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Abstract

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Keywords: Data-driven workforce planning, Empirical operations management, Employee turnover, People operations, Product quality, Productivity, Quality management, Supply chain management

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The Hidden Cost of Worker Turnover: Attributing Product Reliability to the Turnover of Factory Workers*

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Product reliability is a key concern for manufacturers. We examine a significant but under-recognized determinant of product reliability: the rate of workers quitting from the product's assembly line, or its worker turnover. While modern manufacturers make extensive efforts to control defects and assure quality workmanship, some quality variation in the manufactured units may be revealed only after they have been used repeatedly. If this is the case, then the disruptiveness of high turnover may directly lead to product reliability issues. To evaluate this possibility, our study collects four post-production years of field failure data covering nearly fifty million sold units of a premium mobile consumer electronics product. Each device is traced back to the assembly line and week in which it was produced, which allows us to link product reliability to production conditions including assembly lines' worker turnover, workloads, firm learning, and the quality of components. Significant effects manifest in two main ways: (1) In the high-turnover weeks immediately following paydays, eventual field failures are surprisingly 10.2% more common than for devices produced in the lowest-turnover weeks immediately before paydays. Using post-payday as an instrumental variable, we estimate that field failure incidence grows by 0.74-0.79% per 1 percentage increase in weekly turnover. (2) Even in other weeks, assembly lines experiencing higher turnover produce an estimated 2-3% more field failures. We demonstrate that staffing and retaining a stable factory workforce critically underlies product reliability and show the value of connected field data in informing manufacturing operations.

Key words: Data-driven workforce planning; Empirical operations management; Employee turnover; People operations; Product quality; Productivity; Quality management; Supply chain management.

1. Introduction

Product reliability—the extent to which a product fulfills its intended function over a particular period of time—is a critical concern for product manufacturers. Unreliable products can harm firms in a variety of ways, such as through negative online reviews that decrease customer demand,

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warranties or replacement fees that drain profits, or recalls that damage a firm's reputation and financials. The direct costs of unreliable products alone can be enormous: global carmakers spent $46 billion in warranties in 2018, while the 2016 recall of the Galaxy Note 7 smartphone cost Samsung $5.3 billion (Warrantyweek.com 2019, Tsukayama 2018).

Consequently, manufacturing firms seek to control product failure rates in a variety of ways, ranging from quality management systems and standards (Hendricks and Singhal 1997, Corbett et al. 2002, 2005) to the selection of product components (Ramdas and Randall 2008). Inside assembly plants, components are examined and stress-tested for unseen defects. On product assembly lines, manufacturers simplify standardized tasks to soften learning curves and install stringent testing to guard against improper assembly, which can degrade product performance or accelerate wear-out. Yet even standardized tasks carried out under stringent testing standards allow some variability in the quality of manufactured units that is revealed only after they are used repeatedly. Such variability becomes visible in field failures, which are the instances in which the product can no longer be used as intended until repaired or replaced.

While the factors underlying product reliability have been studied extensively, one factor not previously identified is the level of worker turnover in the manufacturing process during a particular unit's production. Worker turnover is prevalent in manufacturing, yet workforce experience and stability may deliver considerable value in maintaining the quality of output, even for units that pass quality control standards. If this is the case, then product reliability may constitute an undetected and unacknowledged cost of fast worker turnover.

In this paper, we evaluate this proposition by tracking nearly fifty million mobile consumer electronics devices for field failures—i.e., repairs and replacements—over four years of consumer use, and tracing each device (whether failed or not) back to the factory conditions under which it was produced. Combining field data and production data, we find that the product's field failure rates strikingly synchronize with factory worker turnover rates, as these rates rise and fall over the course of the manufacturer's pay cycle. Empirically, field failure rates peak when devices are produced in the high-turnover week immediately following payday, becoming 10.2% more likely to fail than when they are assembled in the lowest-turnover week immediately before payday.

We validate that the product's field failure rates correspond closely to the recurring episodes of factory worker quits, even after we control for known factors affecting product reliability, including the firm's organizational learning, the quality of key components, and the assembly lines' workloads. After controlling for these factors and utilizing post-payday turnover as an instrumental variable, we estimate that the post-payday week's peak in worker turnover increases the incidence of field failures by 7.1% to 7.6% (failures become 0.74-0.79% more common per 1 percentage point increase in weekly turnover). Even in other weeks, the mean level of worker turnover boosts field failures by an estimated 1.1% to 2.3%, and by 1.6-3.3% for worker turnover's 75th percentile.

We view our work as making several contributions. First, despite extensive literatures on both product reliability and worker turnover, to our knowledge no previous study links the two together. The strong effects we estimate underscore the importance of staffing and retaining a stable factory workforce in producing reliable products. Second, this work has clear implications for manufacturers seeking to improve the reliability of their products, suggesting that current strategies may not be effective substitutes for more direct efforts at workforce retention and stability. Finally, we demonstrate the value in combining field data with factory operations. Such data are increasingly available (Porter and Heppelmann 2015), and combining them can reveal critical linkages between factory and field.

1.1. Related Literature

Product quality is an important competitive factor in consumer product markets, including for automobiles, consumer technology goods, agricultural goods, and apparel. Consequently, firms adopting quality management systems and standards have reaped significant financial rewards (Hendricks and Singhal 1997, Corbett et al. 2002, 2005). Among quality's core components, product reliability has especially grown in salience. In particular, online technology enables consumers' critical word of mouth to quickly spread through reviews and social media—e.g., 26% of surveyed consumers used social media to complain about a company or product (Srinivasan and Kurey 2014)—and reduces the costs of collecting data about reliability. Firms respond opportunistically to revelations about the reliability of their competitors' products (Ball et al. 2019) and even calibrate the reliability of their own products to fit their shareholders' financial interests (Kini et al. 2016).

As a result, the empirical operations literature has extensively studied factors explaining product reliability. As recent examples, researchers have shown that manufactured product quality depends on how manufacturers utilize plant capacity and over what product variety (Shah et al. 2016), the proximity of key suppliers (Bray et al. 2019), the occurrence of labor strikes and conflict (Krueger and Mas 2004), the selection of components in product design (Ramdas and Randall 2008), and even inspectors' behavioral biases (Ball et al. 2017, Ibanez and Toffel 2019).

At the same time, prior work addresses the relationship between worker productivity and turnover in operations, including Arthur (1994) and Moon et al. (2019) in manufacturing, Emadi and Staats (2019) and Musalem et al. (2019) in call centers, Ton and Huckman (2008) in retailing, and Song and Huckman (2018) in teaching hospitals. Batt et al. (2019) cover the productivity effects of patient handoffs between healthcare work shifts, which closely resemble turnover.

