The Impacts of Clustered Attrition on Retention and Performance

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February 18, 2021

Abstract

Using a comprehensive five-year panel dataset of tens of thousands of employees in a large technology firm, we study how clustered team-level attrition impacts rates of promotions, bonuses and attrition among remaining employees. We deploy a novel identification strategy leveraging changes in the firm's stock vesting schedule to isolate random variation in clustering of voluntary attrition. While a change to smoother vesting schedules leads to smoother attrition patterns, we don't find strong evidence that clustered attrition impacted remaining employee outcomes in our data.

JEL Codes: M50, J63, M15

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1 Introduction

Despite labor being substitutable in the long run, losing well-trained and productive employees to competing firms often constitutes a major cost for a firm and its employees in the short run (Muehlemann and Leiser, 2018). Hiring new employees can be costly and disruptive to firms since inexperienced employees require time and resources to train, often requiring skills transfer from existing employees to newly hired ones (Lazear, 2009). Training can be even more costly with white collar work where learning an organization's tools, culture and processes can take additional time due to idiosyncratic internal differences across firms.

One of the many costs associated with voluntary employee attrition is on remaining workers. Take an example of a team of six software developers building a web-based application. If one worker departs, the remaining five members will face a temporarily increased workload to maintain team productivity levels, until a replacement is hired and trained. Even with harder work of remaining team members, output might fall in the short run as lower priority projects are delayed temporarily, reflecting poorly on the team. Alternatively, the increased short run workload could benefit remaining members if they take on added responsibility, increase their skill sets and succeed, thus putting them in line for promotions and raises.

If a single worker departing from a small team can increase workload and decrease output of the remaining group, two workers leaving could be more than twice as bad for the firm. General disruption of the work environment could impact productivity of the remaining workers both directly and via the returns to scale of the team's production process. The opportunity cost of each employee's time will increase the more they work, even if temporary. If a team's labor is not easily substitutable then intrafirm bargaining and wages could be impacted (Stole and Zwiebel, 1996a and Stole and Zwiebel, 1996b).

Given the choice, both a firm's managers and its employees might prefer to have two people leave at different times of the year than leave all at once. Put another way, a steady flow of voluntary attrition might be more efficient for the firm and remaining employees than an abrupt mass exodus (Alan, 2011). There would also be sharp implications for HR managers: they should allocate more resources to rehire open positions on teams with multiple openings. Complementary further responses could include staffing strategies and compensation structures to prevent such cases of multiple openings within team outright.

In this paper we use a novel proprietary dataset to investigate the causal impact of clustered teammate attrition on remaining worker outcomes. We use data from a large technology company including a complete panel of organizational hierarchy. This data structure allows us to precisely identify and track remaining team member outcomes following attrition events. We test whether experiencing clustered attrition impacts the remaining member's annual awards, probability of promotion, or probability of attrition.

For our analysis, we focus narrowly on voluntary attrition. We exclude all non-voluntary vacancies and all vacancies which are created due to increased head count; this helps to limit the role of confounding factors such as employee behavior or business unit expansion in our estimates. As a result, we restrict the study to only voluntary attrition of existing team members in order to minimize variation in other team-specific attributes.

The specific counterfactual we have in mind is how voluntary attrition clustered in a month impacts team members relative to the same amount of voluntary attrition spread out over a full year. For example, assume there are ten members on a team of developers and in a single year there are three voluntary departures. Consider two ways those departures could occur. The first is if a single employee attrits every four months. We call this "smooth" attrition. The second is if all three departing employees leave in the same month of a year. In both cases, the remaining team members saw a 30% annual attrition rate. In the second case, though, the attrition was heavily clustered. We study the impact of exactly this notion of clustering on remaining teammate outcomes.

To measure the impact of this attrition clustering on remaining teammate outcomes, we examine and compare results across several ordinary least squares regression models including one with team fixed effects to leverage our data on organizational structure. We further show how a change in the firm stock vesting schedule over this period lead to changes in within-year attrition patterns. The stock vest schedule change forms the basis for an reasonably strong instrument measuring how clustering in timing of team-level stock vest patterns impacts clustering in attrition timing which in turn impacts remaining employee outcomes.

Despite our detailed data which includes over 20,000 person-year observations and includes organizational structure, we don't find strong evidence that clustered attrition impacted remaining employee outcomes in our data. The lack of impact is clearest for promotion and annual awards. There is some modest evidence in the OLS specification that increased clustering leads to less attrition of remaining team members but we lose statistical significance in both the fixed effect and IV model. The lack of significance for the attrition outcome in the fixed effects and IV models is largely due to voluntary attrition of remaining team members being a very noisy process: the r^2 of the attrition model is only .01 in the OLS and fixed effect models, which is roughly an order of magnitude lower than the promotion and annual awards models. Put another way, we don't find evidence that systematic variation in clustered attrition leads to systematic impacts on attrition rates, or any other outcomes, of remaining team members.

The clearest evidence for there being little evidence that clustered attrition has a systematic impact relative to smooth attrition for remaining employees is the 95% confidence interval of estimated impacts. In our preferred fixed effects model, for example, a one standard deviation increase in team attrition clustering changes following-year teammate attrition probability with a 95% confidence interval of [-0.007,0.001]. Put another way, the -.007 lower bound implies there is a decrease of 0.7 percentage points in individual attrition probability the year after an one standard deviation increase in attrition clustering. The constant term shows that baseline annual attrition rates are roughly 1% (.007) in our sample. The IV results, despite a strong first stage showing that clustered vesting schedules lead to clustered employee attrition, have even wider confidence intervals. Thus, while we can't rule out a large negative impact of clustered attrition on remaining employee attrition, any relationship if it exists is very noisy at best.

These results do require context. First, background variation in the outcomes of interest is large relative to the variation in attrition clustering. For our estimated coefficients to be statistically significant in the IV regressions, for example, we would need roughly four times the variation in the attrition clustering variable we observe in the data. Hence our results from the IV models also have a small negative point estimate but the standard errors on the point estimate are large. Thus we can conclude that there is no evidence of large negative effects of clustered attrition on remaining employee outcomes.

Second, we study only a single large technology firm and the majority of the employees in our sample are engineers and developers. One would expect that engineers and developers on the same team are substitutable relative to, say, lawyers who have different areas or expertise within the field of law. Put another way, the costs of skills transfer like learning the syntax of an additional computing language might be lower for engineers and developers than in other fields. We view our results as consistent with no systematic effect for substitutable white collar work like engineers and developers.

To date the Personnel Economics literature has largely focused on studying publicly collected data sources such as those from government employment agencies or publicly listed executive compensation (Oyer et al., 2011). As personnel data is among the most sensitive held by firms, few researchers have had the opportunity that we have to examine a treatment that impacts tens of thousands of workers over multiple years, and is highly relevant to other white collar employment situations. Further, we can leverage detailed organizational panel structure in our data not often available to other researchers.

