility (ω). The estimation results in Tables 4 and 5 lead to the following insights:

Insight 1 (VA). The degree of forward looking behavior of the agents is low. Using the estimates for the discount factor (δ_{it}), which represents the degree of forward looking behavior of the agents, and Equation (9) we calculate all agents' discount factors when they joined the firm. the average of the discount factor is 0.343 and its standard deviation is 0.275. This shows that the agents discount the utility of staying with the firm for one more period by 34% on average. We also find that the degree of variation of the discount factor across the agents is high. Figure 3 shows the histogram of agents' discount factor when joining the firm.

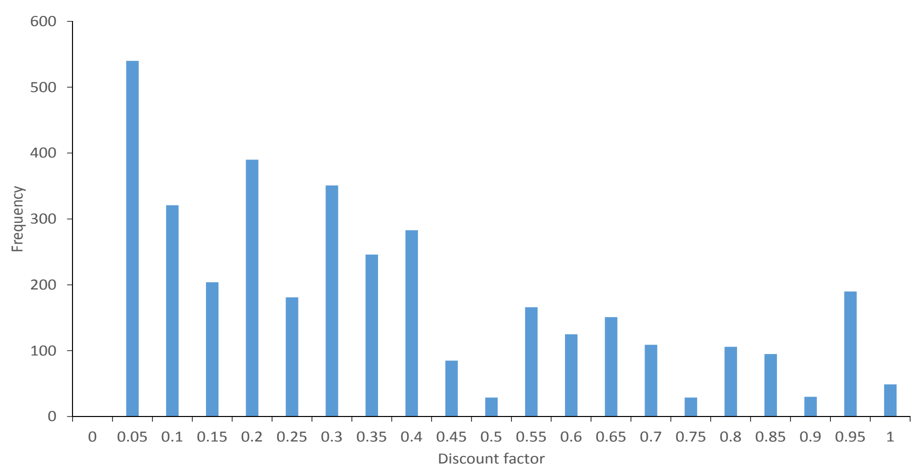

Figure 3: The histogram of agents' discount factor when joining the firm.

As can be seen in Figure 3 most of the agents have discount factors less than 50%. This low degree of forward looking behavior indicates that the agents are not optimistic about the likelihood of staying with the firm and heavily discount the future utility, which can be one of the reasons for a high level of voluntary attrition at the firm.

Table 4: The estimates for the parameters of salary sensitivity (α_{it}), non-monetary utility (η_{it}) and discount factor (δ_{it}) in the voluntary attrition model.

Parameter	Estimate (α_{it})	Standard Error (α_{it})	Estimate (η_{it})	Standard Error (η_{it})	Estimate (δ_{it})	Standard Error (δ_{it})
Intercept	0.16	0.05	6.83	1.25	-0.49	0.03
Tenure	0.05	0.02	-0.51	0.15	-0.97	0.24
Age	-0.01	9.48E-05	0.16	2.67E-03	0.01	2.71E-03
Noida	-0.10	0.02	1.52 †	4.57	0.62	0.12
Male	-0.01	1.13e-03	0.46	0.12	-0.12	0.04
Shift - Day	0.16	0.05	-0.88	0.25	-2.03	0.75
Graduate	-0.09	3.12e-03	2.55	0.51	-0.47	0.13
Under graduate	0.04 †	0.01	2.53	0.88	-1.38	0.54
Other degrees	-0.06	0.01	3.19	1.09	-1.54	0.71
Associate	0.04 †	0.05	-5.19	2.06	0.23	0.10
Senior Associate	-0.01	0.05	-3.29	0.38	2.48	1.02
Supervisor 1	0.05	0.01	-6.58	1.17	2.47	0.65
Supervisor 2	-0.11	0.02	-4.72	1.56	3.06	1.43
Supervisor 3	0.23	0.08	-1.65	1.11	0.23	0.07
Supervisor 4	0.27	0.11	-5.63	1.70	-0.69	0.20
Supervisor 5	0.18	4.78e-03	-5.35	1.12	0.23	0.04
Supervisor 6	0.03	4.07e-03	-0.08	0.02	-0.17	0.03
Supervisor 7	-0.01 †	0.01	-6.29	1.94	2.76	0.57
Supervisor 8	4.05e-03	1.64e-03	-0.54	0.16	0.48	0.16
Supervisor 9	-0.09	0.03	1.70 †	0.93	0.09	0.89
Supervisor 10	0.16	0.04	-4.26	1.14	0.93	0.23
Supervisor 11	-0.04	0.01	0.29	0.10	-0.19	0.04
Supervisor 12	-0.07	1.02E-03	0.72	0.22	0.16	0.03

All parameters except those marked by † are significant at $p < 0.05$.

Table 5: The estimates for the parameters of the outside option utility (ω) in the voluntary attrition model.

Parameter	Estimate	Standard Error
ω_{GDP}	40.29	14.66
$\omega_{Inflation}$	12.74	6.65

All parameters are significant at $p < 0.05$.

Insight 2 (VA). As agents' tenure increases their sensitivity to salary goes up, their willingness to stay with the firm based on their non-monetary utility goes down and their level of forward looking behavior diminishes. These insights follow the sign and significance of the coefficient for tenure in the estimates for α_{it}, η_{it} and δ_{it}, respectively.