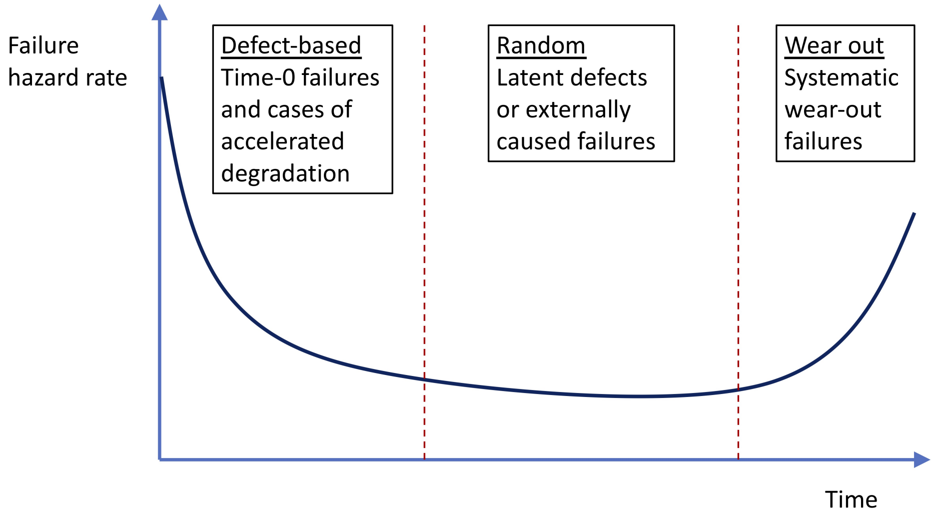
To our knowledge, we are the first to connect these empirical literatures by directly attributing product reliability to factory workforce turnover. Section 2 provides background regarding product field failures, followed by Section 3 introducing our data. In Section 4, we present our empirical analysis and findings. Section 5 concludes with a brief discussion of implications.

2. Field Failures

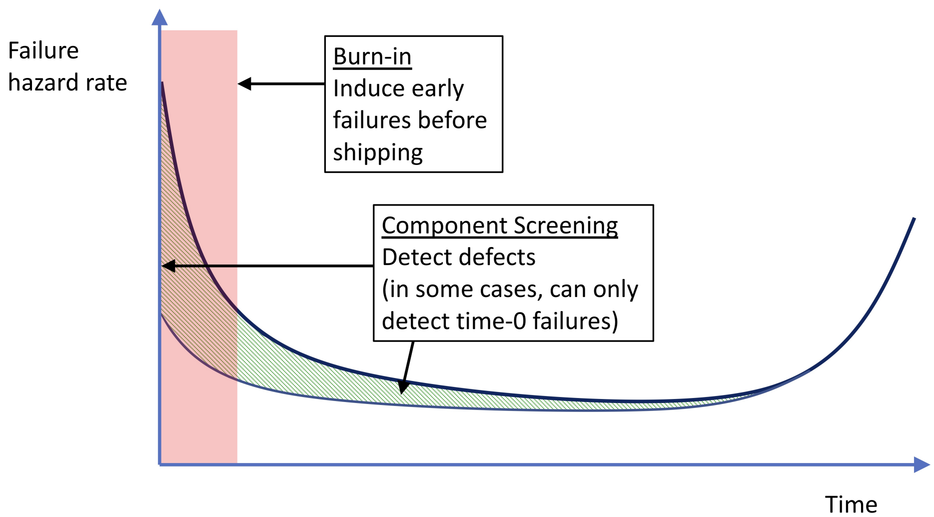
In manufacturing individual products, firms seek to control a number of disparate sources of failures acting over the product's lifetime. These sources commonly contribute to the classical "bathtub curve" representation of the product's failure hazard, which is shown in Figure 1a.

Three phases characterize the bathtub curve. In the early mortality phase, device units fail predominantly as critical time-0 defects come to light and as less immediate defects nonetheless result in the accelerated degradation of the unit's functionality. In the second mature phase, the failure

Figure 1 **Conceptual Illustration of Product Failure Hazard Rates over the Device Lifetime**



(a) Classical bathtub curve and predominant failure modes



(b) Controlling field failures using burn-in and screening of components

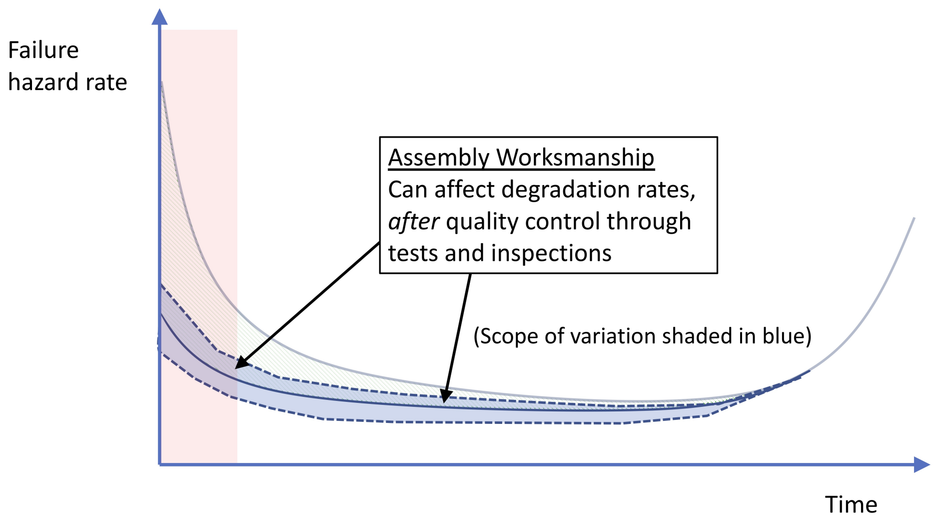
hazard rate stabilizes at a lower level that largely reflects external influences (e.g., a customer damaging the device by dropping it) and slow-acting latent defects emerging in the unit's components. In the final phase, failures accelerate as device components wear out.

However, manufacturing firms exert control over field failures in various ways. To mitigate wear-out, firms often design products' useful lives to conclude prior to wear-out and may modularize easily worn components to be regularly replaced or maintained (Deshpande et al. 2003, Guajardo et al. 2015, Kundu and Ramdas 2019). For this study, we are chiefly concerned with the measures firms take during the manufacturing process, which we show in Figure 1b. During the manufacturing of electronics, devices and components undergo controlled "burn-in" usage under stressful conditions, such as elevated temperatures and voltages, in order to force early failures to manifest. Components may pass additional screening for defects, before they are used in product assembly. As conceptually depicted in Figure 1b, these detection measures can allow a product manufacturer to substantially dampen the failure hazard rates of the manufactured units that actually reach customers.

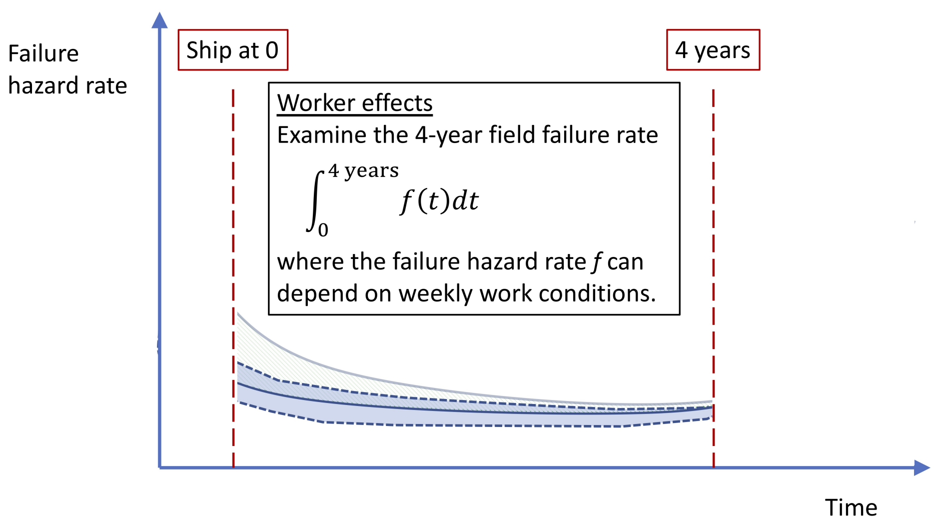
Yet, component defects are not responsible for all the product failures originating from the manufacturing process. In order to function and perform as a whole product, the components must also be well assembled. In the setting we study, quality control tests for assembly work are embedded throughout the assembly lines and carried out by assembly workers on standardized test fixtures. Such rigorous, systematic, and incremental testing is commonplace in electronics manufacturing, in which the individual components are relatively expensive and the demand for reliability is high.

