Web Appendix, "What Do Employee Referral Programs Do? Measuring the Direct and Overall Effects of a Management Practice", by Friebel, Heinz, Hoffman, and Zubanov

Appendix A provides additional discussion and results. For each subsection, we give the relevant section of the main paper that it accompanies. Appendix B contains additional figures and tables. Appendix C is the Data Appendix. Appendix D presents a model accompanying Section 1. Appendix E provides materials used by the firm in the ERPs.

Appendix A Additional Discussion and Results

A.1 World Management Survey (Accompanying the Introduction)

The WMS (Bloom *et al.*, 2014) has traditionally focused on manufacturing. However, in 2009, the WMS surveyed 661 retail establishments. Data on ERP status is available for 537 establishments. Like other WMS surveys, phone interviews were conducted using open-ended questions (Bloom *et al.* (2014) give details). Of the 537 establishments, 352 are in Canada, 126 are in US, and 59 are in UK. Unlike other WMS surveys, which do not ask about ERPs, enumerators explicitly asked managers about whether the establishment had an ERP. The share of establishments with an ERP is 25% in Canada, 15% in the US, and 32% in UK. In many cases, respondents mentioned a bonus, but we currently do not have data on whether the ERP used bonuses. One reason why the WMS rate of referrals is lower than that in CareerBuilder is that the question is asked at the establishment level. A retail firm may decide to have an ERP, but some local managers may choose not to apply it.

A.2 RCTs on Hiring Procedures and Referral Programs (Intro)

RCTs related to firm hiring procedures. As far as we are aware, ours is the first, large-scale, within-the-firm RCT on any hiring procedure. As mentioned in footnote 7 in the main text, development economics RCTs have randomized selection procedures in government (see Ashraf *et al.* (2020) for a prominent example) or NGOs (e.g., Deserranno, 2019), but not in a private firm. Thus, this work cannot examine impacts on profits, and the signaling role of hiring procedures like ERPs may differ when chosen by a profit-maximizing firm compared to when chosen by a government or NGO. Beyond audit studies, there are also RCTs in online labor platforms which change features of worker-firm matching, but these analyze the impact of platform features (i.e., features of the entire market) as opposed to randomizing an individual firm's hiring procedures, the type of research called for by Oyer & Schaefer (2011). Also, studies use RCTs to vary some feature of an organization (e.g., pay structure) and see how that affects the quality or quantity of applicants. Such studies examine who gets hired, but do not study the impact of a hiring procedure.

RCTs on referral programs. As noted in the main text, papers randomize referral programs in non-inside-the-firm contexts to study different questions from ours. For example, on customer referrals, beyond Kumar *et al.* (2010), work studies how different bonuses (Ahrens *et al.*, 2013) or access to premium services (Belo & Li, 2018) motivate e-referrals for online platforms. Beaman & Magruder (2012), Bryan *et al.* (2015), and Fafchamps *et al.* (2020) study whether people can screen for cognitive tests, loan-paying, and agricultural training returns, respectively. Goldberg *et al.* (2019) examine low-cost peer referrals for tuberculosis.

A.3 Additional Discussion on Referral Bonus Levels (Section 2)

We compare our RCT bonuses to those paid in other studies. In our RCT, workers could earn up to 40% of monthly salary for making a referral, and we also paid well in expected value terms taking into account that referrer and referral had to stay 5 months post-referral.[1] In their study in a financial firm, Brown *et al.* (2016) report a modal referral bonus of $1,000 (median of $2,000), which is about 1% of annual salary at the firm (or 12% of the monthly salary), which is similar to our bonuses in expected value, and lower than the maximum value of our bonuses.[2] Our nominal bonuses are similar in percentage terms to the bonuses at the trucking firm in Burks *et al.* (2015), where drivers got $1,000 (or about 1/3 of monthly salary) for referring an experienced driver, though there was also a 6-month tenure requirement.

A.4 Details of the Surveys Used in the Paper (Section 2)

As seen in Figure A1 below, we analyze the following surveys conducted at the study firm:

1. *Pre-RCT Survey of Non-grocery Employees*: In Oct.-Nov. 2015, we surveyed 120 food production workers at the firm about how much money would make them willing to make an employee referral for a hypothetical vacancy in their unit. These responses were used to choose the bonus levels for the RCT, as noted in Section 2. The response rate was 100%.
2. *During RCT Survey of Grocery Store Managers and Employees*: In September-October 2016, we conducted phone surveys of store managers recording their time use and their opinions regarding why the RCT ERPs were generating only a modest number of referrals. The response rate was 92%. In October-December 2016, we conducted phone surveys of cashiers. For each store, we randomly called two cashiers, one with an above- and the other below-median tenure. All participated. We asked the same broad questions as in the manager survey about why referrals were few. These surveys are analyzed in the main text in Section 7, with results in Table 9.[3]
3. *Post-RCT Survey of Grocery Store Managers and Employees*: In summer and fall 2018, we conducted phone surveys of store and regional managers regarding the mechanism for the observed indirect impact of ERPs on attrition. In fall 2018, we conducted similar surveys for employees, but via in-store electronic kiosk.[4] These surveys are analyzed in the main text in Section 4.2.3, with results in Table 6.

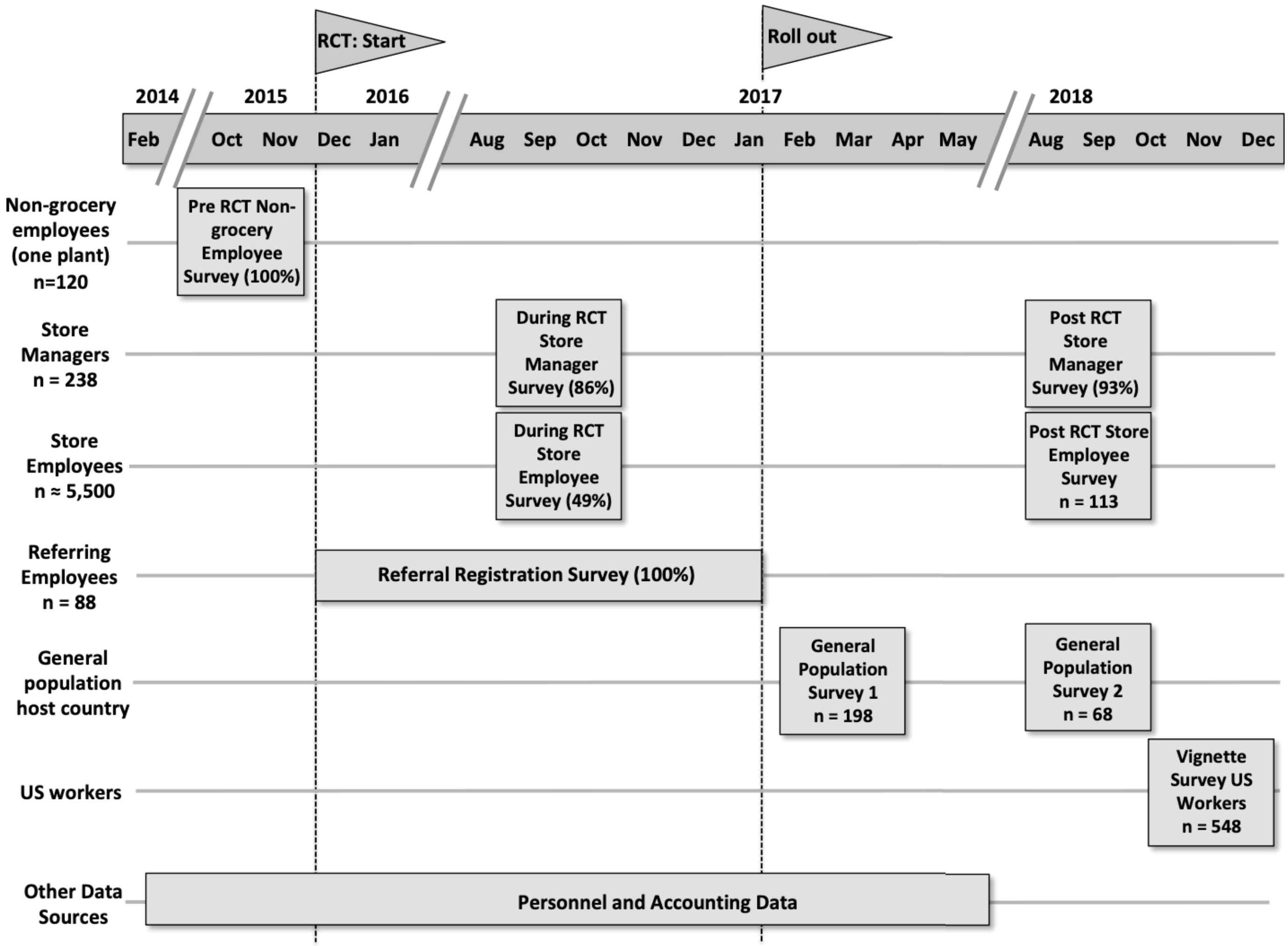
[1]The referral bonus was paid for 45% of referral hires. Thus, the expected value of bonuses was €37.5, €55.5 and €69 in R50, R90, and R120, equivalent to 13-23% of monthly salary, i.e., up to a week of salary.

[2]The bonuses in Brown *et al.* (2016) also require people to stay 6 months.

[3]This survey also had to cover questions on unrelated topics. Thus, we had to be parsimonious in choosing questions relevant for this study.