Existing work studying labor turnover has largely focused on macroeconomic or firm impacts rather than intra-team dynamics within a firm. For example, Lazear and Spletzer, 2012 show that employee churn, the primary source of job openings, is critical in maximizing overall worker productivity through optimal worker-firm matches. In Switzerland, Muehlemann and Leiser, 2018 shows that firms face a rather high cost to hiring: an estimated 16 weeks of wage payments, dominated by the post-match costs of training a new employee. Using data similar to ours, Hoffman and Tadelis, 2021 show staff turnover is one outcome which is highly sensitive to manager quality, and that managers themselves are rewarded for the relevant skill set.

One notable exception is Hoffman and Tadelis, 2021 which focuses on how manager quality impacts employment outcomes like attrition. While Hoffman and Tadelis, 2021 studies similar types of employee outcome, we study a very different mechanism behind those outcomes. Comparing their findings to ours, we find that manager quality appears to matter much more to employee attrition than having team-members leave all at once as opposed to smoothly throughout a year.

Our focus on the impacts of churn on remaining employees is most directly addressed in Jäger and Heining, 2019. Studying the impact of unexpected deaths among the German workforce, Jäger and Heining, 2019 finds that remaining workers benefit from increased wages and retention probabilities. This average positive effect masks heterogeneous impacts: substitutable workers experience larger benefits, while complementary ones see negative impacts, and impacts are exaggerated when external labor markets are thin. The primary distinction between that paper and ours is that we are focused on whether the same number of employees leaving all at once has a differential impact relative to leaving throughout the year. We isolate random variation in clustering, holding number of departures constant. Jäger and Heining, 2019 on the other hand isolates random variation in the number of departures: i.e. comparing teams with no departures to a team with a single unexpected departure.

Our data and research design complements Jäger and Heining, 2019 in several ways. Utilizing our detailed firm-level data, we are able to track immediate team-member impacts in the context of a large, modern corporation. Employee and team dynamics in this setting may may exhibit economically important differences relative to the sample of historic (1975-2011) small German firms they study. Second, we develop a new source of identifying variation based on stock vesting cliffs at the team level. Third, we are able to study annual performance and retention outcomes which are generally not available in government records.

2 Context and Data

We study all voluntary attrition occurring in fiscal years 2014 through 2018 for a single large technology firm. The company we partnered with for the study starts each fiscal year on July 1; fiscal year 2014 is calendar months July 2013 through June 2014. We use data on all non-executive stock eligible employees. We structure the data at a monthly frequency, creating an unbalanced panel following each eligible employee across all fiscal months. Employment information like annual awards, stock vests, performance and team membership are linked using an de-identified unique employee identifier.

Our study focuses on individual employees working on teams defined as a set of employees sharing a common manager. This definition allows for variation in team-size over time, and across different business units throughout the company; we do however exclude any teams with a maximum (across time) team count above 30. We further exclude team-by-year groups which appear for fewer than 4 months in each fiscal year. By reconstructing the firm's organizational hierarchy each month, we can follow teams throughout time. This enables us to estimate the impact of clustered attrition on remaining team members.

The counterfactual we are interested in our study is comparing employee outcomes of two teams that have the same amount of attrition in a year but one team has smooth attrition while the other team has clustered attrition. In order for their to be any clustering, a team must therefore have at least two employees leaves within a year. As a result, we restrict the dataset to teams that have had at least two voluntary attritions in a single year. This reduces our sample size but is appropriate given our research question.

Finally, there are two important reasons for investigating the impact of clustered attrition on remaining team members that motivate our analysis. First, if clustered attrition negatively impacts remaining workers then firms may be able to better retain or manage workers exposed to clustered attrition by better understanding what tends to follow clustered attrition. Second, there are broader economic implications for labor substitutability in the sector we study: if there are no impacts then it is evidence that in this particular setting an individual's productivity does not depend on the timing of voluntary attrition occurring around them in normal work conditions.[1] This implies some degree of substitution between labor as one large, versus many small, turnover events lead to similar outcomes for employees.

3 Econometrics and Identification

Our goal is to study how simultaneous voluntary attritions impact remaining team members relative to the same number of people leaving across a calendar year. To do so, we remove all team-year observations in which one or zero attrition events are recorded. For the remaining team-years that experience two or more voluntary attritions, smooth attrition would be attrition evenly spaced throughout a year. Fully clustered attrition would occur entirely at once.

Our main econometric specification is an OLS regression run at the employee level with several fixed effects. The left hand side variables we investigate are an employee's annual

[1] Of course, mass exodus due to a non-normal time for the firm is very different.

rewards, an indicator variable for promotion, and an indicator variable for voluntary attrition. The right hand side variable of interest is how clustered attrition was in a given year. In each case, we estimate the following econometric model:

$$y_{i,g,t+1} = \beta clustered\ attrition_{i,g,t} + \psi total\ attrition_{i,g,t} + X_{i,g,t}\gamma + \omega_g + \lambda_t + \epsilon_{i,g,t+1} \quad (1)$$

In the model, i indexes an individual, g a group and t a year. X is a matrix of individual and group-level control variables, while ω and λ denote group and year fixed effects. Because we are interested in how clustered attrition in previous periods affect today's employee outcomes, the left hand side variable and several controls are evaluated 1 fiscal year in the future.

The coefficient of interest is β, the measure impact of a unit increase in clustered attrition holding all else equal. The remaining covariates are included to control for potential sources of omitted variable or selection bias arising primarily from the fact that individuals are not randomly assigned to teams within the firm. Therefor, exposure to within-team clustered attrition is not necessarily random. We accounts for observable and unobservable individual and team characteristics related to the impacts of clustered attrition to isolate and study psuedo-random variation in this treatment.

3.1 Measuring Clustered Attrition

To formally investigate clustered attrition, we must have a way to measure and compare how clustered attrition is for teams of different sizes and different total attrition levels. To do this we compute differences between the attrition share each month and a perfectly uniform distribution of attritions. The formulation is shown in Equation 2 where m indexes month, t indexes year and g indexes team.

$$Clustered\ Attrition\ Intensity_{g,t} = \sum_{m=1}^{12} \left| \frac{attritions_{g,m}}{attritions_{g,t}} - \frac{1}{12} \right| \tag{2}$$

Equation 2 shows that we sum within year deviations from evenly distributed attrition for a single team across months in constructing the cluster metric. A value of zero indicates that attrition is perfectly uniform throughout the year; this is however only possible if there are 12 voluntary attritions in a year on a team. A value of perfectly clustered is 1.83 [e.g., $1.83 = 22/12 = (1 - \frac{1}{12}) + 11 \cdot \frac{1}{12}$]. An example is helpful: assume two people leave a team in a given year. If they leave in the same month that team's value is $\frac{22}{12} = 1.83$. If they leave in different months, the metric equals $\frac{20}{12} = 1.67$. For each team we measure attrition clustering once a year so that for a team existing for all five years in the data we would have five clustered attrition measurements for that team.