In shaded blue, Figure 2a illustrates the scope of variation in field failure incidence that results from variable worksmanship *after* quality control measures are put in place. If the tests permit virtually no variation in the quality of worksmanship, the scope will be very narrow. However, nearly inperceptible imperfections in worksmanship can accelerate component degradation leading eventually to field failures. For example, in similar mobile devices, touchscreen multi-touch functionality can depend on the soldering that connects touch-related chips to a circuit interface. The resilience of the soldering is revealed over time under customer usage, e.g., bending or dropping of the device. Similarly, a small imperfection in a battery's placement can eventually lead to an uneven power supply that more quickly degrades the screen display over extended usage. Thus, even state-of-the-art quality testing standards allow some variability in the quality of manufactured units that is revealed only after they are used repeatedly by customers.

Figure 2 Conceptual Illustration of Workers' Effects on Field Failure Rates



(a) Assembly worksmanship can affect the prevalence of accelerated degradation resulting in field failures



(b) Measuring the 4-year field failure rates of the production units built in a given line-week

In the remainder of our study, we consider the possibility that high worker turnover acts through this channel to significantly affect the rate of product field failures. In Section 4, we develop the empirical hypothesis more precisely—to focus on worker turnover's effect on worksmanship through recurring losses in experience and the associated disruptions. As shown in Figure 2b, our study's main outcome variable is the four-year field failure rate of the batch of devices produced in a given line-week.

3. Data

Our study is carried out in collaboration with a major consumer technology goods producer (the "firm") and one of its China-based contract manufacturers. Identifying details are omitted for confidentiality. For the product we study, the firm provided data tracking field failures for nearly 50 million finished devices, the weekly production workloads and backlogs, and the quarterly fallout rates for the product's key components. The contract manufacturer provided the human resources data required to observe when and from which assembly lines the factory's workers quit.

Like Ramdas and Randall (2008), Guajardo et al. (2012), and Chan et al. (2018), our reliability data are sourced from the field performance of manufactured products. All the studied devices passed the stringent quality control testing carried out on their components and on their station-by-station assembly before shipping to customers. The firm is able to effectively track device repairs through its program for warranties and authorized repairs. Because the device model is a premium product, customers typically seek repairs using authorized parts through a network of affiliated US retail locations or by shipping defective devices to the firm with round-trip shipping paid. Warranties cover all manufacturing defects and can be extended to cover three years instead of one. Under certain conditions, the firm replaces the defective unit with a new device before the former is shipped by the customer. Generally, we expect that customers do seek to repair defective units, because we study a premium product typically used nearly daily.

Our main production data are obtained from the firm. The production plans provide us with weekly backlogs, which are the production shortfalls measured against the orders the firm generates from its rolling forecasts of end-sales demand, and our production volume data tracks the weekly units passing through individual assembly lines' benchmark stations. The firm also provides the quarterly fallout rates for six key components: the device's battery, display, housing, circuit board, rear camera, and front camera. Lastly, the contract manufacturer's human resources staffing data track factory worker quits occurring on specific assembly lines and weeks.

We organize our panel dataset around the assembly line-week as the unit of analysis. Critically, we trace the consumer-held devices back to their respective line-weeks of origin and thus are able to attribute a field failure rate to each line-week observation. All told, the data cover 40 weeks (September 2014 through June 2015) for 44 assembly lines dedicated to the product and located within three expansive buildings of a common facility in China. As part of normal capacity management, the third building operates for only 31 of the 40 weeks, with some assembly lines shutting down sooner. Thus, we are left with 1516 assembly line-weeks in total. Because operations and worker turnover trends are irregular during the Chinese New Year holiday, we omit February 2015 from our regression analyses but include it in descriptive plots. We additionally confirmed with firm experts that no atypical production- or labor-related events were logged for the product during the studied time period.

3.1. Outcome Variable

3.1.1. Field failure rate. As our study's outcome variable, we examine the fraction of produced devices that failed in the field. A device is deemed to have failed in the field the first time it receives a known service repair or replacement, at which point we call the device a field failure. For our studied devices produced in September 2014 through June 2015, we observe all field failures as of July 6, 2019. Thus, for each assembly line-week, we attribute a field failure rate, defined as the fraction of field failures (out of its units produced) arising through July 6, 2019. Because each device has been observed in the field for at least four years post-production, such field failure rates should capture virtually all variation in product reliability that originates in the factory assembly process.

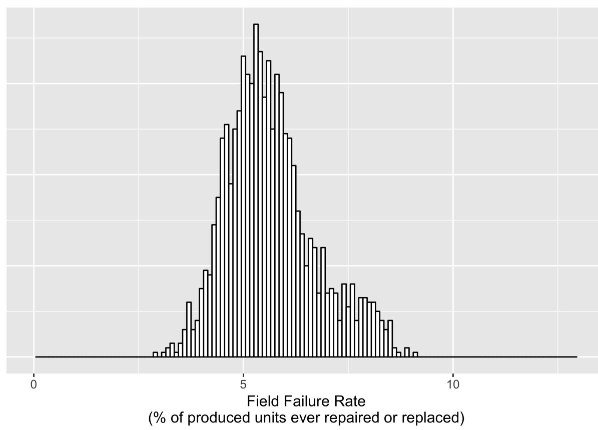
For reasons of confidentiality and data sensitivity, we multiply the field failure rate by a scalar factor between 0.125 and 8, including in the data we provide as the paper's data supplement. The true field failure rate's mean is then a percentage between 1% and 45%, and its coefficient of variation is 0.19. The transformed field failure rate's mean and median are given in Table 3, and its histogram is shown in Figure 4. Our regression results use log field failure rate as the dependent variable, thus the estimated coefficients are not affected by applying the constant factor.

Table 3 Weekly Assembly Line Statistics

	Mean	Median
Field failure rate†	5.6%	5.5%
Number of workers staffed	301	259
Worker turnover	5.1%	3.2%
Workload in units assembled	30,152	31,754

Unbalanced panel of 44 assembly lines observed in 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015.
† The true field failure rate is multiplied by a scalar between 0.125 and 8.

Figure 4 Histogram of Field Failure Rates



Field failure rates for 1516 assembly line-weeks between September 2014 and June 2015. Field failure rates are the percentages of produced units ever receiving a service repair or replacement through July 6, 2019.

3.2. Study Variables

3.2.1. Measure of worker turnover. We measure worker turnover as the fraction of workers on an assembly line who quit the factory during a given week.[1] Due to Chinese labor regulations requiring significant severance pay absent termination for specified reasons, involuntary turnover is virtually non-existent after training (Plevan et al. 2011). The contract manufacturer's data contain the work assignments of 52,214 workers actively staffing the studied assembly lines during the study. By matching these data with the dates on which workers quit the factory, we attribute quits to assembly line-weeks. To arrive at worker turnover, we divide these quits' count by the number of workers staffing the assembly line at the start of the same week. Mean and median worker turnover

[1] We do not focus on the additional movements of workers between assembly lines or between stations on a given assembly line.

are 5.1% and 3.2% per week, respectively, evidencing an upward skew. The mean assembly line headcount is 301, and staffing is relatively steady as new workers replace quits.