Insight 3 (VA). There is significant variability in supervisors' impact on agents' sensitivity to salary, non-monetary utility and degree of forward looking behavior. This insight follows the magnitude and significance of the coefficient for the supervisor indicator variables in the estimates for α_{it}, η_{it} and δ_{it}, respectively.

Insight 4 (VA). The impact of economic factors on agents' voluntary attrition decisions is similar to their impact on the firm's termination decisions. As can be seen in Table 5 the coefficients for GDP and Inflation in the utility of outside option are positive (the same as their sign in the estimates of the involuntary attrition model in Table 3). This shows that a higher GDP and a higher inflation rate not only increase the chance of termination by the firm but also increase the chance of agents leaving the firm.

7 Interpreting Demographics and Supervisor Effects

To get deeper insights about the impact of demographics and supervisors on the firm's termination decisions and agents' voluntary attrition decisions, we have performed principal component analyses (PCA) (see Jolliffe (2002)). Tables 6 and 7 show the coefficients for the demographics and supervisor indicator variables in the involuntary attrition model (IA), the sensitivity to salary in the voluntary attrition model, the non-monetary utility in the voluntary attrition model and the discount factor in the voluntary attrition model. The values in Tables 6 and 7 are the same as those in Tables 3 and 4, which are put together in new tables to make the explanation of the principal component analyses easier.

Tables 6 and 7 represents the impact of demographics and supervisor indicator variables on four axes in a 4-D space. These four axes are: the impact on agents' probability of termination, how much agents value salary, agents' non-monetary utility from staying with the firm and agents' level of forward looking behavior. Using principal component analyses we can represent the impact of demographics and supervisor indicator variables using the two principal components of the matrices in Tables 6 and 7 in a 2-D space. We also can find the relationship/correlation of the new 2-D components with the 4-D components in the original representations.

Table 6: The estimates for the impact of demographics.

Parameters	IA model	VA model - sensitivity to salary - α_{it}	VA model - non-monetary utility - η_{it}	VA model - degree of forward looking behavior - δ_{it}
Tenure	0.22	0.05	-0.51	-0.97
Age	0.03	-0.01	0.16	0.01
Noida	0.82	-0.10	1.52	0.62
Male	0.47	-0.01	0.46	-0.12
Shift - Day	-0.88	0.16	-0.24	-2.03
graduate	-0.12	-0.09	2.55	-0.47
others	-0.35	-0.06	3.19	-1.54
under graduate	-0.94	0.04	2.53	-1.38
Associate	39.98	0.04	-5.19	0.23
Senior Associate	37.08	-0.01	-3.29	2.48

Table 7: The estimates for supervisor indicator variables.

Indicator variables	IA model	VA model - sensitivity to salary - α_{it}	VA model - non-monetary utility - η_{it}	VA model - degree of forward looking behavior - δ_{it}
Supervisor 1	2.14	0.05	-6.58	2.47
Supervisor 2	1.20	-0.11	-4.72	3.06
Supervisor 3	0.24	0.23	-1.65	0.23
Supervisor 4	-0.48	0.27	-5.63	-0.69
Supervisor 5	-0.16	0.18	-5.35	0.23
Supervisor 6	-0.13	0.03	-0.08	-0.17
Supervisor 7	1.38	-0.01	-6.29	2.76
Supervisor 8	-0.25	0.00	-0.54	0.48
Supervisor 9	1.76	-0.09	1.70	0.09
Supervisor 10	-1.15	0.16	-4.26	0.93
Supervisor 11	0.49	-0.04	0.29	-0.19
Supervisor 12	-0.69	-0.07	0.72	0.16

Figures 4 and 5 show the loading plots for the two principal components of the impact of demographics and supervisors, respectively. Figure 4 shows that the two principal components can explain 94.2% (60.2%+34%) of the variation across different demographics in terms of their impact. Similarly, Figure 5 shows that the two principal components can explain 87.8% (50.4%+37.4%) of the variation across different supervisors in terms of their impact. The amount of variation that can be explained by the two principal components for both the impact of demographics and supervisors is high, which shows the two principal components can capture the essence of the effects of demographics and supervisors on involuntary and voluntary attrition decisions.

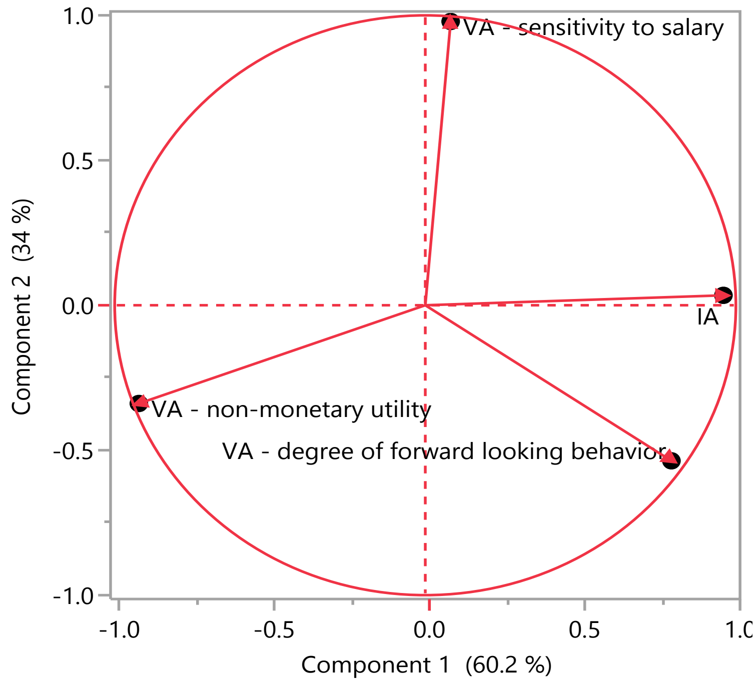

Figure 4: The loading plot for the principal component analysis of the estimates for the impact of demographics.