[4]The reason why these surveys were not conducted until summer and fall of 2018 is because our study firm CEO had earlier left the firm, causing us to lose the ability to conduct surveys. However, in summer 2018, we were able to re-engage with top executives at the firm in order to carry out these post-RCT surveys.

Figure A1: Datasets Used in the Paper



Notes: The *Pre-RCT survey of non-grocery employees* is discussed in Section 2 in describing how we selected the level of the referral bonuses for the RCT. The *During RCT surveys of managers and employees* are analyzed in Section 7, with results in Table 9 (Panel A covers managers, whereas Panel B covers employees). These help gain insight on why the RCT ERPs generated only a modest number of referrals. The *Post-RCT surveys of managers and employees* are analyzed in Section 4.2.3, with results in Table 6. These help gain insight on the mechanism for the indirect effects of ERPs on employee attrition. The *Post-RCT survey of employees* was conducted by the firm using store kiosks, so we do not know how many workers saw the survey on the kiosks (or know the share of workers who agreed to participate conditional on seeing the surveys). The *Referral Registration Survey* provides information on who referred whom and is used throughout the paper. The very brief survey is conducted by the firm as part of the referral process. Starting in January 2017, we only have information on who made referrals, not on who is referred. *General Population Survey 1* is analyzed in Section 7, with results in Figure 5. *General Population Survey 2* is analyzed in Section 7, with results in Panel A of Table 9. The *Vignette Survey of US Workers* is discussed in Sections 4.2.3, 7, and 8. It provides further evidence regarding the mechanism for ERP impacts on attrition, and also allows us to examine results across both lower-skill and higher-skill workers. In addition, it provides further evidence supporting the first part of Prediction 5, i.e., that workers should be more willing to make referrals for more attractive jobs. Appendix A.10 provides details on the *Vignette Survey*.

In all the firm surveys, subjects were told truthfully that we were conducting an international retail survey in partnership with a local university. In addition, subjects were told truthfully that their employer would not see individual-level responses to the survey. Phone surveys were conducted by native speakers recruited from a local university.[5]

In addition to these within-firm surveys, we also did phone surveys of randomly picked members of the general public of the country where the study firm operates:

- *General Population Survey 1*: Conducted in early 2017, this survey collected opinions regarding the attractiveness of different occupations and retail firms. This survey is analyzed in the main text in Section 7, with results in Figure 5.
- *General Population Survey 2*: Conducted in August-September of 2018, this survey explained to subjects that a grocery store firm had instituted an ERP, and that few referrals had been made for grocery jobs, whereas many referrals were made for non-grocery jobs. Subjects were then asked why they thought this was. This survey is analyzed in the main text in Section 7, with results in Panel A of Table 9.

Finally, we also ran a *Vignette Survey of US Workers* described below in Section A.10.

A.5 Who Makes Referrals? (Section 3.1)

Who makes referrals? Since the 88 RCT referrals are made by 75 referrers, most referrers made one referral during the RCT. In the ERP rollout, there are 314 referrals made by 268 referrers, of whom 193 are grocery workers. Broadly consistent with Burks *et al.* (2015), referrals are more common from workers with lower absence rates. In terms of links between referrer and referrals, the most common one is family member (about 1/3 of referrals in the RCT), followed by friend and acquaintance (about 20% each).

What stores do referrals come from? In basic summary statistics, stores where workers make referrals have higher employees and sales than stores with no RCT referrals. However, stores with referrals also hire more workers in general. At the individual level, store characteristics do not much predict whether a hire is a referral. Table 8 shows that ERP impacts on whether hires are referred are larger in stores with higher profits and lower local unemployment, but these differences are not statistically significant.

A.6 Multiple Hypothesis Testing (Sections 4 and 6)

As discussed in Section 3.2, we pre-registered two outcome variables: (1) attrition (primary outcome) and (2) absence (secondary outcome). As we examine both outcomes simultaneously, we account for multiple hypothesis testing by calculating family-wise error rate adjusted p-values based on the Westfall & Young (1993) free step-down procedure. For comparison, we also show Bonferroni-corrected adjusted p-values, as well as conventional

[5] We also did pre-RCT pen-and-paper surveys with about 3k grocery workers and 230 store managers. We asked questions on social connections in and outside the workplace, and on attitudes about one's job, managers, and the firm. These surveys helped us design the RCT, but are not used in analysis. In the pre-RCT worker survey, the rate of informal referrals is 26%, similar to the 27% rate in the *During RCT* survey (see Section 3.1)—this is further evidence that the ERPs did not substantially boost informal referrals.

clustered by store p-values. As seen in Table A1, with the exception of restricting the analysis to new hires during the RCT, the adjusted p-values indicate a statistically significant effect of having an ERP on attrition. In each column, the family of hypotheses has two hypotheses, one for attrition and one for absence.

Table A1: Accounting for Multiple Hypothesis Testing in Table 5. Dep. Var. = Attrition, With Coefficients Multiplied by 100

Type of workers:	All	All	Hires	Inc
Sample period:	RCT	Pre &RCT	RCT	RCT
Column from Table 5:	(2)	(4)	(6)	(8)
ERP	-0.97***	-1.19***	-1.76*	-0.81***
	(0.34)	(0.39)	(1.04)	(0.28)
Conventional clustered p-vals	{0.005}	{0.002}	{0.092}	{0.004}
Westfall-Young p-vals	{0.025}	{0.008}	{0.233}	{0.015}
Bonferroni p-vals	{0.010}	{0.005}	{0.183}	{0.007}

Notes: This table shows family-wise error rate adjusted p-values based on the Westfall & Young (1993) free step-down procedure (5,000 replications) for the ERP vs. Control comparisons in Table 5. In each column, the family of hypotheses includes one for attrition and one for absence. The Westfall-Young p-vals account for clustering by store by using a clustered bootstrap, and are implemented using "wyoung.ado" from Jones *et al.* (2019). For brevity of presentation, we do not show the absence results here, as there is no statistically significant impact of having an ERP on absence either under conventional clustered by store inference (Table B3) or using Westfall-Young p-values.

A.7 Mediation Analysis (Section 4.2.1)

Following Imai *et al.* (2010a,b), consider the following system:

$$M_{it} = \alpha_0 + \alpha_1 ERP_i + X_{it}\delta_2 + u_{it} \tag{1}$$
$$y_{it} = \beta_0 + \beta_1 ERP_i + \gamma M_{it} + X_{it}\delta_2 + v_{it} \tag{2}$$

Here, y_{it} is an outcome of person i in month t (namely, whether i exits the firm during t); M_{it} are the mediator variables, namely whether someone is referred or someone's referrals made to date; ERP_i is a dummy for having an ERP in one's store; X_{it} are controls; and u_{it} and v_{it} are errors. A key goal in the mediation analysis is to estimate β_1 and γ. The mediator effect is $\alpha_1 * \gamma$, whereas the non-referral effect of the ERP is β_1. Imai *et al.* (2010b) show that OLS produces consistent estimates under Assumption 1 below.

Assumption 1

$$y_{it}(e', m), M_{it}(e) \perp\!\!\!\perp ERP_i |\ X_{it} \tag{3}$$
$$y_{it}(e', m) \perp\!\!\!\perp M_{it}(e) |\ X_{it} \tag{4}$$

for any treatment $e, e' \in \{0, 1\}$, for any mediator m, and for any controls X

where $y_{it}(e', m)$ is the potential outcome for worker i in month t under treatment e'; and mediator m and $M_{it}(e)$ is the potential mediator under treatment e. Equation (3) of Assumption 1 will hold because of random assignment. Equation (4), i.e., that potential referral status is independent of potential duration conditional on observables, is much less obvious.[6] For example, a person who is likely to be referred under an ERP may have other positive unobservables relative to someone unlikely to be referred. Given past research suggesting that referrals are positively selected (Brown *et al.*, 2016; Burks *et al.*, 2015), we hypothesize that any bias would be toward biasing upward the estimate of γ. That is, any bias would seem to work against our conclusion that referrals are not a main driver of the ERP effect, making our qualitative conclusion even stronger.

Table A3 shows results. Columns 1-2 show the impact of having an ERP on being referred and referrals made to date using the full panel data. Columns 3-5 shows the impact of having an ERP as the mediators are gradually controlled for. The coefficient only falls in magnitude from -0.97 to -0.92. The estimates imply that only 5% of the impact of having an ERP on attrition is mediated via getting more referrals and having more referrals to date, whereas 95% remains unexplained. Column 5 shows that having made referrals so far to date does not significantly predict whether a person will attrite. Column 6 separate referrals made to date into those made in the last 5 months vs. those not made in the last 5 months. For each referral made in the last 5 months, a person is 1.7pp less likely to attrite, consistent with referrers staying a bit longer to get a bonus.

A.8 Manager Time Use (Section 4.2.2)

During the RCT in fall 2016, store managers were asked about the share of time during the preceding few months that they spent on four time use categories: goods/products, customers, administration, and human resources. We have time use data for store managers in 199 of the 238 stores. To assess whether manager time use was affected by having an ERP, we regressed normalized time use for each category on a dummy for having an ERP. As seen in Table A2, there is no impact of an ERP on time use.

Table A2: No Impact of Having an ERP on Normalized Manager Time Use (N=199)

Time spent on:	Goods		Customers		Administration		HR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ERP	-0.10	-0.11	-0.18	-0.13	0.19	0.20	0.02	-0.00
	(0.17)	(0.17)	(0.19)	(0.20)	(0.16)	(0.17)	(0.18)	(0.18)
Store controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors in parentheses. An observation is a store manager. The dependent variable is normalized time use on each of the 4 categories. Controls are the store-level controls listed in Table 3. HR is based on two separate questions added together (one on managing people and one on dealing with turnover), but we also see a null effect of ERPs if both questions are analyzed separately. In a smaller, unrelated phone survey with 129 store managers in Jan. 2016, there is also no effect of ERPs on whether managers report having recently increased effort to reduce turnover.