3.2.2. Pay cycle. The manufacturer's monthly pay cycle strongly shapes worker quits. Because workers value the compensation they receive on payday, assembly line worker turnover averages 2.9% in the week immediately prior to payweek and 9.3% in the week immediately following payweek. We define the weeks left to payweek variable, which ranges from a maximum of four down to a minimum of zero (during payweek), and our empirical analysis utilizes the indicator variable for post-payday weeks. Much as with annual cohort turnover in hospitals (Song and Huckman 2018), managers fully anticipate the pay cycle effect, in which a wave of worker quits causes experienced workers to be replaced by new workers.

3.3. Control Variables

3.3.1. Assembly line workloads. Existing literature supports the existence of workload and utilization effects on worker productivity in a variety of settings (KC and Terwiesch 2009, Shah et al. 2016). To arrive at a workload metric, we first measure an assembly line's weekly output in device units assembled using the units counted at benchmark stations. The assembled output averages 30,152 units per assembly line-week for a total of 45.7 million units assembled over the data's 1516 observations. The coefficient of variation in assembly line output is 0.28. Finally, we measure the assembly line weekly workload by the weekly output per capita (in workers staffed), which has a median of 115.

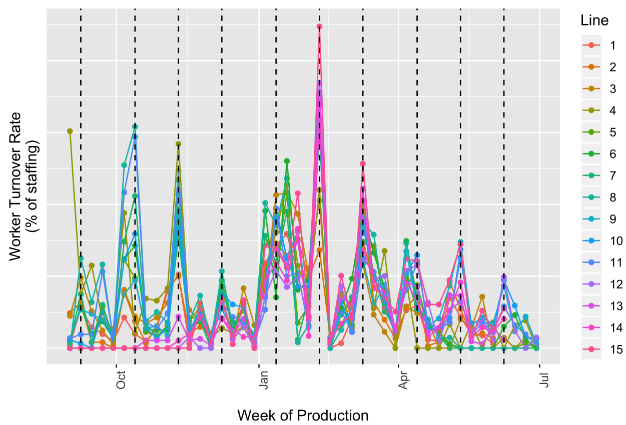
3.3.2. Production backlog. A larger production backlog can raise the urgency of production. The backlog is calculated as the positive shortfall, if any, of the week's projected production against device orders. As such, it also captures any projected shortages in components supplied.

3.3.3. Component fallout rates. While product components naturally depreciate (e.g., Ramdas and Randall (2008), Colak and Bray (2016)), their functionality can be impaired or degrade more quickly due to pre-existing defects. To measure pre-assembly defect rates for key components, our study tracks their fallout rates, which are their rates of detected failure during manufacturing—i.e., through screening and burn-in. We obtain the fallout rates for the device's battery, display, housing, circuit board, front camera, and rear camera for each three-month quarter.

4. Analysis

4.1. Causal Hypothesis and Empirical Motivation

Figure 5 Assembly Line Worker Turnover in Building 1 (Sept. 2014 to June 2015)

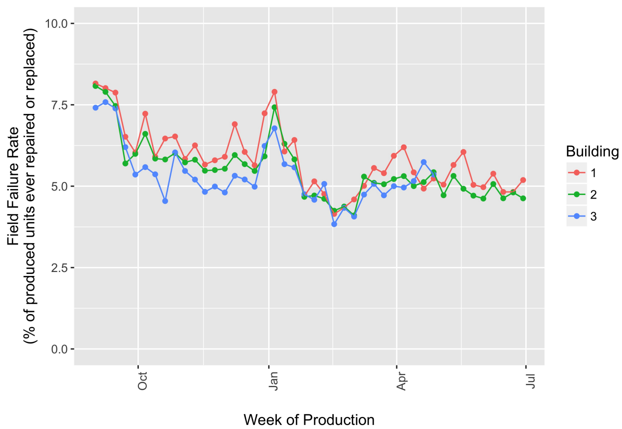


Weekly worker turnover rates for assembly lines in Building 1 between September 2014 and June 2015. Dashed vertical lines correspond to the sample's post-payday weeks.

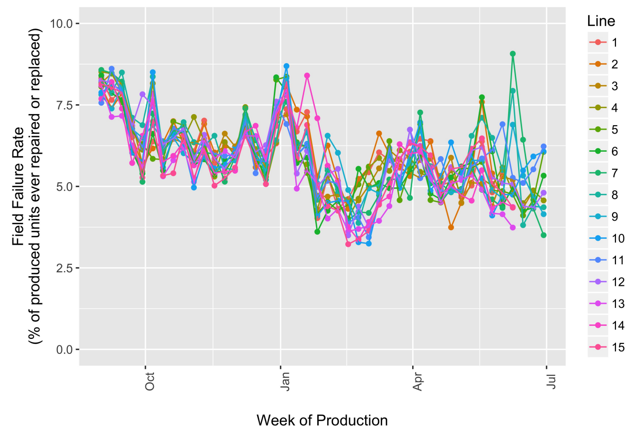
To motivate our analysis, consider the following chain of events. First, workers postpone their departures until being compensated, causing workers' quits to increase sharply following the factory's paydays. Thus, factory worker turnover follows a highly predictable pattern punctuated by monthly post-payday peaks. Representatively using the assembly lines in Building 1, Figure 5 illustrates worker turnover's resulting, cyclical variation over time. After each payday, experienced workers exit, and new workers are recruited to replenish the ranks.

Second, suppose that worker turnover were to impact product reliability. We hypothesize that such an effect would transpire through two primary causal channels. First, worker turnover causes a net loss of experience in staffing the affected assembly lines, as relatively experienced workers exit and new workers take their places. The worksmanship of inexperienced workers may be less reliable. Second, the replacement process itself may be disruptive, requiring attention and effort

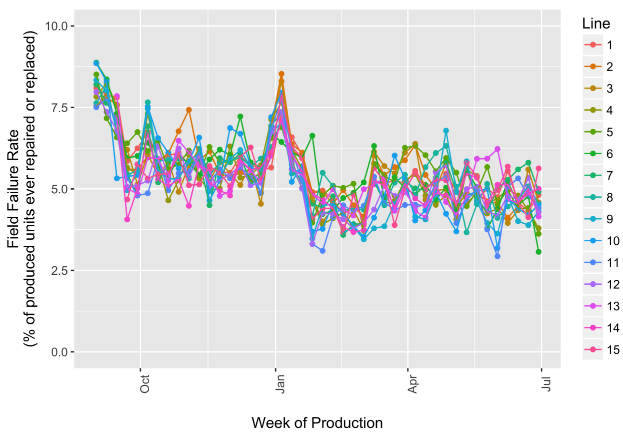
Figure 6 Rates of Device Field Failures Attributed to Their Weeks of Production (Sept. 2014 to June 2015)



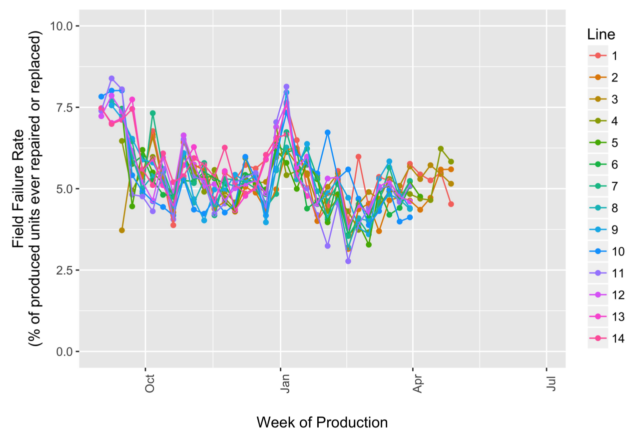
(a) For buildings 1, 2, and 3



(b) For assembly lines in building 1



(c) For assembly lines in building 2



(d) For assembly lines in building 3

For the product's 45.7 million units assembled in the studied facility between September 2014 and June 2015, we tallied for each assembly line-week the numbers of units produced that were repaired or replaced and those that were not. All units were tracked for repairs through July 6, 2019, i.e., at least four years post-production. Field failure rates are the percentages of produced units ever receiving a service repair or replacement during the tracked period.

from both supervisors and workers. For example, experienced workers must handle certain critical workstations, and consequently some workers are required to switch stations in response to turnover.[2] Additionally, the new workers must be assimilated. Both channels plausibly undermine the overall level of worksmanship present on the assembly line.