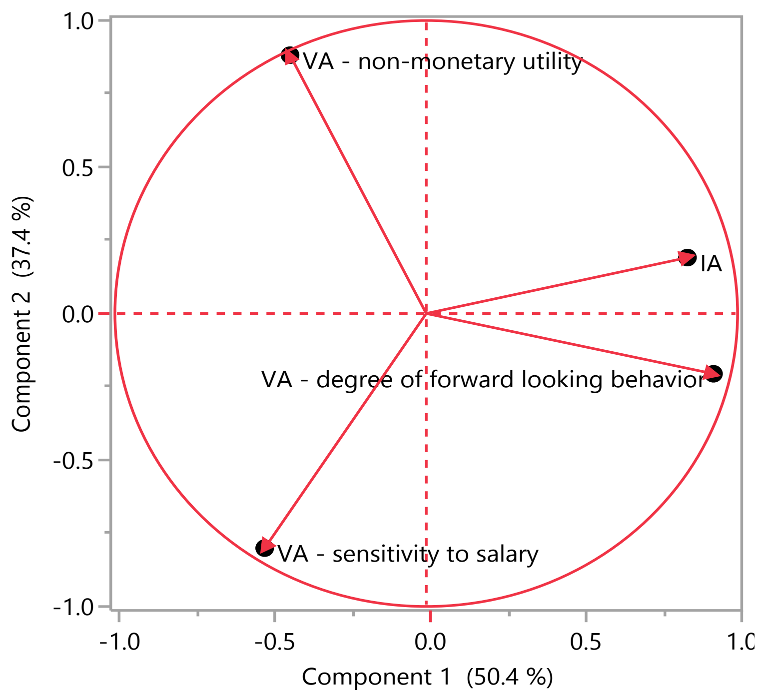

Figure 5: The loading plot for the principal component analysis of the estimates for the impact of supervisors.

As can be seen in Figures 4 and 5 for both the demographics and supervisors the arrows for the impact on the involuntary attrition probabilities and degrees of forward looking behavior are close to each other and pointing to the right direction. Furthermore, the arrows corresponding to the impact on the non-monetary utility and sensitivity to salary are pointing to different directions (one is pointing to the top and the other one to the bottom). Moreover, the direction of the arrow for the impact on the degree of forward looking behavior is more similar to the direction of the arrow for the impact on involuntary attrition than the directions of the arrows for the other factors. These observations support the following findings:

> **Insight 1 (PCA).** Demographic characteristics and supervisors that increase agents' chance of termination also increase their degree of forward looking behavior.

> **Insight 2 (PCA).** Demographic characteristics and supervisors that increase agents' sensitivity to salary also decrease their non-monetary utility.

> **Insight 3 (PCA).** Agents' degree of forward looking behavior is correlated more positively with their chances of termination than their sensitivity to salary or non-monetary utility.[6]

8 Counterfactual Analysis

In this section we perform a series of counterfactual analyses to find the impact of policy changes on the voluntary and involuntary attrition rates of the agents working at the firm. To find the impact of different policies, we use a Monte-Carlo simulation strategy. To be more specific, we consider the population of agents in our data, and simulate the firm's involuntary attrition and the agents' voluntary attrition decisions using the estimates in Section 6 and the model in Sections 4.1 and 4.2. The randomness in the simulation comes from the random shocks in the involuntary (ϵ_{fit}) and voluntary (ϵ_{it}) attrition models. We draw these random shocks from the type-I extreme value distribution for each decision epoch of the firm and the agents. For each policy change, we perform the simulation 50 times and record the average of the results across all simulation iterations.

We first perform a Monte-Carlo simulation for the status-quo of the system. The predictions of our model for the Voluntary Attrition rate (VA rate), Involuntary Attrition rate (IA rate) and the rate of agents who will be active (Current rate or C rate) are 47.03%, 21.26% and 31.71%, respectively. These values are close to the actual rates in the data set (49.54%, 15.24% and 35.22%).

To find the impact of salary changes on the attrition rates, we multiply agents' salary in the data by values from 0.7 to 1.3 with the increment of 0.1 and perform the Monte-Carlo simulation study. Table 8 shows voluntary attrition, involuntary attrition and the current rates for agents in the data for different levels of salary changes. Note that the case with $\times 1$ corresponds to the status-quo prediction.

[6] We also test this insight by calculating agents' probability of involuntary attrition, sensitivity to salary, non-monetary utility and discount factor for all periods during their tenure and find the correlation between these variables. We find that the correlation between agents' discount factor with their sensitivity to salary, their non-monetary utility and their probability of involuntary attrition are -0.3320, -0.1493 and 0.4283, respectively. This shows that agents' degree of forward looking behavior is positively correlated by their chance of termination but is negatively correlated with their sensitivity to salary and non-monetary utility.

Table 8: The impact of salary changes on attrition rates.