An advantage of using this metric is that it is intuitive: attrition would be perfectly smooth if 1/12 of all annual attrition occurs each month. A disadvantage is that it is rare to observe 12 attrition events on a given team in a given year, meaning the metric is not zero in any cases and is not fully continuous. Indeed, panel (A) of Figure 1 shows the vast majority of teams have fewer than 12 employees in them. Despite this issue, there is still meaningful variation in how clustered attrition is within a team and year. In particular, modal team size is 5 in our analysis sample: if two employees attrit at the same time versus at different times within a year, we have reason to believe that there would be noticeable differences for remaining employees in those two scenarios.

Panels (B) and (C) of Figure 1 display histograms of the cluster metrics we use in the analysis. The mean of clustered attrition intensity is 1.63 with a standard deviation of 0.12.[2] Per our example above, the variation in clustering is meaningful: there are many examples in which there is full clustering: around 10% of values have a value equal to the maximum possible value of 1.83. The lower bound of our support is 1, above the theoretical lower

[2]Robustness checks show that a squared metric yields similar results.

bound of 0 which would occur if a team experienced precisely 1 attrition each month of the year. Clustered vesting intensity in panel (C) shows the distribution of our instrument, further discussed in the empirical approach section below (3.2).

3.2 Empirical Setting and Approach

We consider several empirical strategies to investigate the relationship between clustered attrition and remaining team member outcomes. The three outcomes we define and study for remaining team members are: 1) voluntary attrition (quit), 2) promotion, and 3) award. All are measured at the individual-level in the fiscal year following the year used to measure team-level attrition clustering and other controls. The first two outcomes are simple binary variables, taking a value of 1 if they occurred and 0 otherwise. A promotion is defined here as an increase in level. The final outcome, award, is based on the annual performance review from an employee's manager. Higher manager determined impact leads to higher performance review and higher annual bonus. In the data we normalized awards which enables us to compare across employees.

A direct Ordinary Least Squares (OLS) regression of individual outcomes on clustered attrition may not yield a causal estimate due to unobserved factors which could impact both attrition clustering and remaining employee outcomes. Examples could include changes in management, changes in team priorities, changes in pressure associated with the teams work, or a team's rewards. We explore three regression models which each help to inform the relationship of interest: OLS with controls, further adding team fixed effects, and an instrumental variables approach based on changes in firm vesting policy.

Our regression analysis controls for detailed and relevant team characteristics measuring tenure, performance, and turnover each year. We also control for the corresponding employee characteristics, as well as fixed effects for fiscal years. Including these controls addresses many of the concerns that teams or employees experiencing higher levels of clustered attrition could be somehow systematically different than those not. We further validate robustness to such concerns in several exercises discussed in the Results section and shown in the appendix.

There may be lingering concern that accounting for these particular factors does not sufficiently account for complex and hard to measure team characteristics such as management style or work atmosphere which could also be important omitted variables. These factors may be integral to team turnover rates and employee outcomes and are thus critical to consider in our case. To investigate the scope of bias from these unmeasured team-level characteristics, we further add team-level fixed effects to the controlled OLS regressions. Doing so eliminates any fixed team characteristics from the identifying variation, focusing the analysis on within-team dynamics over time. Given our definition of a team as employees working under a common manager, we think this fixed effects analysis offers a compelling piece of evidence in evaluating the scope for unobservable omitted variables.

Our third identification strategy of developing an instrumental variable is motivated by a change in the benefit distribution schedule implemented during our sample period. As in many large companies, employees at this firm are often compensated with shares of stock that vest on a well-defined future schedule[3]. Because accumulated stock vests are an economically significant form of delayed compensation, some workers will postpone separating to collect a final vest before departing, creating firm-wide vesting cliff dates. We use this attrition timing behavior and policy changes to the vest schedule as an additional source of identifying variation in attrition clustering.

Specifically, in fiscal year 2015 the firm switched new awards from annual vests to semi-annual vests, and subsequently in fiscal year 2018 to quarterly vests. Importantly all stock awards maintained the vesting schedule in place at the time of the award. For example, if an

[3] When an awarded share vests, this compensation shifts from a promise to an asset, and is deposited in an employee's private investment account; at which time the employee can sell the shares if they wish. Stock awards are commonly spread evenly over several years and require that employees remain at a firm in order to continue receiving them, creating a disincentive to attrition.

employee was awarded 100 shares in 2014 to vest over 5 years, they would continue to have 20 shares vest annually even after the policy changed. In the Results section, we show that patterns of attrition timing across years is consistent with this policy change, an important finding both for our IV approach and as a standalone fact.

We construct an instrument to capture the degree of attrition clustering driven by these vest schedule policy changes[4]. This instrument uses recorded data on individual-level stock awards to construct a team-by-year measure of stock vest clustering. Using the same formula for clustering as in Equation 1, we compute the monthly difference between the value of realized stock vests and a uniform vest, and sum these up within team by fiscal year. The distribution of this measure is shown in Figure 1 (C), in which we see an approximately normal distribution around a mean just below 1.5.

The degree to which stock vesting is clustered in a given year and team is determined by the interaction of three key factors: 1) policy changes, 2) team composition, and 3) stock price changes. Because we include year and team fixed effects, along with controls for non-constant team composition and individual characteristics, the remaining variation in vest clustering is limited to that driven by the policy changes. Treating these policy changes as plausibly exogenous shocks, we argue that the instrument is valid in this setting precisely because it isolates this source of variation.

4 Results

We begin with an analysis of descriptive statistics followed by a review of OLS regression results. We then examine the relationship between vest schedule changes and attrition patterns. The findings in our IV regressions follow, and we conclude the section with a

[4]We alternatively considered using more direct approaches such as difference-in-differences to measure the impact of these policies. We however decided that a coinciding steady increase in stock prices and the lack of a comparable control group unbound by the policies were substantial enough limitations to rule out such strategies.

review of several robustness exercises.

4.1 Descriptive Statistics

In Table 1 we show the summary statistics for our analysis sample and variables. The analysis sample utilized throughout our regressions is comprised of 20,506 year-by-individual observations. We see that the fiscal years used for the analysis span 2015 to 2018[5]. The average employee has a tenure of about 7.6 years and the average team is approximately 10 people. Like most corporations, this firm has employee levels reflecting more junior to more senior employees. We define promotion as moving from a lower level to a higher level in the data. We do not report average employee levels due to their sensitivity. Despite using them as dependent variables in the econometric analysis, we also do not report summary statistics on promotion probability nor award level due to their sensitivity.

The probability of voluntary attrition is low, at approximately 1% each year, in this sample. As a result of limiting our sample to teams experiencing at least 2 quits in the prior year, the average number of quits in the last year is 2.36, with a long right tail spanning to 15. Recall that all of the individual-level outcomes are measured for the current year, while the team and individual-level controls are measured based on the previous year. Given our selection of a relevant analysis sample such as team size, these summary statistics are not representative of all teams and employees in the broader firm.