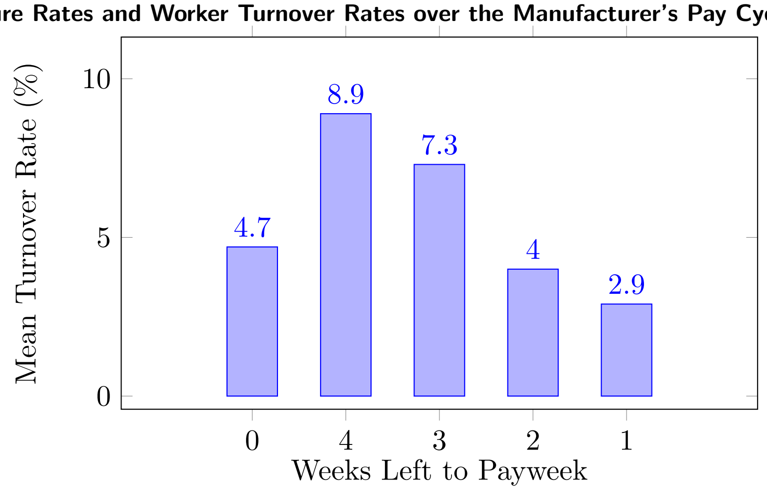
[2] Note that such movements to optimize staffing would tend to mitigate worker turnover's negative effects on productivity and worksmanship—e.g., when compared to not making staffing adjustments and placing new workers into critical stations. However, the movements still cause disruption when compared to no turnover.

It is worth noting that our study is particularly well-suited for examining these effects on assembly workmanship, because the setting rules out a troublesome alternative dependency on inspection experience. Many products are manufactured and then subsequently inspected for quality compliance. Then, field failures can arise from poor worksmanship, lax inspection by inexperienced personnel, or both. On our assembly lines, workers place the work units into standardized testing fixtures after assembly tasks are completed. The test fixture signals ‘pass’ or ‘fail’, and no device continues to the next assembly stage without passing. Thus, the factory’s quality control tests do not require that workers possess the ability or experience to personally inspect units of the product. Accordingly, no effort is made to screen workers as qualified (by experience or otherwise) for the testing roles.

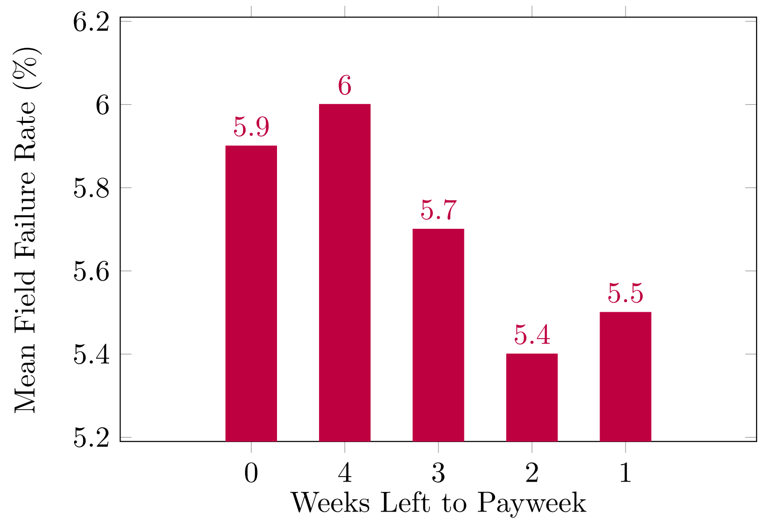
If monthly post-payday worker turnover leads to compromised worksmanship, the facility’s weekly field failure rates should manifest a stark pattern resembling an electrocardiogram. The product’s field failure rate—attributed by date of production—ricochets through regular, monthly cycles of peaks and troughs. Figure 6 shows the data’s actual temporal pattern of field failure rates, plotted both for the three buildings (Figure 6a) and for the individual assembly lines inside each building (Figures 6b, 6c, 6d). Not only does each building and assembly line transparently exhibit a cyclically peaking trend, the assembly lines’ field failure rates co-vary to a striking degree: nearly 41% of variation is explained by the weekly averages. Such co-movement suggests that a common cause lies behind the pattern of peaking failures.

Descriptive evidence, which we corroborate using statistical tests, is consistent with worker turnover being the common cause. Figure 7 illustrates the empirical correspondence between worker turnover (Figure 7a) and field failure rates (Figure 7b) over the monthly pay cycle. Mean worker quits peak at 9.3% for post-payday weeks (such weeks include all instances of four weeks left until the next payweek and some instances of three) and bottom out at 2.9% immediately pre-payweek. Correspondingly, mean field failure rates are proportionally 10.2% higher at peak over trough—that is, field failures are 10.2% more common for devices produced at the peak (Figure 7b). In

Figure 7 Field Failure Rates and Worker Turnover Rates over the Manufacturer's Pay Cycle



(a) Assembly lines' mean weekly turnover rates (% headcount) by week in the pay cycle



(b) Assembly lines' mean weekly field failure rates (% units produced) by week in the pay cycle

We made a break in Figure 7b's vertical axis to better illustrate the variation in mean failure rates in comparison to Figure 7a. Note the heights of the bars in Figure 7b do *not* represent the full magnitudes of the failure rates.

terms of the direct statistical relationship between field failure rates and worker turnover rates, their weekly averages exhibit a positive correlation of 0.14.

Formally, we test whether the post-payday weeks' field failure rates stochastically dominate the failure rates during pre-payday weeks (Table 8). We reject the null hypothesis of a common distribution at the statistically significant and exact p-value of 0.01% (i.e., 0.0001). Thus, a consumer who buys a device produced in a peak-turnover week faces significantly higher odds of needing a service repair or replacement than if she had bought an identical shelf unit *produced* a week earlier.

Table 8 Nonparametric Rank-sum Test for Field Failure Rates Post-payday Stochastically Dominating Field Failure Rates Pre-payday

Using pre-payday weeks as test statistic's subsample		
Rank sum	Subsample size	P-value
107,673	343 out of 681	0.00010

We carry out a Mann-Whitney-Wilcoxon rank-sum test of the null hypothesis that pre-payday and post-payday weeks' field failure rates share a common distribution, against the one-sided alternative hypothesis that post-payday weeks' field failure rates stochastically dominate those of pre-payday weeks. The p-value is calculated using 100,000 randomly drawn rank permutations. Ranks are assigned by field failure rate from lowest to highest, and ties are randomly broken.