[6] Equation (4) would hold if the mediator were directly randomized (Imai *et al.*, 2010b), but one cannot force someone to be a referral hire or to make referrals. We experimented with estimating Equation (2) while instrumenting the mediator (either whether someone is referred or makes referrals) using the level of the referral bonus. Doing so had little impact on β_1 compared to OLS, but produced a large standard error for γ (despite having a strong first stage). Because of this imprecision with IV, we stick with OLS.

Table A3: Mediation Analysis for Impact of ERPs on Attrition

Dep. Var.:	Referred (0-1)	Refs made to date	Attrition (0-1) x 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ERP	0.007***	0.009***	-0.97***	-0.93***	-0.92***	-0.92***			
	(0.002)	(0.002)	(0.34)	(0.34)	(0.34)	(0.34)			
Hire was referred				-6.36***	-6.35***	-6.33***		-6.33***	-6.33***
				(1.34)	(1.33)	(1.33)		(1.35)	(1.35)
Refs made to date					-0.54				-0.51
					(0.85)				(0.87)
Refs made in last 5m						-1.74*			
						(0.92)			
Refs made not in last 5m						1.76			
						(1.71)			
R0							-1.00**	-1.00**	-1.00**
							(0.40)	(0.40)	(0.40)
R50							-0.47	-0.42	-0.42
							(0.45)	(0.45)	(0.45)
R90							-1.59***	-1.52***	-1.51***
							(0.38)	(0.39)	(0.39)
R120							-0.81*	-0.74*	-0.74*
							(0.42)	(0.42)	(0.42)
Observations	74,188	74,188	74,188	74,188	74,188	74,188	74,188	74,188	74,188
Mean DV if ERP=0	4.8e-4	0	6.677	6.677	6.677	6.677	6.677	6.677	6.677
Workers	10,003	10,003	10,003	10,003	10,003	10,003	10,003	10,003	10,003

Notes: Standard errors clustered by store are in parentheses. All columns show OLS models. The controls are the same as in Table 5. The sample is workers at the firm during the RCT. "Refs made to date" means a person's running sum of referrals made to date during the RCT. "Refs made in last 5m" is a person's running sum of referrals during the last 5 months. "Refs made not in last 5m" is a person's running of sum of referrals made during the RCT while excluding referrals made during the previous 5 months. * significant at 10%; ** significant at 5%; *** significant at 1%

A.9 Discussion from Practitioners and Sociology (Section 4.2.2)

Our data show that ERPs reduce attrition separate from generating referrals, and our data and surveys suggest this is due to workers valuing being involved in hiring. This mechanism is highly consistent with two key points raised by business practitioners. First, practitioners state specifically that ERPs make workers feel more involved in the hiring process. One recruiting website argues that ERPs "help increase attachment to the organization and make employees feel as though they have a stake in the future of the business. Employees want to grow, so having a hand in the company's forward motion is exactly what they're looking for." Another recruiting website argues that ERPs make "current employees feel trusted and valued since they are participating in the company's future and growth."[7]

Second, separate from ERPs, practitioners point out that involving workers in hiring can be beneficial to firms by increasing feelings of involvement. For example, DeLong & Vijayaraghavan (2002) describe an investment bank that seems to benefit by strongly involving the firm's bankers, from entry-level to senior-level, in hiring.

Turning to sociology, Fernandez & Weinberg (1997) is a study showing that referrals receive special consideration at different stages of the hiring process. In their Discussion section, the authors briefly consider that the desire to involve lower-level employees could be one reason why referrals receive special consideration in hiring (page 899).

A.10 Vignette Survey of US Workers (Sections 4.2.3, 7, and 8)

Vignettes have a long tradition in economics (Kahneman *et al.*, 1986). Kaur (2019) is a recent example using a vignette to identify mechanisms.

The *Vignette Survey of US Workers* was carried out by the online survey company Pureprofile on our behalf. Participants came from a pool of regular survey takers who have an account with Pureprofile. On average, active members of their pool take around five surveys per month. Most of the surveys are run by commercial companies, but researchers also use online surveys increasingly. The invitation form for the survey was generic and did not mention ERPs. We used respondents between age 18-65.

Table A4: Comparing *Vignette Survey* Participants to the CPS

	Vignette Survey	CPS
Female	.51	.52
Age	47.08	41.28
Black	.08	.12
Hispanic	.08	.2
Asian	.05	.07
Bachelor's or more	.54	.32

Notes: For the CPS, we restrict attention to individuals with age between 18 and 65.

[7] The first quote is from:
`https://recruiterbox.com/blog/4-reasons-why-an-employee-referral-program-may-be-your-best-recruiting-tool` and the second is from `https://www.formstack.com/blog/2016/employee-referral-system-benefits`.

Table A4 compares characteristics of survey participants to the 2018 March CPS. Compared to the CPS, participants in the survey are older, whiter, and more educated, but our survey still contains a broad mix of workers of different skills.

ERPs and respect. As noted with the vignette's full text in Section 4.2.3, the main question in our vignette survey was "Do you think the firm having the employee referral program would make the employee feel more respected?" The survey responses were:

- It is very unlikely to make the worker feel more respected (2.6%).
- It is unlikely to make the worker feel more respected (4.0%).
- It is somewhat unlikely to make the worker feel more respected (4.7%).
- It is uncertain whether it will make the worker feel more respected (20.6%).
- It is somewhat likely to make the worker feel more respected (21.2%).
- It is likely to make the worker feel more respected (26.1%).
- It is very likely to make the worker feel more respected (20.8%).

Section 8 reports a comparison of workers with a bachelor's degree or higher versus workers with less than a bachelor's in terms of whether they believe that having an ERP would make an employee feel more respected, defined as a dummy for one of categories 5-7 above (i.e., somewhat likely, likely, or very likely). We regress whether an employee would feel more respected on a dummy for having a bachelor's or higher with robust standard errors. Of course, the purpose of this regression is not to establish a causal relation between education and survey answers.[8] Rather, this shows that believing ERPs increase workers' feeling of being respected may be even more prevalent among higher-skilled than lower-skilled workers.

Job quality and referrals. In addition to the above, we asked the below vignette:

> *Think of your **current main job**. Assume your employer has an **open job** in your department. One of your friends or relatives would probably match the requirements of the job. On a scale from (1) very unlikely to (7) very likely, would you try to **refer your relative/friend** to your employer?*

We combined answers to this question with questions where we asked *How attractive is your current job?* and *How attractive is your current employer?* on a scale from 1-7. As seen in Table A5 below, a 1σ increase in job attractiveness increases the chance that someone would be willing to make a referral (defined as response 5-7 to the above vignette) by about 20pp. A 1σ increase in firm attractiveness increases referral willingness by 7-8pp. These results support that people are more willing to make referrals for better jobs.

A.11 Calculation of the Costs of Turnover (Section 5)

We base our calculations on the following numbers: an average cashier salary of €350 per month, an average store manager salary of €900 per month, and overall average grocery store worker salary of €400 per month.

[8] Indeed, if one controls for gender, race, and 6 age categories, the coefficient on bachelor's degree or higher falls to 5pp (s.e.=4pp).

Table A5: People who Rate their Job or Employer as More Attractive Report Being More Willing to Make a Referral (N=333 workers). From *Vignette Survey of US Workers.*

Dep. Var.:	Would refer (0 or 1)		Normed willingness to refer	
	(1)	(2)	(3)	(4)
Job attractiveness (normalized)	0.211***	0.197***	0.386***	0.341***
	(0.036)	(0.040)	(0.072)	(0.078)
Employer attractiveness (normalized)	0.074**	0.083**	0.302***	0.337***
	(0.037)	(0.041)	(0.072)	(0.079)
Demographic controls	No	Yes	No	Yes

Notes: Robust standard errors in parentheses. Controls cover gender, race, 6 age categories, and 4 education categories. In columns 1 and 2, the DV is 1 if someone chose 5-7 and is 0 if someone chose 1-4 on a scale from (1) very unlikely to (7) very likely. In columns 3 and 4, the DV is the normalized value of the 1-7 score. The question was not asked to people who were unemployed or self-employed.

Direct costs (administration and training). Based on conversations with several store managers, we assume it takes about 18 hours of worker time and 20 hours of store manager time to hire a new worker. For store managers, this is based on time spent on interviewing candidates, processing the paperwork of each leaver, re-writing work schedules, communicating with staff regarding turnover events, and training the new workers. For workers, we focus on cashiers who are by far the largest group of grocery worker hires. Each newly hired worker undergoes a two-day (=16 cashier hours) formal training. After this, a mentor (another cashier) also spends two hours with each newly hired worker. Summing up, the cost of this time is about €150.

In addition, the head of HR informed us that there were 23 employees in the HR office whose job is to perform administrative tasks related to hiring and turnover. Inclusive of their monthly salaries, as well as the rent and utility cost of housing their offices, we assume these workers have a total monthly cost of €10,000 per month. This entails about €35 per turnover event. Finally, the firm needs to pay job advertising costs and uniform costs for new workers, which we assume add about €65 per turnover event.

Combining all direct costs together yields roughly €250 per turnover event.