Salary ×	VA rate	IA rate	C rate
0.7	49.66%	25.01%	25.33%
0.8	48.37%	23.64%	27.99%
0.9	47.70%	22.27%	30.03%
1 (Status-quo)	47.03%	21.26%	31.71%
1.1	45.66%	20.90%	33.44%
1.2	45.43%	19.90%	34.67%
1.3	44.57%	19.30%	36.13%

As can be seen in Table 8 decreasing salary would lead to higher attrition rates and increasing it would lead to lower rates. However, the impact of salary changes appears relatively small, which is a result of the small values for the coefficient of salary in the involuntary attrition model (-0.05) in Table 3, and the intercept of the sensitivity to salary in the voluntary attrition model (0.16) in Table 4. Table 8 shows that in this firm increasing the salary by 30% would decrease the total attrition rate (i.e. would increase the C rate) by only 4.41%=36.13%-31.71%. This decrease in the attrition rate is due to a 2.46% decrease in the voluntary attrition rate and a 1.96% decrease in the involuntary attrition rate.

To find the impact of the non-monetary utility (η_{it}) on the attrition rates, we change the intercept of the non-monetary utility (η_0) in Equation (9) by adding values between -3 and 3 with the increment of 1, and perform the Monte-Carlo simulation. Table 9 shows the impact of the change in the non-monetary utility on attrition levels.[7] As can be seen in Table 9, increasing the intercept of the non-monetary utility by 2 units (a 29.28% increase relative to 6.83) would decrease the total attrition rate by 12.78% (44.49%-31.71%) and the voluntary attrition rate by 25.47% (47.03%-21.56%). It also increases the involuntary attrition rate (employment termination rate) by 12.69%. This shows that the impact of a 30% increase in the non-monetary utility is considerably more significant than the impact of a 30% increase in salary on decreasing the voluntary attrition rate (25.47% versus 2.46%). This finding suggests that managers should pay more attention to non-monetary factors that may encourage agents to stay longer with the firm.

Although salary is the most common lever that a firm might use, we next consider an alternative driver of attrition - the role of the manager. We consider hypothetical scenarios in which all agents are managed by a specific supervisor. To do so, we replace the parameters for the impact of supervisors in Tables 3 and 4 for all agents with those of a specific supervisor. Table 10 shows the attrition rates for the status-quo of the system and also the hypothetical scenarios in which all agents are managed by a specific supervisor.

As can be seen in Table 10 among supervisors 1 to 12 only supervisors 3, 4 and 6 would

[7] In Appendix A, we perform sensitivity analyses to find the impact of changes in some of the fundamental parameters of the model on the attrition rates. We do not repeat the results of the sensitivity analyses here for brevity.

Table 9: The impact of the change in the intercept of the non-monetary utility in the voluntary attrition model (η_0) on attrition rates.

η_0 +	VA	IA	C
-3	70.93%	13.36%	15.71%
-2	64.27%	14.51%	21.22%
-1	56.42%	17.17%	26.41%
0	47.03%	21.26%	31.71%
1	34.72%	27.58%	37.70%
2	21.56%	33.95%	44.49%
3	11.06%	39.81%	49.13%

decrease the total attrition rate; i.e. increase the C rate. The scenario with supervisor 3 managing all agents has the most significant impact. Table 10 illustrates that if all agents are managed by supervisor 3 the total attrition rates decreases by 15.18%=46.90%-31.71%. This is achieved by a 31.11% decrease in the voluntary attrition rate and a 15.92% increase in the involuntary attrition (termination) rate. This shows that the impact of the supervisor on decreasing the total attrition rate (a decrease of 15.18% in the total attrition rate) is more than three times higher than the impact of a 30% increase in the salary (a decrease of 4.41% in the total attrition rate). It is also higher than the impact of a 29.28% increase in the non-monetary utility (a decrease of 12.78% in the total attrition rate).

Table 10: Attrition rates for hypothetical scenarios in which all agents are managed by a specific supervisor.

Scenario	VA	IA	C
Status-quo	47.03%	21.26%	31.71%
All managed by Supervisor 1	43.52%	48.20%	8.27%
All managed by Supervisor 2	66.74%	28.59%	4.66%
All managed by Supervisor 3	15.92%	37.18%	46.90%
All managed by Supervisor 4	57.57%	9.57%	32.86%
All managed by Supervisor 5	63.71%	10.83%	25.46%
All managed by Supervisor 6	44.89%	19.65%	35.46%
All managed by Supervisor 7	62.09%	32.05%	5.86%
All managed by Supervisor 8	52.50%	15.88%	31.62%
All managed by Supervisor 9	22.14%	54.81%	23.05%
All managed by Supervisor 10	62.06%	6.38%	31.56%
All managed by Supervisor 11	48.21%	24.16%	27.64%
All managed by Supervisor 12	59.61%	10.68%	29.71%

9 Discussion and Conclusion

The field of operations is focused on how to match supply to demand. As such, a great deal of attention has been devoted to topics that address this potential imbalance, ranging from inventory ordering policies to worker scheduling and staffing to optimal contract structure and mechanism design. Increasingly though, the field has turned its attention to the role of people within operating systems. In many ways this is the field returning to its roots - given the pioneering work of individuals within the Scientific Management movement, such as Frederick Taylor (Taylor (1911)), or later scholars such as Wickham Skinner (Hayes (2002)).