4.2 OLS Regression Results

To study the relationship between clustered attrition and teammate outcomes, we regress individual-level outcomes (attrition, promotion, and award) on the degree of clustering in the team's attrition, as defined in equation 1. We further include controls for team characteristics

[5]Note that fiscal year refers to the year that the outcomes are observed, so the 2015 data incorporates attrition patters from fiscal year 2014.

including number of quits, vest amount, size, average employee level, average tenure and average award last year, along with individual controls on employee level, tenure, and last award (all measured in the prior year).

The first three columns of Table 2 shows that we find no discernible impact of clustered attrition except on future voluntary attrition in OLS specifications. Specifically there is a negative and statistically significant relationship between clustered team attrition and future attrition rates of remainers. This indicates that, conditional on year, team and individual controls, remainers on teams highly impacted by clustered attrition are in fact less likely to attrit. A one standard deviation increase in team-level attrition clustering[6] is associated with a 0.003 or 0.3% decrease in individual attrition probability in the following year[7]. This is a relatively large correlation as in our subsample the attrition rate per employee-year is roughly 1%.

The negative impact is consistent with remaining team members having more bargaining power with their managers and also negative selection of remaining team members. However, our other remaining teammate outcomes of promotion and award are not strongly related to team attrition clustering experiences. Coefficients for promotion and award are economically small and inconsistent in size and direction across specifications. Hence the negative impact in attrition is not reflected in the other employee outcomes we examine.

In the fixed effects results shown in the last three columns of Table 2 we see that the negative relationship between clustered team attrition and remainer voluntary attrition in the next year remains very similar in magnitude, but becomes marginally statistically insignificant. The standard errors here more than double because the sample shifts here from 20,506 individuals to 1,950 teams. This result suggests that there is no definitive evidence that team fixed effects capture any key dynamics that were omitted in the direct OLS regres-

[6]1 standard deviation in raw attrition clustering is 0.12, as shown in Table 1

[7]This represents approximately 30% of mean attrition in this setting

sions on remainer attrition. Note that the attrition clustering coefficients remain statistically insignificant in regressions on the other outcomes as well.

Conservatively focusing on the fixed effects models, a one standard deviation increase in team attrition clustering changes following-year teammate attrition probability with a 95% confidence interval of between -0.7 and 0.1 percentage points. This is on a baseline attrition rate per employee-year in our sample of roughly 1% (.007). Hence, large negative effects of clustered employee attrition on remaining employee attrition are not ruled out in the fixed effects model. We view the first order finding, though, to be how noisy the relationship between clustered attrition is with remaining team member attrition. More generally, explaining employee attrition is hard: the fixed effect model has an r^2 of only .01, roughly an order of magnitude lower than the promotion and award models. The negative result relationship of almost half a percentage point could be economically significant in some situation but the interpretation for such a relationship is more limited; we offer thoughts in the discussion. Considered alongside null results on other outcomes, clustered attrition is unlikely to be a powerful targeting device for personnel efforts.

4.3 Vest Schedule Changes and Attrition Patterns

To investigate the role of the vest schedule policy changes on voluntary attrition timing, we plot these dynamics in Figure 2. Panel (A) shows trends in voluntary attrition in our data. The Y-axis represents the number of employees attriting in each month which clearly has a strong seasonal fluctuation between 125 and 600.

Panel (B) of Figure 2 simulates the dollar value of stock vesting from annual awards over the previous 5 years, for a hypothetical worker who receives the same award each year. Red lines highlight two policy changes over our sample, at which times the firm transitioned from an annual to semi-annual vesting of annual stock awards, and finally to a quarterly vesting. Note that annual stock awards (resulting from performance reviews at the end of each year) are vested over 5 years, so any given stock vest will be a composition of all annual awards received in the previous 5 years, for an employee with at least that much tenure. A curious feature of this plot is that while semi-annual and quarterly vests are appearing following the policy changes, the dollar values of the annual vests are hardly declining. This is due to the fact that these values are adjusted for stock price, and reflect an increase in this price over the study period, leading to an over-representation of the oldest stock awards (those that had grown the most) which still only arrived at the annual vest date.

Finally in panel (C) of Figure 2, we overlay the attrition counts with the stock vests and find two clear trends. First, attrition is historically spiking in the exact month that annual stocks are vesting, somewhat assuaging concerns that other seasonal factors are responsible for the attrition. Furthermore, we observe a second mid-year spike in attrition that grows after the first policy change, coinciding with the increasing share of stock awards received at the semi-annual vest in February.

This result itself is informative: large spikes in attrition are created by firm-wide annual compensation cliffs, and distributing this compensation increases the distribution of attrition. Personnel practitioners may be interested in distributing attrition for a wide variety of reasons, such as a more even load of rehiring efforts. The cost of this could be slightly shorter average retention if employees no longer feel compelled to wait for a large annual vest, but we find no indication that long-run attrition rates increase as a result of distributing these compensation packages. Finally, the strong overlap between attrition spikes and vest dates in Figure 2C is a strong piece of graphical evidence illustrating the relevance of our instrument.

4.4 Instrumental Variable Results

We also use clustering of vest as an instrument for clustering of attrition, both measured at the team-year level. The intuition behind this approach is that variation in the clustering of stock vests is driven primarily by the interaction of compensation policy and team composition. As such, we believe that the scope for vest clustering to impact remaining teammate outcomes through mechanisms besides team member attrition (i.e. a key threat to the validity of this research design) is minimal. To that end, the first stage regressions in Table 3 show that whether or not we control for fluctuating team or employee characteristics, vest clustering is robustly positively associated with attrition clustering, showing it is a relevant instrument.

The first three columns of Table 3 show this result numerically: even after including all of the other controls, including year and team fixed effects, team vest clustering is positively associated with attrition clustering. With a t-statistic of just above 2 in the case of full controls (column 3) and an R^2 of 0.006 when used as a lone regressor (column 1), the instrument explains a distinct but relatively small part of the variation in attrition clustering.

The IV columns in Table 3 shows the findings using this instrument when using all controls: in this case we find no meaningful impact of clustered team attrition on the outcomes of remaining teammates. While the point estimates are much larger in this regression, very large standard errors driven by a narrow source of identifying variation overwhelm any statistical significance. Given the statistical limitations of the IV regression in this setting, we interpret the results cautiously. The IV analysis is a supporting piece of evidence that there are unlikely to be large negative impacts of clustered attrition on remaining teammates.

To evaluate the robustness of these findings, we perform a series of alternative regression specifications in the Appendix. We test whether our findings differ between engineers and non-engineers, whether a squared difference rather than an absolute value in Equation 1 matters, and whether an instrument using shares rather than vest value change the IV results[8]. Our results show little sensitivity in these exercises, as all of the results remain quantitatively and qualitatively very similar.

[8]These results can be found in the online appendix.