Total costs. Beyond administrative costs, turnover also often has consequences in terms of productivity (Blatter *et al.*, 2012; Boushey & Glynn, 2012). Turnover events can be disruptive to incumbent workers' productivity and new workers often require time to get up to full speed. Blatter *et al.* (2012) study total hiring costs (inclusive of direct costs and lost productivity) for different types of firms and jobs using rich data from Switzerland. For large firms like ours (i.e., for firms with 100+ employees), Blatter *et al.* (2012) estimate average hiring costs to be 17 weeks of salary. For the job of cashier, the average hiring cost (i.e., across firms of different sizes) is 10 weeks, and they find that hiring costs increase in skill. Because Blatter *et al.* (2012) do not report hiring costs specifically for cashiers in large firms, we assume an intermediate value. To be conservative, we weight skill as more important than firm size, and assume a hiring cost of 12.5 weeks, which translates into a monetary value of €1,150.[9,10] Since Blatter *et al.* (2012) do not include costs that turnover may have on the firm's reputation or talent pool, our estimates may be somewhat conservative regarding long-run cost.

Recall from Section 4.1 that having an ERP led to a 2% increase in sales and a 2-2.3% increase in store-level operational profits, though the coefficients were statistically insignificant. While the coefficients were somewhat imprecise, these results are very broadly consistent with broader benefits of reducing turnover beyond direct costs.

Our full turnover cost is also consistent with a recent study by Kuhn & Yu (2020) on a retail firm in China. Kuhn & Yu (2020) exploit having daily sales data, coupled with a strongly enforced two-week notification period before attrition events, to estimate the cost of turnover events using an event study approach. They estimate that turnover events cost the firm 63 days worth of worker wages. Since their workers work 6 days per week, this is equivalent to a turnover cost of 10.5 weeks of pay. This is similar to our assumed total hiring cost of 12.5 weeks.

A.12 Profit Calculation Details (Section 5)

Absences. We do not account for absence in the profit calculation, as there is no impact of ERPs on absence. In addition, the overall absence difference between referrals and non-referrals is not statistically significant.

Savings from referrals hired in RCT. We use the formula $\theta_p t_p c$. The attrition difference between referrals and non-referrals, t_p, is given by column 1 of Table 4, whereas θ_p is the share of RCT worker-weeks in ERP stores from referrals.

Savings from non-referral hires in RCT. Using $\theta_p t_p c$, here, t_p is the impact of having an ERP on attrition for non-referral hires and is estimated by running column 2 of Table 5 but restricting to non-referral hires. θ_p is the share of RCT worker-weeks in ERP stores from non-referral hires.

Savings from incumbents. We calculate the turnover benefits from pre-RCT incumbents using the residual in total savings in turnover costs after the savings from referral and non-referral hires is taken out. That is:

$$\begin{aligned}\text{Savings from pre-RCT incumbents} &= \text{Total savings in turnover costs}\\ &- \text{Savings from referrals hired in RCT}\\ &- \text{Savings from non-referral hires in RCT}\end{aligned}$$

[9] For cashiers, Blatter *et al.* (2012) estimate that direct recruitment costs comprise 21% of total hiring cost for cashiers. This is very close to the value of €250 that we use.

[10] Rather than making an assumption based on Blatter *et al.* (2012), an alternative approach we have experimented with is to relate store-level turnover to store-level profits using our data. For example, there is a negative relation between turnover and profit in a regression of store-level monthly profit per worker on store-level monthly turnover, store fixed effects, and time fixed effects. And adding the costs from such an approach with the direct costs, we can arrive at a similar level of profit to the assumed value of €1,150. In addition, Appendix Table B7 shows cross-sectionally in pre-RCT data that higher-attrition stores also have higher shrinkage, lower sales per worker, and lower operational profit per worker.

Pr(both). To calculate $Pr(both)$, i.e., the probability that both the referrer and referral stay 5 months, we count up the number of instances where both parties stayed five months divided by the total number of referrals. Our data extend 5 months after the RCT, so we are able to see 5 months of data post-referral for all referrals made during the RCT. We use a single number for $Pr(both)$ as opposed to letting it vary by referral bonus group.

A.12.1 Firmwide ERP Rollout and Different Jobs

In order to calculate profits under the firmwide ERP rollout starting in January 2017, we need to make some additional assumptions beyond those made in the RCT. This is for two reasons. First, the firm rolled out the new ERP (€30 upon hire, €100 after 3 months) to the entire firm at once and did not randomize. Second, as discussed in the main text in footnote 18, during the rollout (i.e., starting January 2017), we only observe data on who makes referrals, not on who is referred.

Contribution to turnover savings from referrals hired during the rollout. These savings are given by $\theta_r^R t_r^R c$, where θ_r^R is the share of observations from referrals in the rollout and t_r^R is the attrition benefit of referrals relative to non-referrals in the rollout. The superscript "R" is for rollout, whereas the subscript "r" is for referral.

Because we do not observe who is referred in the rollout, we take θ_r^R to be the share of observations from referrals in the RCT times the ratio of referrals made per hire in the rollout relative to the RCT.

Since we do not have experimental variation in the rollout ERP, we make an assumption about t_r^R using rough extrapolation of the RCT results. In the RCT, the difference between referral and non-referral attrition decreases as the size of the bonus increases in Table 4. Given that R120 has a referral/non-referral attrition difference of roughly 6pp per month, for a higher bonus of €30 + €100, we assume $t_r^R = 5$pp per month.

Total savings in turnover costs from rollout. During the RCT, the overall impact of the ERP on employee turnover did not systematically vary with the level of the referral bonus, as can be seen in the odd columns of Table 5. Thus, for the profit calculations, we assume that total turnover savings from the rollout ERP is the same as total turnover savings from the RCT ERPs, plus the incremental benefit of turnover savings from referrals hired during the rollout relative to during the RCT.[11]

Different jobs. To calculate overall turnover benefits of the RCT ERP separately by job, we perform our main turnover regression separately by job. The overall turnover benefits during the rollout is assumed the same as during the RCT, plus incremental benefits from referral hires. The turnover savings from referrals are scaled using referrals per hire. The attrition difference between referrals and non-referrals is given by the data during the RCT and is assumed to be 5pp per month in the rollout.

[11] That is, $t^R c = tc + \left(\theta_r^R t_r^R c - \theta_r t_r c\right)$, where t^R is the impact of the rollout ERP on turnover relative to no ERP; t is the impact of the RCT ERP on turnover; θ_r is the share of observations from referrals in the RCT; and t_r is the difference in attrition between referrals and non-referrals during the RCT.

A.13 Alternative Explanations for Larger Impact of ERPs in Higher-Performing Stores (Section 6)

Product selection is generally similar across stores, with the vast majority of RCT worker-months (over 90%) occurring at stores offering a full-service format. Product selection does not drive our results, as the Table 8 results are robust to restricting to full-service stores or to including interaction terms of ERP*(# of products offered) or ERP*(Share of products that are fresh goods), as seen in Table B10. Workplace technology is also similar across stores, and results are robust to controlling for an interaction of ERP with the number of store checkouts (total, manned, or self-checkout). Our performance heterogeneity is not just reflecting store size, as results are robust to controlling for ERP*(Head count) or ERP*(Store square meters). Competition from Lidl does not explain the results, as results are robust to including the interaction term ERP*(Dummy for Lidl store nearby). Demand shocks seem unlikely to account for us finding similar results on different performance measures, not only on sales and profits, but also on shrinkage, which is strongly affected by theft and thus presumably less affected by demand shocks. We are agnostic as to whether ERPs may be complementary with respect to management practices or the quality of store managers, as the two are often quite correlated Bender *et al.* (2018). Bloom *et al.* (2019) document substantial intra-firm, cross-plant variation in management quality. Based on numerous visits of the authors to firm stores, operational management practices appear relatively similar across stores, suggesting that differences in management are likely to reflect differences in HRM practices.

A.14 Further Discussion on Referrals and Diversity (Section 6)

This Appendix discusses demographic issues related to ERPs. This analysis is not pre-registered. We also note that grocery workers are mostly female and disproportionately young, so conclusions drawn here may not necessarily hold in other contexts.

Heterogeneity in ERP impacts by worker demographics. Table A6 characterizes heterogeneity in ERP impacts by worker demographics. Column 3 shows that overall ERP impacts on attrition do not significantly vary between younger and older workers. However, column 4 shows that ERP impacts on attrition are larger for men than women, though impacts on attrition are statistically significant and robust for both.[12] Part of why ERPs have larger impacts for men is that men have higher attrition than women at the firm (11.5pp vs. 5.4pp per month during the RCT), though the impact of ERPs as a share of mean attrition is still larger for men. Another possibility is that when men are in gender non-congruent roles (i.e., most grocery workers are female), they may be more sensitive to feelings of respect relative to women.

ERP impacts on diversity of hires. Beyond examining heterogeneity in ERP effects by age/gender, we can also consider diversity of hires as an outcome. For this analysis, we turn instead to Appendix Table B1. Having an ERP does not affect the age of hires, but it increases the share of female hires by 4pp, marginally significant at the 10%

[12]E.g., if we estimate column 4 in Table 5 separately by gender, we obtain an ERP X RCT coefficient for women of -0.82(se=0.37) and a coefficient for men of -3.32(se=1.07).