The increased attention on people operations is a result of two related factors. First, the literature has come to appreciate that the people within a system function differently than inanimate objects, such as inventory, because the people dynamically respond and adapt to their circumstances. For example, in a seminal paper in the area of people operations, Kc and Terwiesch (2009) show that individual service rates are not exogenous, but rather are a function of the load of the server. A growing body of work shows that elements of the operating system can change individual productivity, learning, and even whether individuals choose to stay in the system, or not (e.g., Tan and Netessine (2014); Tucker (2015); Buell et al. (2016); Song et al. (2015)).

The second driver of the growth in this field is the increasing availability of granular data from within and across firms. The use of large public and private datasets with both archival and sensor collected data helps to identify new findings, leading to an increased understanding of the first point and additional company implementation (Kim et al. (2014); Freeman et al. (2016); Staats et al. (2017)). This increase in attention has impacted not only the academy, but practice is also responding as can be seen by firms, such as Google, building up People Operations departments to consider how to hire, train, staff, develop, and retain the right people so that the organization can operate at a high level.

We respond to the need for further research in the area of people operations by building a structural model that incorporates demographic, monetary, non-monetary, supervisor and external characteristics into a dynamic, structural model. This meaningful addition to the theoretical and practical literature leads to four additional, significant contributions. First, we focus upon the strategic behavior of employees. We find agents' level of forward looking behavior by estimating their discount factors. We show that although there is variability, the average of agents' discount factor is 0.34, which shows a low level of forward looking behavior. In other words, agents are myopic, or short-term focused, rather than being more strategic and long-term focused. Consequently, they may not delay leaving the firm for the hope of having a higher utility in future periods.

The strategic behavior of consumers has been investigated extensively in the Operations Management literature (Shen and Su (2007), Netessine and Tang (2009) and Li et al. (2014)), and its impact has been studied in different areas from revenue management (Jerath et al. (2010)) to inventory procurement (Cachon and Swinney (2009)). Moreover, it has been also shown that consumers' strategic behavior may have either a positive or a negative impact on a firm's revenue (Aviv and Pazgal (2008), Levin et al. (2009), Su (2007), and Cho et al. (2009)). However, to the best of our knowledge this work is the first that not only provides a framework to find agents' level of strategic behavior but also shows how this behavior would impact the attrition level, which would translate directly to profit/loss for the firm. We believe that there is a significant opportunity for the operations literature to consider the myopic vs. strategic behavior of employees, in addition to the prior work on consumers. Both building models around this and further empirical analysis would be valuable.

We note that although our counterfactual analyses show that a higher level of forward looking behavior would result in a lower voluntary attrition level, our framework does not reveal a management strategy that encourages a higher level of forward looking behavior among agents. Future work should examine the role other factors play in the level of forward looking behavior of agents. In addition, future work should look to identify practical strategies that firms can pursue to raise the level of forward-looking behavior.

Second, we find that the most common lever managers are likely to pull in managing attrition - salary increases - has a limited impact. We find that agents' sensitivity to salary is low. Consequently, they do not change their attrition behavior dramatically with an increase in salary. Our counterfactual analyses show that increasing agents' salary by 30% would decrease the voluntary attrition level by only 2.5%. We also estimate agents' non-monetary utility and show that increasing it would have a more significant impact on the voluntary attrition level. As discussed in Section 8 increasing the intercept of the non-monetary utility by 2 units (29% relative to 6.83) would decrease the voluntary attrition level by 25.5%. These findings illustrate that even though firms might be focused on pulling a monetary lever such as salary to control attrition, agents may not be responsive to this strategy. This firm does not use variable, performance-based compensation in this account and so one possible extension of this work would be finding the impact of monetary compensations other than salary on agent attrition using more granular data. In addition, future work could focus on methods to increase agents' non-monetary utility through providing a better work climate or career development opportunities. With the use of our model it is possible to incorporate this information, assuming there is data, in order to examine the differential effects and conduct counterfactual analysis.

Third, we highlight the role of experience in the attrition process. Experience is an important area of study within the people operations' domain, as prior work highlights how experience can help, or hurt, operational outcomes (Lapré et al. (2011); Staats et al. (2016)). We estimate the impact of agents' tenure on their attrition behavior. We show that as agents stay longer with the firm their sensitivity to salary increases while their non-monetary utility and level of forward looking behavior decline. This finding is consistent with a view that employee relationships with a firm grow more transactional over time (Rousseau and McLean Parks (1993)). Other than salary we do not observe how agents' treatment in the firm has changed through the course of their tenure. A possible extension of our work would be building on more granular data to explore practical ways to increase agents' non-monetary utility, and also to improve how agents perceive their future with the firm, which may increase their level of forward looking behavior.

Finally, we put a structure around finding individual manager's impact on agents' attrition behavior by estimating managers' effect on agents' probability of involuntary attrition, sensitivity to salary, non-monetary utility and degree of forward looking behavior. Conventional wisdom claims that individuals do not leave a firm, but rather leave a manager. Prior research supports this contention (Griffeth et al. (2000)). With our model we are able to disentangle how this complex relationship unfolds in the context of our firm. We find that there is significant variability in attrition across managers and that these managers differentially impact individuals' response. Moreover, our structural model permits us to analyze the impact of changing how managers interact with employees.