5 Discussion

Using detailed individual-level panel data in a large technology firm, we are able to carefully investigate the implications of clustered attrition on remaining team members. Having several co-workers depart simultaneously can cause disruptions to work flows and make it challenging to complete team-level goals. Alternatively, several vacancies on a team may increase the demands on remaining members and create opportunities for growth. While we can't rule out large effects of cluster vacancies on voluntary attrition of remaining team members this is mostly driven by the noisy relationship rather than evidence consistent across outcomes. Put another way, we do not find any consistent evidence that clustered attrition has negative impacts on remaining team members. This suggests that the second explanation of increased demand driven by labor substitutability is more plausibly the dominating mechanism.

Specifically, our only distinguishable evidence of clustered attrition impacts is on remaining teammate attrition propensity. Employees left after a team experiences a clustered attrition event are less likely to attrit in the following year. While the empirical methods we deploy to test endogeneity concerns with this relationship decrease the precision of coefficients substantially, the magnitude of them is markedly stable. This indicates that fixed team factors and other drivers of team attrition clustering are unlikely to represent a large source of bias.

Even these limited results on future attrition propensity should be considered cautiously. The magnitude of the effect is not trivial, however there are plausible alternative explanations. It could be the case that those leaving in clusters leave behind teammates who had lower attrition propensities to begin with, relative to teams with dispersed attrition. Furthermore, clustered attrition may not be an entirely one sided employee decision: managers may seek to restructure a team through by encouraging or coordinating voluntary attrition in a specific month. This would also lead to a selection mechanism of remaining employees have a naturally lower attrition probability.

Our other outcomes of interest, remaining teammate promotions and awards, show no indication of meaningful treatment effects. Impacts on both outcomes are far too small and imprecise to be statistically distinguishable from 0. Furthermore, coefficient directions are inconsistent across specifications and small in magnitude relative to baselines for these outcomes. Based on these results, there is no evidence, despite our very detailed firm data, that concentrated team attrition shocks create more opportunity that dispersed ones.

The dearth of impacts on these outcomes may be specific to our particular setting or the nature of our treatment. Since we only look at annual outcomes the year following multiple team attritions, we may miss shorter or longer term impacts on the remaining employees trajectory in the firm. In this setting we focus narrowly on comparing clustered attrition to dispersed attrition in teams which sustain over several years. This particular comparison may not create team-level labor substitution dynamics at the magnitudes that a large shock to attrition itself could create, for example as examined in Jäger and Heining, 2019. Furthermore, focusing on teams that remain intact across years both limits our sample size and focuses our analysis on this subset of the firm. For example there may be important team formation or destruction dynamics that are outside the scope of our analysis. Finally, larger attrition events or those occurring in firms not in the technology sector may have substantially different impacts than those we're able to study.

Given these findings, the implications for personnel practices are limited. Team attrition clustering may be a marginally useful feature to consider when modelling future attrition probabilities, but we find no compelling evidence that large team impacts of clustered attrition are present. As the policy change we examined is a change in benefit distribution timing, firms considering such changes can deduce that a more even distribution of benefits across time will generate a reduction in attrition clustering (as shown in Figure 2), but is unlikely to lead to large changes in the employee outcomes we study.

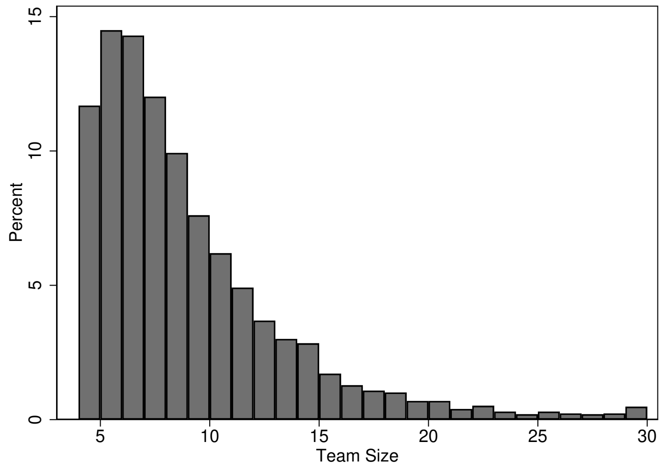
These findings also have implications for micro-founded models of team level productivity and intra-firm bargaining. They imply some degree of substitution between labor as one large, versus many small, turnover effects lead to similar outcomes for remaining employees. In particular, the result is consistent with at least some degree of separability between individual employee labor inputs for an individual's, and by extensions a team's, production function. Multiple caveats for this broader insight are in order.

Our results do not contradict the leading results in the field from Jäger and Heining, 2019: we find no evidence that remaining teammates are negatively impacted following attrition events. While the margin of treatment is different, we build on the evidence that remaining teammates are likely positively selected, and if anything they may benefit from increased demand for their skills. Our work adds to this conclusion in a meaningful way by tracking a panel of employees on well-defined teams and measuring personal employment outcomes within the firm. This level of data precision fills in a literature that has generally not been able to observe and track labor shocks in well defined team units.

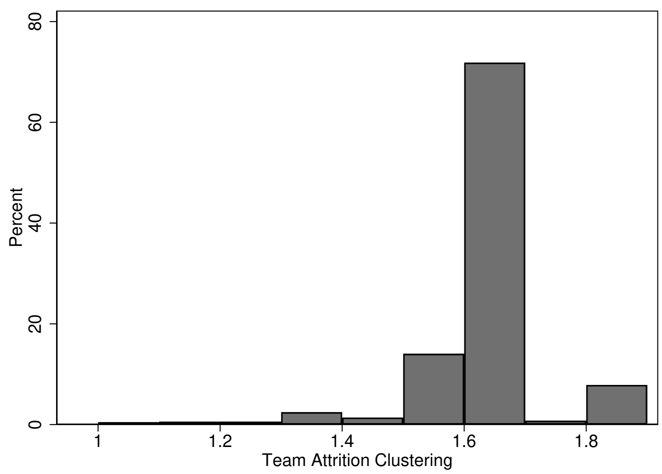
Future research on labor substitutability and intra-team dynamics will benefit from continued investigation of such firm microdata. One interesting area of exploration would be to examine the impacts of increased labor demand on re-hiring patterns. It is possible that dynamics such as clustered attrition or general labor demand shocks may change the pool of applicants that human resource representatives are able to draw from. This could be an important factor in personnel composition such as diversity or team cohesion.