Table A6: Treatment Heterogeneity by Demographics: Direct and Overall Effects

Dep. var.:	Hire is a Ref (0-1)		Attrition (0-1)	
	(1)	(2)	(3)	(4)
ERP	2.74***	2.56***	-0.53*	-0.79***
	(0.72)	(0.61)	(0.31)	(0.29)
ERP X Male	-0.97		-3.37***	
	(1.13)		(1.23)	
ERP X Young		-0.21		-0.21
		(0.91)		(0.79)

Notes: The table presents analyses similar to those in Panels A-B of Table 8 except we analyze heterogeneity here with respect to demographic variables. Standard errors clustered at the store level are in parentheses. Coefficients multiplied by 100 for readability. * significant at 10%; ** significant at 5%; *** significant at 1%

significance level. Part of the impact reflects that ERPs increase referrals and referrals are 10pp more likely to be female than non-referrals, but much of this effect is unexplained by the simple homophily channel. Note that the tendency of ERPs to boost the share of hires who are female does not drive any of our results on the impact of ERPs on attrition because we control for a worker's gender throughout the paper's analysis.

Referrals and demographic gaps. In our data, referrals yield high-value hires from workers in traditionally disadvantaged groups. A common concern in EU countries is youth unemployment. In the country we study, youth unemployment far exceeds the rate for older workers. In informal interviews with five store managers at our firm, all expressed concern that young workers are more likely to quit than older workers. Column 4 of Panel A of Table B1 shows this is true: among non-referrals, young workers (i.e., < 25 at time of hire, following the OECD definition) are almost 50% (6.7 pp per month) more likely to quit than older workers. However, referred youth are no more likely to quit than non-referred older workers. If a firm worries that young workers will quit shortly after hire, our results suggest that referrals may neutralize this concern.[13] Another common policy concern is that women have higher rates of absenteeism than men (Ichino & Moretti, 2009). Among non-referrals, women have 46% more absences than men (Column 5 of Panel B of Table B1). However, referred women are no less likely to be absent than non-referred men. Also, the referral advantage in absenteeism occurs only in women.

A.15 Reasons Other than Job Attractiveness for the Relatively Small Number of Referrals Made for Grocery Store Jobs (Section 7)

Were employees unaware of the ERPs? The firm took many steps to ensure that the ERPs would be well-understood and well-publicized to workers. This included the letters and posters described in Section 2, plus phone calls to ensure that store managers publicized the ERPs, plus guidance to regional managers to ensure that store managers

[13]One concern is that young workers might be working summers off from school, and would naturally quit at the end of summer. However, the results in column 4 are very similar when dropping summer months.

were compliant. Also, in the fall 2016 survey, we asked workers if they were aware that the firm welcomed referrals, and 87% said yes in treatment stores. This indicates persistent awareness of the ERPs even though many workers attrited during the RCT. Further, in Panel B of Table 9, the explanation of employees not being aware of the ERP / not knowing how it worked shows quite limited support. A related issue would be if people forgot about the ERPs after a few months. In such a scenario, some referrals would be made after the ERPs were introduced, but effects would peter out over time. However, Figure 2 shows that this is not the case.[14]

Did workers not have friends looking for jobs? If employees do not have friends to refer, then an ERP may have little impact on referrals. However, we believe that this explanation is unlikely to explain our results for three reasons. First, during 2016, the unemployment rate was roughly 8% (and much higher for youth who make up a sizable share of the firm's workforce), so there was a significant share of people who were unemployed. Second, in the *During RCT Surveys of Store Managers and Employees* listed in Table 9, not having friends to refer received much less support than grocery jobs being undesirable as an explanation for the result. For example, while 48% of managers mentioned grocery jobs being undesirable as an explanation, only 10% mentioned employees not having friends to refer. Third, the firm has operations throughout the country where it is located, in both urban and rural areas. Even if someone moved or had contacts living elsewhere in the country, those contacts could have found a job at a local facility.

Was the referral process difficult? Store employees could have perceived it as burdensome to call the HR department to register a referral. We do not think this is a strong explanation because the process was designed to be very brief (just a few questions about how someone knows their referral). Store employees likely have a relatively low opportunity cost of time, given that they are willing to work for just over €2 per hour. Given the possibility of earning €135 in one treatment arm, it seems unlikely that a short phone call would be of sufficient cost to dissuade someone from making a referral.[15]

Was the expected value of the bonus too low? Given the five-month tenure requirement for a referral to be paid, would this make the expected value of the bonus too low? In our data, the chance that both the referral and referrer stay for five months after the referral is hired is about 45%. This means that the expected bonus is roughly equal $15 + .45 * 50 =$€37.5 in the R50 treatment, €55.5 in R90, and €69 in R120. Relative to a post-tax monthly wage of roughly €300 for cashiers, this still is a sizable bonus (about 13-23% of monthly salary). Though our judgment of what is a "sizable bonus" may be subjective, the literature on incentives shows strong effects of bonuses of this magnitude (Bandiera *et al.*, 2011).

After the RCT, the rollout ERP paid €30 at hire, plus €100 after 3 months. Since about 60% of referrals during the RCT would have lead to payments, the expected value of the new bonus was €90. This is even larger than R120, and also provides the money sooner.

[14] Over the four quarters of the RCT in Figure 2, the number of referrals made is 24, 17, 21, and 26, whereas the ratio of referrals per hire is 3.8%, 2.3%, 2.3%, and 3.7%. The ratio is lower in June-August 2016 because there is more hiring then.

[15] Of course, if people are highly present-biased, this could help explain why they are not willing to make referrals. We cannot rule this out, but it seems unlikely in our case.

A.16 Responsiveness of Referrals to the Bonus Level Across Jobs (Section 7)

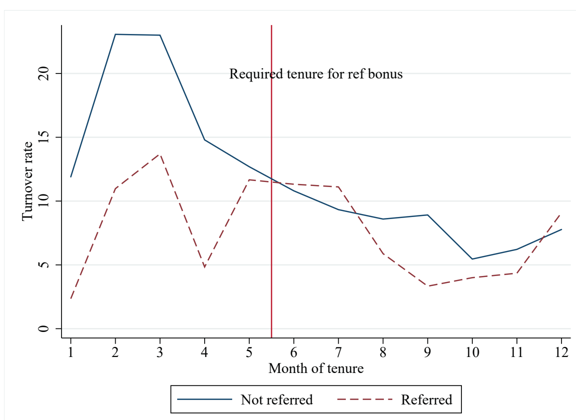
In Appendix D, our simple model predicts that, under a reasonable assumption, there should be greater responsiveness of referrals to bonuses for better jobs. The results of the firmwide rollout are broadly consistent with this prediction.

For non-grocery jobs, there was no ERP before the firmwide rollout. Thus, it is somewhat challenging to use the non-grocery evidence to examine whether referrals are more responsive to bonuses in good jobs than in bad jobs. Still, as far as we know, formal referrals were not being made for non-grocery jobs before the firm's rollout in January 2017. Thus, one can think of our evidence as tracing out a referral responsiveness curve, where initially there were 0% referrals at a bonus of €0, and 37% referrals made per hire at the bonus of €130.

In addition, Table 10 in the main text shows that we can provide evidence on the prediction by separating grocery jobs into cashier and non-cashier grocery jobs (e.g., butcher, baker, assistant manager), with non-cashier jobs seen as more attractive. During the RCT, the ratio of referrals made by the group to hires was 5% for non-cashier grocery jobs compared to 3% for cashier jobs. Post-RCT, the ratio was 17% for non-cashier grocery jobs, and 11% for cashier jobs.

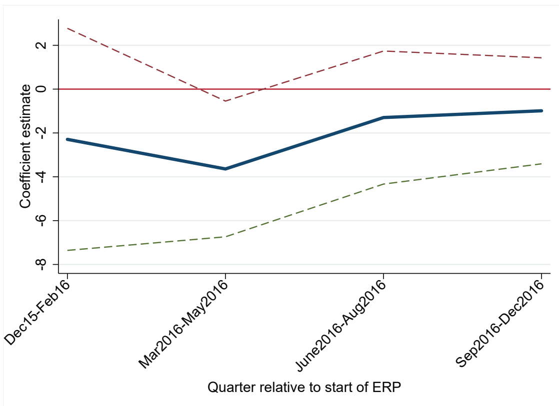
Appendix B Additional Figures and Tables

Figure B1: Attrition Hazard for Referrals vs. Non-referrals

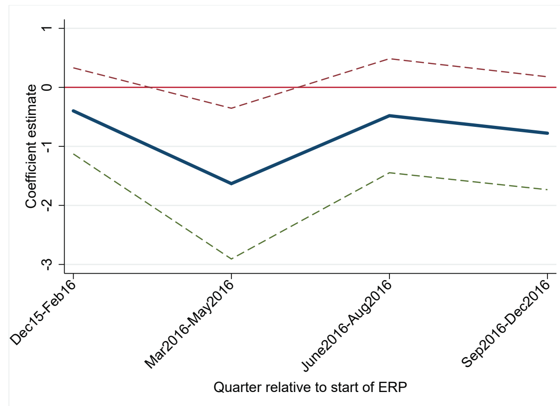


Notes: This figure shows the monthly quiz hazard as a function of worker tenure comparing referred vs. non-referred workers. The sample is grocery workers hired during the RCT. The referral and referrer must stay 5 months after the referral is hired in order for the referrer to be paid. The vertical tenure threshold line is drawn in between x=5 and x=6 because both referral and referrer must stay at least 5 months.