Our counterfactual analyses show that if all supervisors adopt the management style of the most successful supervisor, the voluntary attrition rate would decrease by 30%. Furthermore, we find that this successful supervisor separates employees at a higher rate than normal, i.e. terminates agent employment with a higher probability. This result is related to our finding that an increasing chance of termination is related to an increasing level of forward looking behavior, which in turn decreases voluntary attrition. Separating employees at a higher rate can be perceived as a fair behavior by employees and has been linked to decreasing the voluntary attrition (Aquino et al. (1997) and Jones and Skarlicki (2003)). Even though we show supervisors are significantly different in terms of their impact on agent' attrition behavior, our data does not allow us to do a deeper analysis on what management styles/strategies give rise to this difference. Future work should focus on supervisors' specific actions/decisions that impact agents' attrition decisions. These actions can be incorporated into a modeling framework or be studied using field experiments.

9.1 Limitations

Although our paper has a number of strengths, as with any paper it also has limitations to highlight. First, although we have data for several thousand individuals over multiple years, the data comes from one company. Future work should seek to generalize our model to more and different types of firms. Second, although our modeling framework presents a broad and detailed approach to capturing the attrition outcome - we do not have all possible information with which to evaluate the decision. For example, we have highlighted how new and detailed data on the work context could provide additional insight. In addition, factors, such as personal situation at home, could provide more insight. Furthermore, we do not observe employees' operational performance in our data set. Future work could focus on the impact of employees' operational performance measures on the firm's employment termination decisions and on agents' expectations about their future utility (e.g. salary) in the firm and their voluntary attrition decisions. We believe that we offer the most comprehensive model, to date, to study the attrition question, and that this lack of data does not create a problem of bias, however, future work could gain more insight were it to add more information. Finally, in the case of the variable, shift, some individuals are coded by the company system as Not Determined. We include the variable in the model for the sake of completeness, but note that our findings are meaningfully unchanged if we remove it. This is another area where future work might gain more insight with a detailed understanding of the shift structure of work.

9.2 Managerial Implications

Increasingly organizations are building people operations' areas or departments within the firm - a mix of a human resources department with finance, operations, and analytics in order to better understand how to hire, train, staff, develop, and retain individuals to help the organization excel. Our work contributes directly to this area and organization operational success more generally. Throughout the paper we have discussed how organizations can and should approach attrition in a different manner. We see that by gaining a more complete and forward-looking view of attrition through our structural model we can help managers better plan for attrition that may occur. Moreover, we are able to help managers rethink how they should approach keeping the right workers within the firm.

First, if employees are not forward-looking then it changes the value of different interventions - including increasing salary. Although raising salary is an easy way to respond to an attrition challenge, our results suggest that it is unlikely to be particularly impactful in our context. Instead managers should consider what strategies they could pursue to alter individuals' forward-looking behavior. If they are not able to do this then they should also recognize the need for interventions in the here and now - not changes that may not be felt for many years (e.g., an improved retirement plan or education benefit) and so will be discounted heavily. Instead, what immediate changes could improve the situation for employees?

Second, our results show that the impact of non-monetary utility on the voluntary attrition level is more significant than the impact of salary: increasing salary by 30% decreases the voluntary attrition by 2.5% while increasing the non-monetary utility by the same percentage would decrease the voluntary attrition by more than 25.5%. This suggests that managers should pay more attention to non-monetary factors that may encourage agents to stay longer with the firm. This may also give a higher return on investment to managers in terms of decreasing the voluntary attrition level.

Third, we see that with experience individuals grow more transactional in their relationship with the firm. As a result, managers need to be aware of this and consider ways to combat it. Fourth, we highlight the critical role that managers play in the attrition process. Successful operational leaders not only look to improve the system, but also must work with managers to help them adopt policies and practices that may lead to improved voluntary attrition - perhaps even being more willing to separate underperformers.

9.3 Conclusion

Altogether, our work provides a framework to study involuntary and voluntary attrition jointly and in so doing makes a meaningful contribution to the growing academic literature on people operations. This framework can also be used by managers to find the impact of economic conditions, agent demographics, their tenure and supervisors on their chance of employment termination and also their probability of voluntarily leaving the firm. We provide deep insights about the effect of different factors on agents' sensitivity to salary, their non-monetary utility and their degree of forward looking behavior. This framework not only can be used to get a better understanding of the attrition process but also can be used to perform extensive policy experiments from altering salary lever to changing supervisors. With a better understanding of people operations both theory and practice can improve.

References

Aksin, Z., B. Ata, S. Emadi, and C. Su (2013). Structural estimation of callers delay sensitivity in call centers. *Management Science 59*(12), 2727–2746.

Aksin, Z., B. Ata, S. Emadi, and C. Su (2016). Impact of delay announcements in call centers: An empirical approach. *Operations Research, Forthcoming*.

Aquino, K., R. W. Griffeth, D. G. Allen, and P. W. Hom (1997). Integrating justice constructs into the turnover process: A test of a referent cognitions model. *Academy of Management journal 40*(5), 1208–1227.

Aviv, Y. and A. Pazgal (2008). Optimal pricing of seasonal products in the presence of forward-looking consumers. *Manufacturing & Service Operations Management 10*(3), 339–359.

Buell, R. W., T. Kim, and C.-J. Tsay (2016). Creating reciprocal value through operational transparency. *Management Science*.

Cable, D. M., F. Gino, and B. R. Staats (2013). Breaking them in or eliciting their best? reframing socialization around newcomers authentic self-expression. *Administrative Science Quarterly 58*(1), 1–36.