Figure 1: Distribution of Key Variables in Analysis Data

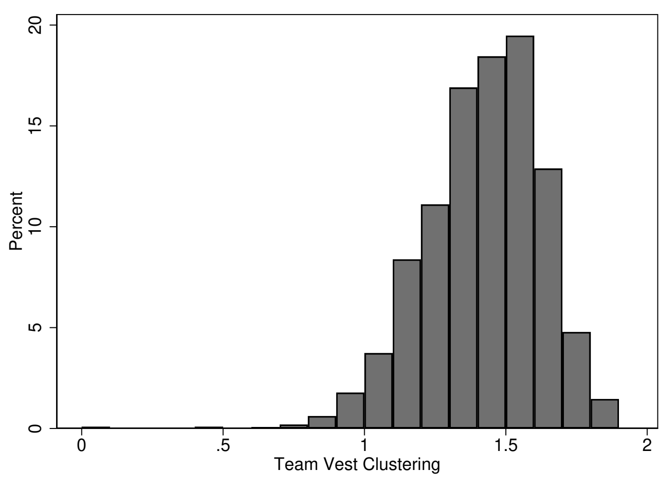
(A) Trimmed Team Size



(B) Clustered Attrition Intensity



(C) Clustered Vesting Intensity



Note: Each histogram shows the distribution of a key variable in our analysis. Panel (A) shows team size, defined as a group of employees who share a common manager. In a given year, we exclude all observations from a team if there are more than 20 members or the team appears in fewer than 4 months. Panel (B) shows the within year dispersion of team member stock vests. The degree of vest clustering is based on the formulation of clustering in equation 2, capturing deviations from a uniform distribution. Vest clustering is the instrument we investigate as a source of endogenous variation in clustered attrition. Panel (C) shows the distribution of attrition clustering, measured as deviations from attrition occurring uniformly throughout the year as defined in equation 2.

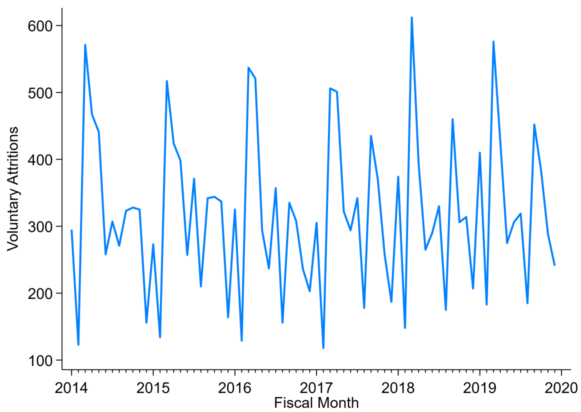
Table 1: Summary Statistics on Key Variables of Analysis Sample

	Mean	SD	Min	Max
Fiscal Year	2016.6	1.08	2015	2018
Employee Tenure (Months)	91.43	65.99	0.00	394.00
Team Size	10.52	5.68	4.00	30.00
Team Number of Voluntary Attritions	2.36	0.83	2.00	15.00
Team Voluntary Attrition Clustering	1.63	0.12	1.00	1.83
Observations	20,506			

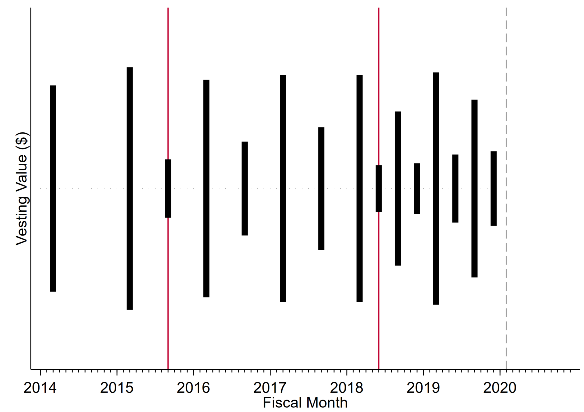
Note: The table shows summary statistics for the analysis sample of employees used in our regression results. Each fiscal year begins on July 1 of the corresponding calendar year. Team refers to a group of employees sharing a common manager. Team voluntary attrition clustering is defined in equation 2.

Figure 2: Spikes in Voluntary Attrition Around Stock Vesting

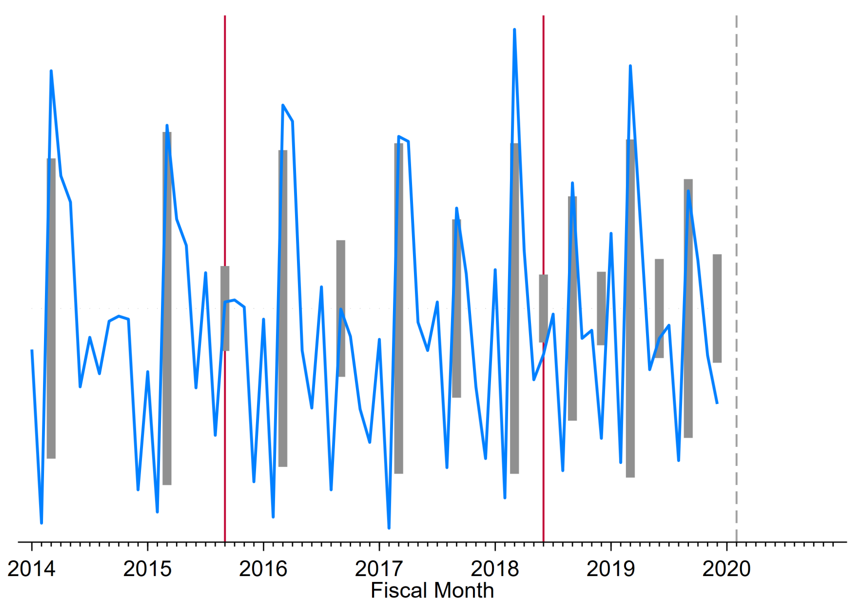
(A) Voluntary Attrition Counts



(B) Stock Vest Value From Annual Rewards



(C) Voluntary Attrition Counts Against Stock Vest Value



Note: Panel (A) shows the number of employees in our analysis sample who attrit in each fiscal month. The fiscal year begins on July 1 of the corresponding calendar year. Panel (B) shows the value of stock vests for a hypothetical worker who receives a constant award each year. Vertical red lines show policy changes from annual to semi-annual vests, and subsequently to quarterly vests. Changes in the price of the firm stock are also reflected in this hypothetical vest schedule. Panel (C) shows panel (A) and panel(B) overlaid. Month-to-month attrition spikes closely follow changes in the vest schedule.

Table 2: Impact of Clustered Attrition on Teammates: OLS Regressions

	Attrition	Promotion	Award	Attrition	Promotion	Award
Team Attrition Clustering	-0.022***	0.014	-0.025	-0.027	-0.018	0.023
	(0.008)	(0.039)	(0.028)	(0.018)	(0.058)	(0.047)
Team Number of Quits	-0.001	0.020***	-0.003	-0.007*	0.004	0.004
	(0.001)	(0.006)	(0.004)	(0.003)	(0.008)	(0.006)
Team Award Last Year	0.001	-0.081***	0.004	-0.002	0.018	-0.022
	(0.005)	(0.019)	(0.023)	(0.011)	(0.036)	(0.041)
Employee Award	-0.002	0.067***	0.181***	-0.002	0.067***	0.190***
	(0.002)	(0.008)	(0.010)	(0.002)	(0.008)	(0.010)
Constant	0.027	3.117***	-0.281	0.007	-2.431***	0.549
	(0.054)	(0.230)	(0.181)	(0.274)	(0.794)	(0.705)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Team Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	20506	20506	20506	20506	20506	20506
R^2	0.001	0.079	0.052	0.001	0.057	0.047