4.2. Regression Analyses

We carry out two empirical analyses to further support the paper's causal hypothesis. First, we regress field failure rates on worker turnover, using the indicator variable for post-payday weeks as an instrumental variable. By exploiting the arrival of post-payday quits as an exogenous shock to worker turnover, we identify turnover's effect on field failures. Second, we offer corroborating evidence by regressing field failure rates on worker turnover in the weeks other than post-payday, including under specifications that control for week fixed effects. Thus, we show that even in non-post-payday weeks, the weekly batches manufactured by assembly lines experiencing greater worker turnover eventually fail at higher rates in the field.

In both analyses, we control for alternative influences on field failure rates. First, we control for firm learning, as the firm accrues assembly experience over time, e.g., about the best way to handle and install a specific component (Ramdas and Randall 2008). Importantly, the learning trend includes learning using earlier field failures observed by the firm as feedback.[3] Reverse causality is largely addressed by the panel structure of the data, which tightly links worker turnover to the field failures emerging from the output built in the very same week. As of that week, these devices have

[3] Additionally, the firm subjects a small subset of each week's output to its own field testing.

yet to be shipped and retailed, so the field failures are yet to occur and cannot provide feedback. Our conversations with the firm also reveal that, despite closely monitoring quality, the firm had not known of the correlation between turnover and field failures—the results of this study were surprising. As a result of learning, a device produced later in time is typically more reliable, and components' incoming defect rates also tend to fall over time. From the literature, we identify and control for two additional factors plausibly affecting assembly workmanship: workloads, or utilization (Shah et al. 2016); and backlogged orders, representing the urgency of work.

Lastly, we emphasize that our goal is to estimate worker turnover's final causal effect on field failures, net of all mitigating actions taken by line managers.[4] Our objective is to show that the magnitude of worker turnover's final effect on field failures is significant, which we view as a stronger claim—just as the effect of an illness may be large *despite* medical treatment.

4.3. Regression Results

4.3.1. Specification. We carry out regressions of the form:

$$\log\left(\text{Field failure rate}_{lt}\right) = \alpha_l + \beta \cdot (\text{Worker turnover})_{lt} + \gamma \cdot X_{lt} + \epsilon_{lt}, \tag{1}$$

where X_{lt} are the control variables for assembly line l in week t. The coefficient β measures the effect of assembly line worker turnover. To allow for differences in reliability across assembly lines, we present results both with and without the assembly line fixed effects α_l. Our main regressions use the indicator variable for post-payday weeks as an instrumental variable for $(\text{Worker turnover})_{lt}$.

4.3.2. Instrumental variable regression estimates. Table 9 presents our instrumental variable (IV) regression results controlling for organizational learning using month fixed effects. Specification (1) is the base specification with worker turnover and the month fixed effects. Specifications (2) and (3) additionally control for assembly line outputs and workloads, respectively. Lastly, Specification (4) controls for the product's order backlog. Whereas Specifications (1)-(4)

[4] For example, such mitigations include personnel movements, within and between lines, to ensure that critical workstations are handled by experienced workers. See our earlier discussions.

specify a common intercept as the baseline field failure rate, Specifications (5)-(8) replicate their results after including assembly line fixed effects.

Table 10 shows the first-stage (IV) regression. Relevance is clearly satisfied, and the post-payday weeks indicator is applied as an instrument for worker turnover throughout Table 9.

Table 9 IV panel regressions: Log field failure rates on post-payday worker turnover and workloads

	(1)	(2)	(3)	(4)
—With monthly time fixed effects—				
Worker turnover (%)	0.783^{***}	0.777^{***}	0.771^{***}	0.778^{***}
	(0.184)	(0.185)	(0.180)	(0.180)
Workload as log output		0.012		
		(0.012)		
Workload as log output per worker			0.009^{*}	0.009^{*}
			(0.004)	(0.004)
Log backlog+1				−0.001
				(0.001)
R^2	0.30	0.30	0.31	0.31
—With assembly line and monthly time fixed effects—	(5)	(6)	(7)	(8)
Worker turnover (%)	0.761^{***}	0.759^{***}	0.740^{***}	0.748^{***}
	(0.172)	(0.173)	(0.168)	(0.169)
Workload as log output		0.005		
		(0.012)		
Workload as log output per worker			0.018^{**}	0.018^{**}
			(0.006)	(0.006)
Log backlog+1				−0.001
				(0.001)
R^2	0.35	0.35	0.35	0.35

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Post-payday week indicator is used as an instrumental variable for worker turnover. Specifications (5)-(8) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), *projected* as of the week's start.

Estimation results are consistent across the regressions in Table 9. Across all specifications, worker turnover's estimated effect on field failure incidence is a 0.74-0.79% increase per 1 percentage point increase in worker turnover level. At the average rate of turnover for post-payday weeks, worker turnover makes field failures 7.1-7.6% more common. For all specifications, the estimated effect is highly statistically significant at p-values of 0.001 or smaller.

Table 10 **IV first-stage regression: Worker turnover (%) on post-payday week**

	(1)	(2)
Post-payday week indicator	0.054***	0.054***
	(0.003)	(0.003)
Include line fixed effects		Y
R^2	0.14	0.16
F-test statistic	249.6	279.2
Significance levels → *** - 0.001	** - 0.01	* - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Specification (2) includes fixed effects for 44 assembly lines.

While our main results use month fixed effects as learning controls based on closest regression fit, a few alternatives are shown in Appendix A. When we alternatively control for organizational learning as a time trend or by using cumulative units assembled to date, the estimated impacts are similar and slightly more modest: 5.1-5.8% impact in post-payday weeks at p-values of 0.01 or less. Process learning is highly significant and reduces the incidence of field failures proportionally by an estimated 0.7-0.8% weekly, which, for example, would shave 0.04% weekly off the mean field failure rate of 5.6%. Appendix B replicates the results using an alternative measure of turnover.

In Table 11, we add the key component fallout rates as controls. Because the fallout rate data are quarterly, we cannot use month fixed effects and instead use the specification of firm learning as a time trend—the relevant baseline results are shown as Table EC.1 in Appendix A. Across the components regressions, which we present with and without assembly line fixed effects, the estimated impact is a 0.61-0.71% increase per 1 percentage point increase in worker turnover, at p-values of 0.001 or smaller. At the average rate of turnover for post-payday weeks, field failures become 5.8-6.8% more common due to worker turnover. At the same time, firm learning causes the incidence of field failures to fall by an estimated 0.4-0.7% weekly, and component fallout rates significantly predict field failures.

In both Tables 9 and 11, we estimate statistically significant workload effects: a 50% increase in workload results in a 0.4-0.9% increase in the field failure rate, which when combined with the 50% expanded output amounts to a 0.55-1.34% increase in the week's number of produced units that will later fail in the field. In Appendix B, we show that our turnover estimates remain similar when we alternatively control for workloads as overtime hours.