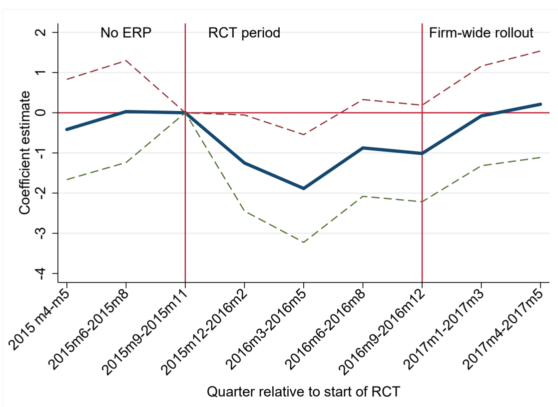
Figure B2: Event Studies on Impact of ERPs: Additional Subsamples and Outcomes. Solid Lines are Coefficients, Dotted Lines Show 95% Confidence Intervals



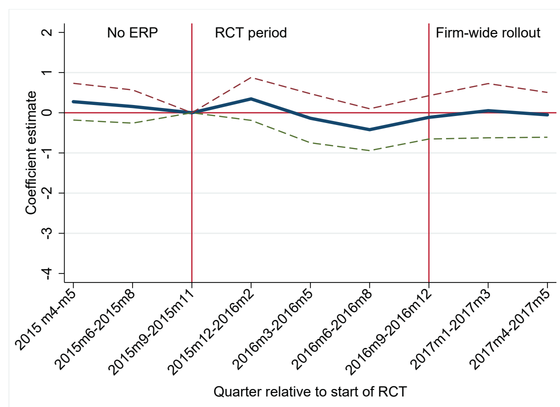
(a) Sample is New Hires During RCT



(b) Sample is Incumbents During RCT



(c) Outcome is Voluntary Exits ("Quits")



(d) Outcome is Involuntary Exits ("Fires")

Notes: These figures are similar to the main event study in panel (a) of Figure 4. The difference is they analyze different samples or look at different individual outcomes (other than overall attrition). Panel (a) here analyzes grocery workers hired during the RCT, whereas panel (b) here analyzes grocery workers who were incumbents at the firm when the RCT began (i.e., they had been hired in the past). For both panel (a) and (b) here, it is not possible for the event study to go before the RCT because RCT hires and RCT incumbents do not attrite prior to the start of the RCT. Panel (c) analyzes voluntary attrition as the outcome variable, whereas panel (d) analyzes involuntary attrition. In panels (c) and (d), there are only 3 quarters graphed before the RCT because information on exit codes only begins in 2015m4.

Table B1: Referrals, ERPs, and Demographics (Age and Gender)

Panel A: Age					
Dep. Var.:	Age of New Hires			Attrition (0-1) x 100	Monthly absences
	(1)	(2)	(3)	(4)	(5)
Hire was referred	-2.68*			-6.80***	-0.20
	(1.48)			(1.33)	(0.32)
Young X referred				0.09	-0.05
				(1.96)	(0.50)
Young (age<25)				6.67***	-0.13
				(0.65)	(0.09)
R0		0.68			
		(0.84)			
R50		-0.49			
		(0.77)			
R90		0.30			
		(0.73)			
R120		0.76			
		(0.81)			
ERP			0.32		
			(0.60)		
Observations	3,787	3,787	3,787	14,879	14,879
Mean dep. var.	31.36	31.36	31.36	15.69	1.363

Panel B: Gender					
Dep. Var.:	New Hire is Female (0-1)			Attrition (0-1) x 100	Monthly absences
	(1)	(2)	(3)	(4)	(5)
Hire was referred	0.093			-12.36***	0.73**
	(0.077)			(1.90)	(0.31)
Female X referred				6.81***	-1.31***
				(2.39)	(0.41)
Female				-5.59***	0.46***
				(0.82)	(0.11)
R0		0.037			
		(0.029)			
R50		0.036			
		(0.026)			
R90		0.049			
		(0.030)			
R120		0.041			
		(0.032)			
ERP			0.040*		
			(0.022)		
Observations	3,810	3,810	3,810	14,879	14,879
Mean dep. var.	0.718	0.718	0.718	15.69	1.363

Notes: In columns 1-3, an observation is a grocery worker hired during the RCT. In columns 4-5, an observation is a grocery-worker month during the RCT. Columns 1-4 show OLS regressions and column 5 shows negative binomial regressions. Standard errors clustered by store are in parentheses. In Panel A here, the controls in columns 1-3 are the same as the controls in Panel A of Table 3 except we do not use age controls. In columns 4-5 of Panel A here, the additional controls are the same as in Table 4. In Panel B here, the controls in columns 1-3 are the same as the controls in Panel A of Table 3 except we do not control for gender. In columns 4-5 of Panel B here, the additional controls are the same as in Table 4, plus age controls. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B2: Robustness Check on Comparing Referrals vs. Non-referrals: Adding Store Fixed Effects

Dep. var.:	Attrition (0-1) x 100			Monthly absences		
Method:	Linear Probability Model			Negative Binomial		
	(1)	(2)	(3)	(4)	(5)	(6)
Hire was referred	-7.55***			-0.11		
	(1.24)			(0.29)		
Referred X first 5m		-9.17***			-0.37	
		(1.59)			(0.34)	
Referred X after 5m		-3.73*			0.38	
		(1.95)			(0.64)	
Referred X R50			-11.97***			0.51
			(1.96)			(0.58)
Referred X R90			-6.51***			-0.13
			(2.19)			(0.70)
Referred X R120			-7.18***			-0.34
			(1.89)			(0.35)
Observations	14,879	14,879	14,879	14,879	14,879	14,879
Mean DV if referred=0	15.91		15.91	1.362		1.362
Workers	3796		3796	3796		3796
Mean DV in first 5m if ref=0		17.75			1.152	
Mean DV after first 5m if ref=0		9.100			2.143	
F(R50 vs. R90)			0.07			0.49
F(R50 vs. R120)			0.08			0.20

Notes: This table is similar to Table 4. The difference is we additionally control for store fixed effects. Because we control for store fixed effects, we no longer control for pre-RCT means of store-level variables.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table B3: The Impact of the ERPs on Monthly Absence

Type of workers:	All	All	All	All	Hires	Hires	Inc	Inc
Sample period:	RCT	RCT	Pre &RCT	Pre &RCT	RCT	RCT	RCT	RCT
Coefficients shown:	Treatment dummies		Treatment X RCT period dummies		Treatment dummies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R0	-0.04		-0.19*		-0.01		-0.03	
	(0.10)		(0.10)		(0.16)		(0.11)	
	[0.697]		[0.081]		[0.961]		[0.880]	
R50	-0.04		-0.03		-0.17		0.02	
	(0.11)		(0.11)		(0.17)		(0.13)	
	[0.686]		[0.827]		[0.408]		[0.911]	
R90	0.04		0.05		-0.05		0.07	
	(0.11)		(0.10)		(0.17)		(0.11)	
	[0.700]		[0.628]		[0.772]		[0.628]	
R120	0.07		-0.15		0.01		0.07	
	(0.11)		(0.11)		(0.16)		(0.12)	
	[0.533]		[0.190]		[0.976]		[0.614]	
ERP		0.01		-0.08		-0.05		0.04
		(0.09)		(0.08)		(0.14)		(0.09)
		[0.856]		[0.378]		[0.763]		[0.781]
Store FE	No	No	Yes	Yes	No	No	No	No
Observations	74,188	74,188	203,798	203,798	14,879	14,879	55,953	55,953
Mean DV if ERP=0	1.452	1.452	1.288	1.288	1.329	1.329	1.492	1.492
Workers	10,003	10,003	16,942	16,942	3,796	3,796	5,870	5,870

Notes: This table is similar to Table 5 except the outcome is monthly absences and the specifications are negative binomial instead of OLS. To ensure the likelihood converges, for the year-month of hire dummies, month-years of hire at or before 2002m1 are lumped together. Because the maximum likelihood procedure is slower than OLS, we perform randomization inference using 100 replications instead of 1,000. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B4: Impact of having an ERP on Store-level Outcomes

Dep. var.:	Monthly hires	Log shrinkage rate	Log sales per worker	Log operational profits per worker	Log hours
	(1)	(2)	(3)	(4)	(5)
Panel A: Impact of Having an ERP During RCT					
ERP	-0.128	-0.025	0.020	0.020	-0.012
	(0.112)	(0.024)	(0.015)	(0.021)	(0.015)
Observations	3,016	2,993	2,993	2,989	3,017
Mean DV if ERP=0	1.285	-3.793	9.109	7.530	7.886
Panel B: Diff-in-diff Impact Using Pre-RCT and RCT Periods					
ERP X RCT	-0.222*	-0.017	0.020	0.023	-0.020
	(0.125)	(0.026)	(0.017)	(0.021)	(0.018)
Observations	8,223	5,603	8,182	5,594	5,633
Mean DV if ERP=0	1.144	-3.704	9.048	7.488	7.879

Notes: Standard errors clustered by store are in parentheses. An observation is a store-month. In Panel A, we control for the controls listed in footnote 19, plus region dummies, year-month dummies, and pre-RCT store-level mean of the dependent variable. In Panel B, we control for store dummies and year-month dummies. The shrinkage rate is the share of inventory lost to theft, spoilage, and other reasons, so higher shrinkage is worse. Operational profits per worker are store-level sales minus cost of goods minus wages minus shrinkage. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B5: Demographic Homophily Between Referrers and Referrals

	(1) Age	(2) Female
Age of referrer	0.45***	
	(0.12)	
Referrer is female		0.36**
		(0.14)
Observations	60	84
Mean dep. var.	27.71	0.774

Notes: We control for month-year of hire dummies and whether someone is a cashier. There are fewer observations in column 1 because referrers are missing age if they were hired before the start of the data and do not attrite during the data.