The table reports OLS regression results of individual-level personnel outcomes on team and individual characteristics. Outcomes are defined at the beginning of Section 4. Annual fixed effects are included in all regressions. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show exposure to team-level attrition clustering is associated with decreased own voluntary attrition in the following year, but not with future promotion or award rates. However, once narrowing focus to within-team variation, there is no statistically significant relationship between clustered attrition and future team member outcomes. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table 3: Impact of Clustered Attrition on Teammates: IV of Team Attrition Clustering

	First Stage			IV		
	(1)	(2)	(3)	Attrition	Promotion	Award
Team Vest Clustering	0.051***	0.023**	0.023**			
	(0.014)	(0.011)	(0.011)			
Team Attrition Clustering				-0.141	-0.616	-1.400
				(0.337)	(1.248)	(1.223)
Team Number of Quits		-0.094***	-0.094***	-0.017	-0.052	-0.131
		(0.014)	(0.014)	(0.033)	(0.118)	(0.119)
Team Level		0.006	0.006	0.003	0.021	0.022
		(0.005)	(0.005)	(0.005)	(0.014)	(0.016)
Team Award Last Year		-0.002	-0.003	-0.002	0.017	-0.025
		(0.013)	(0.013)	(0.011)	(0.036)	(0.044)
Employee Award			0.002*	-0.002	0.068***	0.192***
			(0.001)	(0.002)	(0.009)	(0.011)
Constant	-1.556***	-1.472***	-1.473***	-0.169	-3.350	-1.637
	(0.020)	(0.322)	(0.322)	(0.633)	(2.184)	(2.008)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20506	20506	20506	20506	20506	20506
R^2	0.006	0.474	0.474			

The first three columns of the table report the first stage regression results of team-level attrition clustering on team and individual characteristics. The last three columns report instrumental variables regression results of individual-level personnel outcomes on team and individual characteristics; notably including instrumented team attrition clustering. Annual and team fixed effects are included in all regressions. Outcomes are defined at the beginning of Section 4. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. First stage results show that vest clustering is a relevant instrument for attrition clustering (both defined using equation 2), though the share of variation explained by the instrument is very low. IV results indicate that the instrumental variables approach yields no evidence that clustered attrition leads to significant impacts on remaining teammates. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

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Online Appendix

Tables on the following pages show robustness checks for the regression results in the main paper. The first four tables show results for subsets of the employee population: first only on those classified as engineers by the firm, and then only on those classified as not being engineers. The next two tables (A5 and A6) run the analysis of the paper using a squared difference metric in place of the absolute value. The final table shows the IV results when using the team-level share of employees attriting rather than the number of employees. All results are consistent with those discussed in the text, showing robustness to a range of possible empirical approaches.

Table A1: Impact of Clustered Attrition on Teammates: OLS Regressions, Engineers Only

	Attrition	Promotion	Award	Attrition	Promotion	Award
Team Attrition Clustering	-0.021*	0.053	0.009	-0.027	0.074	0.034
	(0.011)	(0.053)	(0.030)	(0.023)	(0.079)	(0.045)
Team Number of Quits	-0.002	0.009	0.001	-0.008*	0.014	0.006
	(0.002)	(0.009)	(0.004)	(0.004)	(0.011)	(0.007)
Team Award Last Year	-0.002	-0.021	-0.006	-0.029	0.020	-0.062
	(0.009)	(0.033)	(0.021)	(0.022)	(0.064)	(0.040)
Employee Award	0.001	0.094***	0.194***	0.001	0.097***	0.200***
	(0.004)	(0.014)	(0.010)	(0.004)	(0.014)	(0.010)
Constant	-0.092	1.884***	-0.304	0.143	-1.559*	0.508
	(0.087)	(0.310)	(0.211)	(0.381)	(0.936)	(0.719)
Team Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	12938	12938	12938	12938	12938	12938
R^2	0.002	0.075	0.073	0.002	0.056	0.067

The table reports OLS regression results of individual-level personnel outcomes on team and individual characteristics on the subset of employees who work as engineers. Outcomes are defined at the beginning of Section 4. Annual fixed effects are included in all regressions. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by non-engineers. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table A2: Impact of Clustered Attrition on Teammates: IV of Team Attrition Clustering, Engineers Only

	First Stage			IV		
	(1)	(2)	(3)	Attrition	Promotion	Award
Team Vest Clustering	0.071***	0.039***	0.039***			
	(0.019)	(0.014)	(0.014)			
Team Attrition Clustering				-0.302	0.630	-1.127
				(0.281)	(0.890)	(0.713)
Team Number of Quits		-0.091***	-0.091***	-0.033	0.065	-0.099
		(0.016)	(0.016)	(0.029)	(0.084)	(0.069)
Team Level		0.003	0.003	0.007	0.019	0.014
		(0.007)	(0.007)	(0.007)	(0.016)	(0.015)
Team Award Last Year		-0.004	-0.008	-0.031	0.024	-0.071
		(0.022)	(0.023)	(0.022)	(0.066)	(0.046)
Employee Award			0.004***	0.002	0.094***	0.205***
			(0.002)	(0.004)	(0.015)	(0.011)
Constant	-1.528***	-1.622***	-1.623***	-0.328	-0.604	-1.485
	(0.026)	(0.423)	(0.423)	(0.678)	(1.838)	(1.436)
Observations	12938	12938	12938	12938	12938	12938
R^2	0.011	0.500	0.500			

The first three columns of the table report the first stage regression results of team-level attrition clustering on team and individual characteristics. The last three columns report instrumental variables regression results of individual-level personnel outcomes on team and individual characteristics; notably including instrumented team attrition clustering. Annual and team fixed effects are included in all regressions. Outcomes are defined at the beginning of Section 4. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by non-engineers. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table A3: Impact of Clustered Attrition on Teammates: OLS Regressions, Only Non-Engineers

	Attrition	Promotion	Award	Attrition	Promotion	Award
Team Attrition Clustering	-0.022**	-0.049	-0.081	-0.020	-0.210**	-0.004
	(0.011)	(0.040)	(0.055)	(0.025)	(0.087)	(0.103)
Team Number of Quits	-0.002	0.004	-0.006	-0.002	-0.026*	-0.011
	(0.001)	(0.007)	(0.008)	(0.003)	(0.015)	(0.015)
Team Award Last Year	0.006	-0.039*	-0.012	0.014	0.012	0.009
	(0.005)	(0.020)	(0.038)	(0.012)	(0.039)	(0.063)
Employee Award	-0.004*	0.042***	0.171***	-0.005**	0.041***	0.180***
	(0.002)	(0.010)	(0.015)	(0.002)	(0.010)	(0.016)
Constant	0.078	2.474***	0.255	-0.109	-4.430***	1.191
	(0.081)	(0.275)	(0.315)	(0.333)	(1.418)	(1.668)
Team Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	7568	7568	7568	7568	7568	7568
R^2	0.003	0.075	0.038	0.001	0.068	0.035