Table 11 IV panel regressions: Log field failure rates after adding component fallout rates as controls

Control for quarterly fallout rate of:	Battery		Display		Housing	
	(1)	(2)	(3)	(4)	(5)	(6)
Worker turnover (%)	0.672***	0.617***	0.678***	0.622***	0.707***	0.640***
	(0.181)	(0.169)	(0.182)	(0.169)	(0.191)	(0.178)
Learning as time trend in weeks	−0.006***	−0.007***	−0.006***	−0.007***	−0.004***	−0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Workload as log output per worker	0.010*	0.018***	0.010*	0.018***	0.012**	0.021***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Log fallout rate	0.681***	0.566***	0.169***	0.140***	0.350***	0.280***
	(0.085)	(0.081)	(0.021)	(0.020)	(0.057)	(0.054)
Include line fixed effects		Y		Y		Y
R^2	0.28	0.33	0.28	0.33	0.27	0.32
Control for quarterly fallout rate of:	Circuit board		Rear camera		Front camera	
	(7)	(8)	(9)	(10)	(11)	(12)
Worker turnover (%)	0.682***	0.614***	0.664***	0.611***	0.702***	0.639***
	(0.198)	(0.185)	(0.180)	(0.168)	(0.187)	(0.175)
Learning as time trend in weeks	−0.004***	−0.006***	−0.006***	−0.007***	−0.004***	−0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Workload as log output per worker	0.013**	0.022***	0.010*	0.018***	0.011**	0.020***
	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
Log fallout rate	0.278***	0.209**	0.184***	0.154***	0.782***	0.634***
	(0.071)	(0.068)	(0.023)	(0.022)	(0.114)	(0.108)
Include line fixed effects		Y		Y		Y
R^2	0.26	0.31	0.28	0.33	0.28	0.33

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Odd-numbered specifications are pooled regressions with an intercept, whereas even-numbered specifications include fixed effects for 44 assembly lines.

4.3.3. Regression estimates from non-post-payday weeks. We next examine worker turnover's effects in weeks other than post-payday. In these weeks, a revolving subset of assembly lines faces relatively higher worker turnover than the others, as illustrated in Figure 5. We investigate whether these lines' product batches later experience elevated field failure rates.

The corroboration serves a three-fold purpose. First, it strengthens our confidence that the previously shown estimates result from worker turnover rather than from other post-payday factors. Second, when we add week fixed effects, it adds to the accumulating evidence that our findings are not driven by component quality, which is shared across lines in the same week. Third, showing that a similar effect exists in non-payday weeks has substantive implications, by suggesting that turnover's effect hinges on worker experience, not innate ability. When assembly worksmanship depends mainly on ability rather than experience (e.g., each new worker cohort enters as a mix of ability types), the post-payday empirical pattern could be explained by self-selection among quits: namely, the most capable workers decide to leave post-payday, causing field failures to rise—i.e., the effect stems not from the exit itself, but from *who* exits then. This alternative theory is undermined when worker turnover is always significantly harmful, throughout the pay cycle.

Table 12 **Panel regressions: Log field failure rates on worker turnover in non-post-payday weeks**

	—With pooled intercept—			
	(1)	(2)	(3)	(4)
Worker turnover (%)	0.418^{***}	0.438^{***}	0.397^{***}	0.395^{***}
	(0.104)	(0.106)	(0.098)	(0.106)
Learning as time trend in weeks	-0.007^{***}	-0.007^{***}	—	—
	(0.000)	(0.000)		
Workload as log output per worker		0.004		0.000
		(0.004)		(0.004)
Week fixed effects			Y	Y
R^2	0.25	0.25	0.58	0.58
	—With line fixed effects—			
	(5)	(6)	(7)	(8)
Worker turnover (%)	0.349^{***}	0.381^{***}	0.209^{*}	0.261^{*}
	(0.104)	(0.105)	(0.098)	(0.104)
Learning as time trend in weeks	-0.008^{***}	-0.008^{***}	—	—
	(0.000)	(0.000)		
Workload as log output per worker		0.011		0.007
		(0.006)		(0.005)
Week fixed effects			Y	Y
R^2	0.30	0.30	0.65	0.65

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,178 production-active line-weeks in Sept. 2014 – Jun. 2015, after excluding post-payday weeks. Specifications (5)-(8) include fixed effects for 44 assembly lines.

Table 12 shows our regression results after excluding post-payday weeks. Worker turnover's effect on field failures is consistently statistically significant, and we estimate that field failures become 0.21-0.44% more common per each 1 percentage point increase in turnover. At the 5.1% average rate, worker turnover raises field failure incidence by 1.1-2.3%, and similarly by 1.6-3.3% at the 75th percentile rate of 7.5% worker turnover.

5. Concluding Remarks

In this paper, we highlight the role of a stable factory workforce in assuring reliable products. Notwithstanding the manufacturer's stringent, unit-by-unit quality control testing, we find that product reliability at the factory varies significantly from week to week. However, we conclude neither that product reliability depends on the luck of the draw nor that it cannot be controlled precisely. Instead, we argue that products are more reliable when the workforce is more stable, which is a conclusion stronger than any we find in the literature and one that went seemingly unnoticed by a highly sophisticated consumer technology firm and its manufacturer.

Yet the descriptive results of this paper are compelling without sophisticated analysis. According to Figure 6, field failure rates and product reliability regularly rise and fall. By comparing the failure rates against worker turnover, we find that the two patterns align. After controlling for a range of factors and applying an instrumental variable, our estimates suggest that worker turnover's post-payday peaks make field failures 7.1% to 7.6% more likely. Even in other weeks, the mean level of worker turnover boosts field failures by an estimated 1.1% to 2.3%, and by 1.6-3.3% for worker turnover's 75th percentile. Evidence using within-week variation and the instrumental variable each support that our findings are driven by assembly worksmanship, not the quality of components or self-selection on ability. Our significant findings contribute to growing research interest in empirically examining the role of workforce dynamics and their management in operations.

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Electronic Companion

Appendix A: Robustness under Alternative Controls for Learning

In Table 9 of the main text, we present the regression model that specifies firm learning to most closely fit the data—using monthly time fixed effects. In this Appendix A, we replicate our main regression results under two alternative specifications for firm learning. Table EC.1 shows our regression results after replacing the monthly fixed effects with a time trend. We specify the time trend as linear in weeks, but the end specification is geometric (e.g., learning causes the field failure rate to reduce by a fixed fraction each week) due to the logarithm applied to the left-hand side. Table EC.2 shows results when using cumulatively assembled output to represent the firm's stock of accrued learning.

Table EC.1 Replicating Table 9 Including Learning as a Time Trend Instead of Monthly Time Fixed Effects

—With pooled intercept—				
	(1)	(2)	(3)	(4)
Worker turnover (%)	0.599**	0.603**	0.580**	0.599**
	(0.185)	(0.188)	(0.181)	(0.183)
Learning as time trend in weeks	−0.008***	−0.007***	−0.008***	−0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Workload as log output		−0.004		
		(0.012)		
Workload as log output per worker			0.012**	0.012**
			(0.004)	(0.004)
Log backlog+1				−0.003*
				(0.001)
R^2	0.25	0.25	0.25	0.25
—With line fixed effects—				
	(5)	(6)	(7)	(8)
Worker turnover (%)	0.565**	0.575**	0.537**	0.549**
	(0.172)	(0.175)	(0.168)	(0.170)
Learning as time trend in weeks	−0.008***	−0.008***	−0.008***	−0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Workload as log output		−0.012		
		(0.012)		
Workload as log output per worker			0.021***	0.021***
			(0.005)	(0.005)
Log backlog+1				−0.001
				(0.001)
R^2	0.30	0.30	0.31	0.31

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Post-payday week indicator is used as an instrumental variable for worker turnover. Specifications (5)-(8) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), projected as of the week's start.