Table B6: The Impact of the ERPs on Attrition: Restrict to Stores with No Referrals Made during the RCT

Type of workers:	All	All	All	All	Hires	Hires	Inc	Inc
Sample period:	RCT	RCT	Pre &RCT	Pre &RCT	RCT	RCT	RCT	RCT
Coefficients shown:	Treatment dummies		Treatment X RCT period dummies		Treatment dummies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R0	-1.01**		-0.93**		-1.07		-1.05***	
	(0.39)		(0.47)		(1.13)		(0.34)	
R50	-0.54		-1.16**		-1.08		-0.47	
	(0.51)		(0.55)		(1.54)		(0.44)	
R90	-1.62***		-1.79***		-3.13**		-1.29***	
	(0.42)		(0.43)		(1.39)		(0.37)	
R120	-1.00**		-1.10**		-3.29**		-0.49	
	(0.47)		(0.48)		(1.40)		(0.41)	
ERP		-1.02***		-1.21***		-1.93*		-0.85***
		(0.35)		(0.39)		(1.05)		(0.29)
Store FE	No	No	Yes	Yes	No	No	No	No
Observations	59,677	59,677	164,860	164,860	11,536	11,536	45,490	45,490
Mean DV if ERP=0	6.677	6.677	5.434	5.434	17.24	17.24	4.362	4.362
Workers	8034	8034	13725	13725	2964	2964	4800	4800

Notes: This table is similar to Table 5 except we restrict attention to workers in stores where no referrals are ever made during the RCT. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix C Data Appendix

Referrals data. Beyond the 88 referrals reported in Section 3.1, there is also one additional referral made that we cannot match to other records. Store managers were not eligible to participate in the ERP, as they have general authority over hiring decisions. Our analysis on the overall attrition impacts of ERPs includes store managers, but results are similar if store managers are excluded.

Table B7: Correlation Coefficients for the Different Dimensions of Heterogeneity

	Log shrinkage rate	Log sales per worker	Log operational profit per worker	Attrition rate	Unemployment rate
	(1)	(2)	(3)	(4)	(5)
Log shrinkage rate	1.00				
Log sales per worker	-0.45	1.00			
Log profits per worker	-0.55	0.86	1.00		
Attrition rate	0.37	-0.26	-0.11	1.00	
Unemployment rate	-0.07	0.03	-0.07	-0.30	1.00

Notes: Correlation coefficients are reported. The five characteristics are store-level means calculated during the pre-RCT period. Correlations are calculated using our worker-month panel during the RCT period (i.e., the correlations are weighted by a store's worker-months during the RCT). The unemployment rate is the 2015 municipal unemployment rate.

Table B8: Heterogeneity in Referral Differences by Different Dimensions of Heterogeneity. DV = Worker Attrites in a Month (x100)

Characteristic:	Log shrinkage rate	Log sales per worker	Log operational profit per worker	Attrition rate	Unemployment rate
	(1)	(2)	(3)	(4)	(5)
Hire was referred	-6.88***	-6.90***	-6.90***	-6.99***	-6.93***
	(1.16)	(1.16)	(1.18)	(1.17)	(1.17)
Referred X Char	2.43***	-0.67	-0.80	1.23*	0.87**
	(0.84)	(1.01)	(1.15)	(0.65)	(0.43)

Notes: Standard errors clustered at the store level are in parentheses. Each column is similar to column 1 of Table 4, with the difference being that we add two regressors: ERP X Characteristic and Characteristic. An observation is a worker-month during the RCT among people hired during the RCT. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B9: Estimating the Impact of ERPs on Attrition Using the Firmwide ERP Rollout in a Difference-in-Differences Design. DV = Worker Attrites in a Month (x100)

	(1)
Control store X Post-RCT rollout	-1.36***
	(0.45)
Mean DV in control stores	6.136
Observations	100,257
Workers	11,193

Notes: This table is similar to column 4 of Table 5 except the data are from the RCT and post-RCT periods (Dec 2015-May 2017). The key regressor is being in a control store (i.e., a store assigned to no ERP for the RCT) interacted with a dummy for the time being in the post-RCT rollout period (i.e., Jan 2017-May 2017). We control for store fixed effects, current year-month fixed effects, and the other controls also included in column 4 of Table 5. The coefficient on the key regressor represents the change in attrition in control stores as a result of the rollout (relative to the change in attrition in treatment stores). "Mean DV in control stores" means the mean attrition in worker-months at stores that were assigned to no ERP during the RCT. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B10: Robustness for Panel B of Table 8

Characteristic: (all normalized)	Log shrinkage rate Higher is worse. (1)	Log sales per worker (2)	Log operational profit per worker (3)	Attri-tion rate (4)	Unemploy-ment rate (5)
Panel A: Restrict to Full-Service Grocery Stores.					
ERP X Characteristic	0.60*	-0.74**	-0.83*	-0.20	0.72**
	(0.33)	(0.35)	(0.47)	(0.27)	(0.28)
Panel B: Add ERP*(Pre-RCT Mean # of Products Offered).					
ERP X Characteristic	0.62**	-0.56*	-0.59	0.02	0.64**
	(0.31)	(0.30)	(0.36)	(0.26)	(0.25)
Panel C: Add ERP*(Pre-RCT Share Products that are Fresh Goods).					
ERP X Characteristic	0.63**	-0.61**	-0.77**	0.10	0.60**
	(0.31)	(0.28)	(0.32)	(0.23)	(0.24)
Panel D: Add ERP*(Pre-RCT Mean # of Total Checkouts).					
ERP X Characteristic	0.66**	-0.58*	-0.62*	0.03	0.64**
	(0.33)	(0.30)	(0.36)	(0.25)	(0.25)
Panel E: Add ERP*(Pre-RCT Mean Head Count).					
ERP X Characteristic	0.63**	-0.55*	-0.60*	0.03	0.62**
	(0.32)	(0.30)	(0.36)	(0.25)	(0.25)
Panel F: Add ERP*Store Square Meters.					
ERP X Characteristic	0.61**	-0.55*	-0.57	0.02	0.63**
	(0.30)	(0.30)	(0.36)	(0.24)	(0.25)
Panel G: Add ERP*(Dummy for Lidl Store Nearby).					
ERP X Characteristic	0.65**	-0.56*	-0.63*	0.07	0.67***
	(0.30)	(0.29)	(0.35)	(0.24)	(0.25)

Notes: This table is a robustness check to Panel B of Table 8. It shows how the key interaction term coefficients change as either the sample is restricted (as in Panel A) or where we also include regressors for an additional characteristic and the interaction of ERP times that characteristic (Panels B-G). In Panels B, C, D, and F, the additional characteristic is normalized. Panel D is robust to looking separately at manned checkouts or self-checkouts. * significant at 10%; ** significant at 5%; *** significant at 1%

Table B11: Overall ERP Impacts on Attrition: Split by Above/Below Median Store Performance and Unemployment

Characteristic: (all binarized)	Shrinkage rate Higher is worse. (1)	Sales per worker (2)	Operational profit per worker (3)	Attri-tion rate (4)	Unemploy-ment rate (5)
Below Median	-1.55**	-0.75	-0.27	-1.39***	-1.39***
	(0.60)	(0.54)	(0.51)	(0.43)	(0.46)
Above Median	-0.32	-1.22**	-1.53***	-0.95*	-0.22
	(0.43)	(0.49)	(0.43)	(0.54)	(0.44)

Notes: Each entry is similar to column 2 in Table 5, with the difference that we are splitting by above or below median of the store performance and unemployment variables. * significant at 10%; ** significant at 5%; *** significant at 1%

Age. Although we find a significant difference between referral and non-referral hires in age, we do not control for age in our main regressions. Date of birth is only available at the time of hire or attrition (and is not available in monthly payroll records), causing age to be missing for workers joining the firm before 2014 who never attrite. This causes age to be missing in a fashion that is correlated with attrition (i.e., people with missing age are more likely to never attrite). However, results are robust if we control for age while restrict attention to individuals hired during our data (who thus consistently have age data). Age is missing for 24 workers hired during the RCT.

Gender. When worker gender is missing, we impute it based on name by using gender-specific endings that exist in the language of the country where our firm is based. After imputation, gender is missing for one grocery worker hired during the RCT.

Race. The firm's personnel data do no contain variables for race or nationality, as racial/ethnic heterogeneity is very limited in the country we study.

Attrition codes. Employees receive up to 4 attrition codes, which are assigned by the store manager. We classify someone as "fired" if any of the 4 codes indicate a termination for cause. Exit codes are missing for many workers exiting before 2015m4. In contrast, starting in 2015m4 and after, exit codes are missing for less than 4% of terminations. Thus, we restrict our analysis of quits and fires to 2015m4 and after.

Multiple spells. Some workers in our data have multiple spells, where they return to working at the firm after a break in the record. In our population of workers, it is not uncommon to take breaks in employment. When a worker has multiple spells, we only count the final attrition event, and not the earlier ones. In addition, if a worker has a date of hire which is more recent than the current date, we assign the date of hire to that worker's earliest date on record. Our results are similar if we instead consider only the most recent spell.[16] For referrals made in the RCT, we impose that referral spells be counted so as to not exclude referrals, for reasons of statistical precision. That is, for a small number of people who are hired as a referral despite having an earlier spell, we count those as separate spells. Results are similar if we do not do this.

[16]That is, the results are similar if we do not assign hire dates to the earliest date on record, and instead merely drop observations which have negative tenure.