Cachon, G. P. and R. Swinney (2009). Purchasing, pricing, and quick response in the presence of strategic consumers. *Management Science 55*(3), 497–511.

Cho, M., M. Fan, and Y.-P. Zhou (2009). Strategic consumer response to dynamic pricing of perishable products. In *Consumer-Driven Demand and Operations Management Models*, pp. 435–458. Springer.

Chung, D. J., T. Steenburgh, and K. Sudhir (2013). Do bonuses enhance sales productivity? a dynamic structural analysis of bonus-based compensation plans. *Marketing Science 33*(2), 165–187.

Daula, T. and R. Moffitt (1995). Estimating dynamic models of quit behavior: the case of military reenlistment. *Journal of Labor Economics 13*(3), 499–523.

Dill, W. R., D. Gaver, and W. Weber (1966). Models and modelling for manpower planning. *Management Science 13*(4), 142–167.

Freeman, M., N. Savva, and S. Scholtes (2016). Gatekeepers at work: An empirical analysis of a maternity unit. *Management Science*.

Glebbeek, A. C. and E. H. Bax (2004). Is high employee turnover really harmful? an empirical test using company records. *Academy of Management Journal 47*(2), 277–286.

Green, L. V., S. Savin, and N. Savva (2013). nursevendor problem: Personnel staffing in the presence of endogenous absenteeism. *Management Science 59*(10), 2237–2256.

Griffeth, R. W., P. W. Hom, and S. Gaertner (2000). A meta-analysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implications for the next millennium. *Journal of management 26*(3), 463–488.

Hayes, R. H. (2002). Wick skinner: a life sailing against the wind. *Production and Operations Management 11*(1), 1–8.

Heckman, J. J. (1979). *Statistical models for discrete panel data*. Department of Economics and Graduate School of Business, University of Chicago.

Heskett, J. L., T. O. Jones, G. W. Loveman, W. E. Sasser, and L. A. Schlesinger (2008). Putting the service-profit chain to work. *Harvard business review*.

Holtom, B. C., T. R. Mitchell, T. W. Lee, and M. B. Eberly (2008). 5 turnover and retention research: A glance at the past, a closer review of the present, and a venture into the future. *Academy of Management annals 2*(1), 231–274.

Jerath, K., S. Netessine, and S. K. Veeraraghavan (2010). Revenue management with strategic customers: Last-minute selling and opaque selling. *Management Science 56*(3), 430–448.

Jolliffe, I. (2002). *Principal component analysis*. Wiley Online Library.

Jones, D. A. and D. P. Skarlicki (2003). The relationship between perceptions of fairness and voluntary turnover among retail employees. *Journal of Applied Social Psychology 33*(6), 1226–1243.

Kc, D. S. and C. Terwiesch (2009). Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science 55*(9), 1486–1498.

Kim, S.-H., C. W. Chan, M. Olivares, and G. Escobar (2014). Icu admission control: An empirical study of capacity allocation and its implication for patient outcomes. *Management Science 61*(1), 19–38.

Lapré, M. A., I. M. Nembhard, et al. (2011). Inside the organizational learning curve: Understanding the organizational learning process. *Foundations and Trends® in Technology, Information and Operations Management 4*(1), 1–103.

Levin, Y., J. McGill, and M. Nediak (2009). Dynamic pricing in the presence of strategic consumers and oligopolistic competition. *Management science 55*(1), 32–46.

Li, J., N. Granados, and S. Netessine (2014). Are consumers strategic? structural estimation from the air-travel industry. *Management Science 60*(9), 2114–2137.

Misra, S. and H. S. Nair (2011). A structural model of sales-force compensation dynamics: Estimation and field implementation. *Quantitative Marketing and Economics 9*(3), 211–257.

Mukherjee, A., N. Malhotra, P. S. Budhwar, A. Varma, N. Malhotra, and A. Mukherjee (2009). Insights into the indian call centre industry: can internal marketing help tackle high employee turnover? *Journal of Services Marketing 23*(5), 351–362.

Nair, H. (2007). Intertemporal price discrimination with forward-looking consumers: Application to the us market for console video-games. *Quantitative Marketing and Economics 5(3)*, 239–292.

Narayanan, S., S. Balasubramanian, and J. M. Swaminathan (2009). A matter of balance: Specialization, task variety, and individual learning in a software maintenance environment. *Management Science 55*(11), 1861–1876.

NASSCOM (2016). *Business Process Management (BPM), http://www.nasscom.in/indian-itbpo-industry.*

Netessine, S. and C. S. Tang (2009). *Consumer-driven demand and operations management models: a systematic study of information-technology-enabled sales mechanisms*, Volume 131. Springer Science & Business Media.

Nevo, A. (2000). A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics & Management Strategy 9*(4), 513–548.

Oliva, R. and J. D. Sterman (2001). Cutting corners and working overtime: Quality erosion in the service industry. *Management Science 47*(7), 894–914.

Olivares, M., C. Terwiesch, and L. Cassorla (2008). Structural estimation of the newsvendor model: an application to reserving operating room time. *Management Science 54*(1), 41–55.

Park, T.-Y. and J. D. Shaw (2013). Turnover rates and organizational performance: a meta-analysis.

Rousseau, D. M. and J. McLean Parks (1993). The contracts of individuals and organizations. *Research in organizational behavior 15*, 1–1.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica 55(5)*, 999–1033.

Rust, J. (1994). Structural estimation of markov decision processes. *Handbook of econometrics 4*, 3081–3143.