Table EC.2 Replicating Table 9 specifying learning by cumulative output instead of a time trend

—With pooled intercept and learning as cumulative output—				
	(1)	(2)	(3)	(4)
Worker turnover (%)	0.600**	0.602**	0.581**	0.595**
	(0.185)	(0.188)	(0.181)	(0.183)
Workload as log output		−0.002		
		(0.012)		
Workload as log output per worker			0.012**	0.012**
			(0.004)	(0.004)
Log backlog+1				−0.002
				(0.001)
R^2	0.25	0.25	0.25	0.25
—With line fixed effects and learning as cumulative output—				
	(5)	(6)	(7)	(8)
Worker turnover (%)	0.567**	0.575**	0.538**	0.544**
	(0.172)	(0.175)	(0.168)	(0.171)
Workload as log output		−0.010		
		(0.012)		
Workload as log output per worker			0.021***	0.021***
			(0.006)	(0.005)
Log backlog+1				−0.001
				(0.001)
R^2	0.30	0.30	0.31	0.31

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Post-payday week indicator is used as an instrumental variable for worker turnover. Specifications (5)-(8) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), projected as of the week's start.

Across all alternative specifications for learning, worker turnover's estimated effects remain statistically significant at p-values of 0.01 or smaller. In size, they fall in the range of a 0.54-0.60% increase per 1 percentage point increase in worker turnover, which attributes a 5.1-5.8% increase in field failure incidence in response to the average rate of turnover in post-payday weeks.

Appendix B: Additional Robustness Checks

We provide three further robustness checks. Table EC.3 utilizes an alternative measure of turnover. To reduce sensitivity to fluctuations in assembly line staffing levels, the denominator in worker turnover is set as the assembly line's monthly average staffing level. That is, for assembly line l in week t, we use the following normalized measure:

$$\frac{\text{Worker quits}_{lt}}{\text{Average staffing level}_{lm(t)}}, \tag{EC.1}$$

where $m(t)$ denotes the month containing week t. While we may expect that the metric could impart a mild attenuation bias in estimating turnover's effect, this issue is addressed by using the instrumental variable.

Table EC.3 Replicating Table 9 using normalized turnover rates

	(1)	(2)	(3)	(4)
—With pooled intercept—				
Normalized worker turnover (%)	0.696^{***}	0.692^{***}	0.688^{***}	0.693^{***}
	(0.163)	(0.164)	(0.160)	(0.160)
Workload as log output		0.011		
		(0.012)		
Workload as log output per worker			0.007	0.008
			(0.004)	(0.004)
Log backlog+1				−0.000
				(0.001)
R^2	0.31	0.31	0.31	0.31
—With line fixed effects—	(5)	(6)	(7)	(8)
Normalized worker turnover (%)	0.676^{***}	0.675^{***}	0.659^{***}	0.665^{***}
	(0.152)	(0.153)	(0.149)	(0.149)
Workload as log output		0.004		
		(0.012)		
Workload as log output per worker			0.017^{**}	0.017^{**}
			(0.005)	(0.005)
Log backlog+1				−0.001
				(0.001)
R^2	0.35	0.35	0.36	0.36

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Normalized worker turnover is calculated as an assembly line's weekly quits over its average staffing level in the calendar month. Post-payday week indicator is used as an instrumental variable for normalized worker turnover. Specifications (5)-(8) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), projected as of the week's start.

Across specifications in Table EC.3, the estimated effect of worker turnover on the field failure incidence is a 0.66-0.70% increase per 1 percentage point increase in the normalized turnover metric, with statistical significance at p-values of 0.001 or smaller. At the average rate of 10.2% in normalized turnover for post-payday weeks, worker turnover increases the incidence of field failures by an estimated 7.0-7.4%.

Table EC.4 adds data observations from February 2015, which we omit from our main regressions in order to avoid the complex dynamics surrounding the Chinese New Year holiday. Much of the factory workforce leaves to spend the holiday in their home provinces, and a significant number find it a convenient opportunity to quit. Assembly lines reduce output, and some do not operate at all; even when they operate, they may be ramping activity levels up or down to accommodate the holiday. Rather than deal with such non-standard work conditions, we decided to excise February 2015 completely from the previous results.

Table EC.4 Replicating Table 9 including Feb. 2015

—With monthly time fixed effects—				
	(1)	(2)	(3)	(4)
Worker turnover (%)	0.703***	0.688***	0.688***	0.681***
	(0.135)	(0.138)	(0.132)	(0.137)
Workload as log output		0.016		
		(0.010)		
Workload as log output per worker			0.009*	0.009*
			(0.004)	(0.004)
Log backlog+1				0.000
				(0.001)
R^2	0.37	0.38	0.38	0.38
—With assembly line and monthly time fixed effects—				
	(5)	(6)	(7)	(8)
Worker turnover (%)	0.689***	0.681***	0.664***	0.658***
	(0.127)	(0.129)	(0.124)	(0.128)
Workload as log output		0.009		
		(0.010)		
Workload as log output per worker			0.016**	0.016**
			(0.005)	(0.005)
Log backlog+1				0.000
				(0.001)
R^2	0.42	0.42	0.42	0.42

Significance levels → *** - 0.001 ** - 0.01 * - 0.05

Unbalanced panel of 1,672 production-active line-weeks in Sept. 2014 – Jun. 2015, including Feb. 2015. Line-weeks in Feb. 2015 with no or almost no activity due to the Chinese New Year remain omitted. Post-payday week indicator is used as an instrumental variable for worker turnover. Specifications (5)-(8) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), projected as of the week's start.

However, we find that the estimation results are similar when we include the February 2015 line-weeks with at least some real activity. Across Table EC.4's specifications, we estimate that worker turnover increases field failure incidence by 0.67-0.71% per 1 percentage point increase in turnover rate. At the post-payday weeks' average level, these estimates attribute a 6.4-6.8% increase in field failure incidence to worker turnover. The worker turnover estimates are highly statistically significant across the board at p-values of 0.001 or smaller.

Lastly, for Table EC.5's results, we replace output per worker by assembly line shift overtime hours as a workload measure.

Table EC.5 Replicating Table 9 Controlling for Overtime as Workload

—With monthly time fixed effects—		
	(1)	(2)
Worker turnover (%)	0.691***	0.697***
	(0.191)	(0.191)
Overtime hours	0.002***	0.002***
	(0.000)	(0.000)
Log backlog+1		−0.000
		(0.001)
R^2	0.31	0.31
—With assembly line and monthly time fixed effects—		
	(3)	(4)
Worker turnover (%)	0.689***	0.696***
	(0.178)	(0.191)
Overtime hours	0.001**	0.001**
	(0.000)	(0.000)
Log backlog+1		−0.001
		(0.001)
R^2	0.36	0.35
Significance levels → *** - 0.001	** - 0.01	* - 0.05

Unbalanced panel of 1,516 production-active line-weeks in Sept. 2014 – Jun. 2015. Post-payday week indicator is used as an instrumental variable for worker turnover. Specifications (3)-(4) include fixed effects for 44 assembly lines. Backlogs are the week's excess of (A) the firm's production targets (effectively, orders) over (B) clear to build (feasible production), projected as of the week's start.

Across Table EC.5's specifications, we estimate that worker turnover increases field failure incidence by 0.69-0.70% per 1 percentage point increase in turnover rate (versus 0.74-0.79% in the main text's Table 9). At the post-payday weeks' average level, these estimates attribute a 6.6-6.7% increase in field failure incidence to worker turnover (versus 7.1-7.6%). The worker turnover estimates are highly statistically significant across the board at p-values of 0.001 or smaller (same).

A 10-hour increase in overtime results in a 1.26-1.62% increase in the field failure rate. The estimates are statistically significant at p-values of 1% or smaller.