The table reports OLS regression results of individual-level personnel outcomes on team and individual characteristics on the subset of employees who do not work as engineers. Outcomes are defined at the beginning of Section 4. Annual fixed effects are included in all regressions. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by engineers. Additional controls include team vest amount, team size in previous year, team tenure, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table A4: Impact of Clustered Attrition on Teammates: IV of Team Attrition Clustering, Only Non-Engineers

	First Stage			IV		
	(1)	(2)	(3)	Attrition	Promotion	Award
Team Vest Clustering	0.008	-0.011	-0.011			
	(0.021)	(0.016)	(0.016)			
Team Attrition Clustering				-1.193	6.510	-0.724
				(1.919)	(10.632)	(4.818)
Team Number of Quits		-0.108***	-0.108***	-0.128	0.699	-0.088
		(0.013)	(0.013)	(0.206)	(1.137)	(0.520)
Team Size		-0.004**	-0.004**	-0.005	0.027	-0.006
		(0.002)	(0.002)	(0.007)	(0.039)	(0.020)
Team Level		0.006	0.006	0.006	-0.033	0.033
		(0.007)	(0.007)	(0.016)	(0.091)	(0.044)
Team Award Last Year		0.006	0.007	0.021	-0.028	0.014
		(0.017)	(0.017)	(0.027)	(0.135)	(0.067)
Constant	-1.617***	-1.594***	-1.593***	-1.927	5.981	0.077
	(0.029)	(0.465)	(0.465)	(3.011)	(16.706)	(7.542)
Observations	7568	7568	7568	7568	7568	7568
R^2	0.000	0.436	0.436			

The first three columns of the table report the first stage regression results of team-level attrition clustering on team and individual characteristics. The last three columns report instrumental variables regression results of individual-level personnel outcomes on team and individual characteristics; notably including instrumented team attrition clustering. Annual and team fixed effects are included in all regressions. Outcomes are defined at the beginning of Section 4. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by engineers. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, employee award, and employee tenure.

Table A5: Impact of Clustered Attrition on Teammates: OLS Regressions, Squared Difference

	Attrition	Promotion	Award	Attrition	Promotion	Award
Team Attrition Clustering	-0.016***	0.004	-0.008	-0.019**	0.011	-0.003
	(0.004)	(0.024)	(0.017)	(0.009)	(0.035)	(0.027)
Team Award Last Year	0.001	-0.081***	0.004	-0.002	0.018	-0.022
	(0.005)	(0.019)	(0.023)	(0.011)	(0.036)	(0.041)
Employee Award	-0.002	0.067***	0.181***	-0.003	0.067***	0.190***
	(0.002)	(0.008)	(0.010)	(0.002)	(0.008)	(0.010)
Constant	-0.008	3.140***	-0.322*	0.055	-2.408***	0.514
	(0.052)	(0.220)	(0.176)	(0.277)	(0.785)	(0.707)
Team Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	20506	20506	20506	20506	20506	20506
R^2	0.001	0.079	0.052	0.001	0.057	0.047

The table reports OLS regression results of individual-level personnel outcomes on team and individual characteristics using a squared metric rather than absolute value for the definitions of clustering (Equation 2). Outcomes are defined at the beginning of Section 4. Annual fixed effects are included in all regressions. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by using the absolute value metric. Additional controls include team quits, team vest amount, team size in previous year, team tenure, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table A6: Impact of Clustered Attrition on Teammates: IV of Team Attrition Clustering, Squared Difference

	First Stage			IV		
	(1)	(2)	(3)	Attrition	Promotion	Award
Team Vest Clustering	0.037**	0.024	0.024			
	(0.015)	(0.017)	(0.017)			
Team Attrition Clustering				0.092	-2.579	-1.328
				(0.282)	(2.117)	(1.261)
Team Number of Quits		-0.071***	-0.071***	0.002	-0.178	-0.093
		(0.016)	(0.016)	(0.021)	(0.158)	(0.094)
Team Level		0.016**	0.016**	0.001	0.058	0.035
		(0.008)	(0.008)	(0.006)	(0.039)	(0.025)
Team Award Last Year		0.003	0.002	-0.002	0.026	-0.018
		(0.026)	(0.026)	(0.011)	(0.075)	(0.055)
Employee Award			0.001	-0.003	0.070***	0.192***
			(0.002)	(0.002)	(0.010)	(0.011)
Constant	-0.409***	0.448	0.448	0.012	-1.409	1.025
	(0.007)	(0.480)	(0.480)	(0.279)	(1.603)	(1.055)
Observations	20506	20506	20506	20506	20506	20506
R^2	0.002	0.146	0.146			

The first three columns of the table report the first stage regression results of team-level attrition clustering on team and individual characteristics. The last three columns report instrumental variables regression results of individual-level personnel outcomes on team and individual characteristics; notably including instrumented team attrition clustering. Annual and team fixed effects are included in all regressions. Outcomes are defined at the beginning of Section 4. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by using the absolute value metric. Additional controls include team vest amount, team size in previous year, average employee rank on team, average employee tenure on team, employee level, and employee tenure.

Table A7: Impact of Clustered Attrition on Teammates: IV of Team Attrition Clustering, Share Clustering

	First Stage			IV		
	(1)	(2)	(3)	Attrition	Promotion	Award
Team Vest Clustering	0.049***	0.020*	0.020*			
	(0.015)	(0.012)	(0.012)			
Team Attrition Clustering				-0.231	-0.879	-1.917
				(0.413)	(1.545)	(1.667)
Team Number of Quits		-0.094***	-0.094***	-0.026	-0.077	-0.180
		(0.014)	(0.014)	(0.041)	(0.147)	(0.164)
Team Size		-0.002**	-0.002**	-0.001	0.003	-0.004
		(0.001)	(0.001)	(0.001)	(0.005)	(0.006)
Team Level		0.007	0.006	0.004	0.024	0.027
		(0.005)	(0.005)	(0.005)	(0.015)	(0.020)
Team Award Last Year		-0.002	-0.003	-0.003	0.016	-0.027
		(0.014)	(0.014)	(0.011)	(0.037)	(0.047)
Employee Award			0.002*	-0.002	0.068***	0.193***
			(0.001)	(0.002)	(0.009)	(0.011)
Constant	-1.560***	-1.452***	-1.452***	-0.296	-3.709	-2.325
	(0.021)	(0.322)	(0.322)	(0.737)	(2.580)	(2.618)
Observations	20506	20506	20506	20506	20506	20506
R^2	0.005	0.473	0.473			

The first three columns of the table report the first stage regression results of team-level attrition clustering on team and individual characteristics. The last three columns report instrumental variables regression results of individual-level personnel outcomes on team and individual characteristics; notably including instrumented team attrition clustering. Annual and team fixed effects are included in all regressions. Outcomes are defined at the beginning of Section 4. Standard errors are clustered by team. * indicates statistical significance at the 10% level, ** at 5% and *** at 1%. Results show that the regressions in the overall sample are not driven by using the number of employees attriting. Additional controls include team vest amount, average employee rank on team, average employee tenure on team, employee level, and employee tenure.