Rust, J. (1996). Estimation of dynamic structural models, problems and prospects: discrete decision processes. In *Advances in econometrics: Sixth world congress*, Volume 2, pp. 119–170. Cambridge Univ Pr.

Shen, Z.-J. M. and X. Su (2007). Customer behavior modeling in revenue management and auctions: A review and new research opportunities. *Production and operations management 16*(6), 713–728.

Sohoni, M. G., E. L. Johnson, and T. G. Bailey (2004). Long-range reserve crew manpower planning. *Management Science 50*(6), 724–739.

Song, H., A. L. Tucker, K. L. Murrell, and D. R. Vinson (2015). Public relative performance feedback in complex service systems: Improving productivity through the adoption of best practices.

Staats, B. R., H. Dai, D. Hofmann, and K. L. Milkman (2017). Motivating process compliance through individual electronic monitoring: An empirical examination of hand hygiene in healthcare. *Management Science 63*(5), 1563–1585.

Staats, B. R., D. S. KC, and F. Gino (2016). Maintaining beliefs in the face of negative news: The moderating role of experience. *Management Science*.

Su, X. (2007). Intertemporal pricing with strategic customer behavior. *Management Science 53*(5), 726–741.

Tan, T. F. and S. Netessine (2014). When does the devil make work? an empirical study of the impact of workload on worker productivity. *Management Science 60*(6), 1574–1593.

Taylor, F. W. (1911). *The principles of scientific management.* Harper & Brothers.

Ton, Z. and R. S. Huckman (2008). Managing the impact of employee turnover on performance: The role of process conformance. *Organization Science 19*(1), 56–68.

Tucker, A. L. (2015). The impact of workaround difficulty on frontline employees response to operational failures: A laboratory experiment on medication administration. *Management Science 62*(4), 1124–1144.

WSJ (2017). *How to Reduce Employee Turnover, http://guides.wsj.com/management/recruiting-hiring-and-firing/how-to-reduce-employee-turnover/.*

Yu, Q., G. Allon, and A. Bassamboo (2016). How do delay announcements shape customer behavior? an empirical study. *Management Science, forthsoming*.

A Sensitivity Analysis

In this appendix, we perform sensitivity analyses to find the impact of some fundamental parameters of the model on the attrition rates. We perform Monte-Carlo simulations as described in Section 8 to find the attrition rates for the four following cases:

- If we change the intercept of the nominal utility of terminating an agent (λ_0) in Equation (3) by adding values between -3 and 3 with the increment of 1. The results for this experiment are illustrated in Table 11.
- If we change the intercept of the sensitivity to salary (α_0) in Equation (9) by adding values between -0.15 and 0.15 with the increment of 0.05. The results for this experiment are illustrated in Table 12.
- If we change the intercept of the non-monetary utility (η_0) in Equation (9) by adding values between -3 and 3 with the increment of 1. The results for this experiment are illustrated in Table 13.
- If we change the intercept of the model for the degree of forward looking behavior (δ_0) in Equation (9) by adding values between -3 and 3 with the increment of 1. The results for this experiment are illustrated in Table 14.

As can be seen in Tables 11, a lower value for λ_0 would lead to a lower attrition level. Furthermore, Tables 12 to 14 show that higher values for α_0, η_0 and δ_0 would lead to lower attrition levels. In addition, the results in Tables 11 to 14 show that the prediction of the model is extremely sensitive to the parameters of the model and the fact that our stats-quo prediction (corresponding to +0 in the tables) are close to the rates observed in the data support the accuracy of our model and estimation results.

Table 11: Sensitivity to the intercept of the involuntary attrition model (λ_0).

λ_0+	VA	IA	C
-3	62.73%	1.69%	35.58%
-2	60.52%	4.49%	34.98%
-1	55.57%	10.45%	33.98%
0	46.72%	21.58%	31.70%
1	33.95%	38.45%	27.60%
2	19.13%	59.18%	21.70%
3	8.20%	76.62%	15.18%

Table 12: Sensitivity to the intercept of the sensitivity to salary in the voluntary attrition model (α_0).

α_0 +	VA	IA	C
-0.15	70.95%	14.38%	14.67%
-0.1	63.14%	16.04%	20.81%
-0.05	55.45%	18.01%	26.54%
0	47.03%	21.26%	31.71%
0.05	35.88%	26.42%	37.71%
0.1	24.83%	31.47%	43.70%
0.15	16.46%	35.59%	47.95%

Table 13: Sensitivity to the intercept of the non-monetary utility in the voluntary attrition model (η_0).

η_0 +	VA	IA	C
-3	70.93%	13.36%	15.71%
-2	64.27%	14.51%	21.22%
-1	56.42%	17.17%	26.41%
0	47.03%	21.26%	31.71%
1	34.72%	27.58%	37.70%
2	21.56%	33.95%	44.49%
3	11.06%	39.81%	49.13%

Table 14: Sensitivity to the intercept of the degree of forward looking behavior in the voluntary attrition model (δ_0).

$\delta_0 +$	VA	IA	C
-3	53.13%	17.37%	29.51%
-2	51.86%	18.29%	29.86%
-1	50.47%	19.29%	30.24%
0	47.03%	21.26%	31.71%
1	39.46%	26.25%	34.30%
2	29.52%	31.57%	38.91%
3	20.36%	35.91%	43.72%