Appendix D Theory Appendix

D.1 Formal Model

We present a simple model to fix ideas on how ERPs affect employee outcomes, both directly in terms of affecting referrals and indirectly via creating respect. The model takes up three ideas. First, an ERP provides the firm with more precise signals about a candidate's match quality (Simon & Warner, 1992; Brown *et al.*, 2016; Dustmann *et al.*, 2015). In contrast to these models, we assume that the information resides with an employee instead of the overall firm. Second, workers have social preferences toward friends they may refer (Bandiera *et al.*, 2005, 2008, 2009; Beaman & Magruder, 2012; Rubineau & Fernandez, 2015; Ashraf & Bandiera, 2018). Third, and potentially most important, our model incorporates workers caring about being respected (Ellingsen & Johannesson, 2008). More precisely, employees who are pro-social want the firm to think that they are pro-social.[17]

Set-up. The firm employs an incumbent worker, I, and wants to hire an additional worker. Following Ellingsen & Johannesson (2008), I can be of two different types $\Sigma \in \{0, \sigma\}$, where $0 < \sigma < 1$. Type Σ represents the social preferences of I toward an individual, N, of their social network, who could be referred for the job opening. In our model, Σ reflects altruism, but it could also represent reputational considerations. For simplicity, we assume that $\Sigma = \sigma$ for sure, but assume that I initially believes the firm to believe that $\Sigma = 0$. This simplifying assumption is discussed in Appendix D.3.

Incumbent I observes N's match quality m, and chooses whether to refer them, $R = \{0, 1\}$. The firm observes m only after the worker is hired. The match reflects that a particular job suits some people better than others (e.g., some people are better than others at interacting with customers), and we assume $m \sim F(m)$, with the pdf denoted by $f(m)$. Making a referral requires a cost of effort $k > 0$. Furthermore, I has an outside option, $\varepsilon \sim G(\varepsilon)$, and decides whether to stay in the firm or leave it. The timing is:

1. I believes that there is some chance that nature informs the firm via a private signal that workers have $\Sigma = \sigma$.
2. I believes the firm decides whether to have an ERP. I does not know it is an RCT.
3. If there is an ERP, I has one network contact, N, and decides whether to refer them.
4. I decides whether to leave the firm.

Incumbent's Payoffs. I gets utility from three sources: (1) the ERP bonus, $b \equiv \widetilde{b} - k$, (2) N's utility, $U^N(\cdot)$, and (3) her belief, $\hat{\Sigma}$, about the firm's esteem for her. Letting $U^I(R = 1)$ and $U^I(R = 0)$ be utility from making or not making a referral, respectively, we have:

$$U^I(R \;=\; 1) = (1 - \Sigma)b + \Sigma U^N(R = 1) + B(\hat{\Sigma}) \tag{5}$$

$$U^I(R \;=\; 0) = \Sigma U^N(R = 0) + B(\hat{\Sigma}) = B(\hat{\Sigma}), \tag{6}$$

[17] We assume the worker cares about being regarded as pro-social because (1) it is realistic for our setting; (2) referral models naturally contain altruism so it is simple to include the worker caring about this; and (3) doing so follows Ellingsen & Johannesson (2008). The model's logic would still hold if the worker cared about the firm thinking it had another trait about which the firm credibly signals a positive belief by having an ERP (e.g., the firm would not want to have an ERP for a worker with bad judgment).

Here, N's utility depends on the job match, m, and job overall attractiveness, q, with $U^N(R=1) = m + q$. Match m represents all person-specific rewards from the job. Job attractiveness, q, is the same for all workers, and may depend not only on the wage but also on its non-pecuniary aspects, such as working conditions and reputation in society. In (6), we normalize N's utility if he is not referred to 0.

The third term, $B(\cdot)$, represents I's benefit from feeling esteemed or respected (Ellingsen & Johannesson, 2008). The term, $\hat{\Sigma}$, is I's belief of the firm's belief about Σ. We assume that $B(\hat{\Sigma}) = \hat{\Sigma}$ for $\Sigma = \sigma$ and $B(\hat{\Sigma}) = 0$ for $\Sigma = 0$, i.e., I's utility increases in firm beliefs if she is altruistic, but she doesn't care what the firm thinks if she is selfish. We assume that I's prior is $\hat{\Sigma} = 0$, i.e., I initially believes that the firm considers her to be selfish.

Firm Profits. The firm's payoff from a referral is $\pi = m - \widetilde{b}$. Bad matches are expensive for the firm, because the firm has to spend resources on training costs. With the share of referrals in the total number of employees denoted by r, the expected profit of the firm with an ERP is:

$$\pi = r\Big(E[m|m > m^*] - \widetilde{b}\Big) + (1-r)E[m] - cPr(Q),$$

where $E[m|m > m^*]$, and $E[m]$ are the expected quality matches of the referred and non-referred workers, respectively; c is the cost of attrition for an incumbent worker; and $Pr(Q)$ is the probability that the incumbent worker exits and is equal to $1 - G(\sigma)$.[18] In contrast, firm profits without an ERP are $E(m) - c(1 - G(0))$.

Our model yields five predictions. We provide intuition here and proofs in Appendix D.2. The model's simplifying assumptions are discussed more in Appendix D.3.[19]

Prediction 1. *Higher referral bonuses will increase referrals.*

Prediction 2. *Referrals will be of higher quality than non-referrals. However, as referral bonuses increase, the quality of referrals decreases.*

Referrals are higher quality because I can observe N's match quality, and I prefers to make a referral when m is higher. There is no information on non-referrals so they are hired at random. As b increases, I is willing to refer someone who is less suited for the job, and average referral quality decreases.

Prediction 3. *Having an ERP increases retention. This should occur even in store where no referrals are made.*

Having an ERP makes I feel respected, as she believes that the firm would only choose to have an ERP if it believed that I had positive social preferences ($\Sigma = \sigma$). This makes I less likely to quit, and because it does not work through referrals, occurs even in stores where no referrals are made. Note that if $\Sigma = 0$, I would make referrals irrespective of m.

[18] The term, $Pr(Q)$, is a reduced form of having an incumbent with larger m than a potential new hire.

[19] The short-cuts discussed are: (i) because of the static game, the bonus is paid upon hire and not after five months; (ii) social preferences only relate to a potential referral (and not intrinsically to the firm); (iii) the worker can only have two types; (iv) the worker's belief updating is non-Bayesian.

Prediction 4. *As long as the referral bonus is not too large, having an ERP increases firm profits. The relationship between referral bonuses and firm profits from hiring referrals (vs. hiring non-referrals) is ambiguous.*

Profits increase through two channels. First, having an ERP enables referrals, allowing the firm to exploit I's private information—this improves profits if b is not too large. Second, profits benefit from I staying longer. Turning to how the bonus level affects profits from referrals, on one hand, larger bonuses increase referrals, who are valuable relative to non-referrals. On the other hand, larger bonuses cost money and lower average referral quality.

Prediction 5. *More referrals will be made for attractive jobs than for less attractive jobs. Suppose that* $f'(m^*) < 0$, *which occurs if referrals are few. Then, the more attractive the job, the more responsive are referrals to bonuses.*

The first sentence reflects that I has social preferences toward potential referrals. For the third sentence, note that if a job has very low q and referrals are rarely made, then I is unlikely to be marginal, and increased bonuses may do little to push I to make a referral. However, for a higher quality job, I is more likely to be marginal.

Predictions 1-4 are tested using the RCT. Prediction 5 is tested using surveys and the firmwide ERP rollout.

D.2 Solving the Model

We first show that there exists a separating equilibrium where the worker believes the firm will choose to have an ERP if the firm received a private signal that I is altruistic, but that the firm will not have an ERP if it does not receive such a signal. In contrast, there is no separating equilibrium in the opposite direction, i.e., where the firm would have an ERP if and only if it did not receive such a signal. We then derive the five predictions within the context of the separating equilibrium.

Let $t \in \{0, 1\}$ denote whether the firm receives a private signal that the worker is altruistic, and let $ERP \in \{0, 1\}$ denote whether the firm has an ERP. Further, let m^* denote the threshold match quality where I makes a referral if $m > m^*$; likewise, let ε_0^* be the threshold value where I will quit the firm if her ε is higher and when no ERP is used, and let ε_1^* be the threshold value under an ERP.

We show it is a Perfect Bayesian Equilibrium where the worker believes the firm chooses $ERP = t$; where $m^* = -\frac{1-\sigma}{\sigma}b - q$; and where $\varepsilon_0^* = 0$ and $\varepsilon_1^* = \sigma$.

To show this, we first derive the optimal behavior of I given the firm's strategy. If there is no ERP, the firm believes that the worker is selfish, so I's utility if she stays at the firm is $B(\hat{\Sigma}) = B(0) = 0$ compared to ε at the outside option, so $\varepsilon_0^* = 0$. In contrast, if there is an ERP, $\hat{\Sigma} = \sigma$, so $\varepsilon_1^* = \sigma$. Under an ERP, I chooses where to make a referral, which occurs when $(1-\sigma)b + \sigma(m+q) > 0$, yielding $m^* = -\frac{1-\sigma}{\sigma}b - q$.

Now, we check that the firm's strategy is optimal given the worker's strategy. If $t = 1$, the firm's profits from having an ERP are
$r\big(E[m|m > m^*] - \widetilde{b}\big) + (1-r)E[m] - c(1 - G(\sigma))$, which is larger than $E(m) - c(1 - G(0))$, provided that the referral bonus $\widetilde{b}$ is not too large. In contrast, if $t = 0$, the firm thinks

there is no retention benefit of having an ERP, as the firm thinks the worker is selifsh in the absence of a good signal, and selfish workers don't care about the firm's esteem. Specifically, the firm's profits from having an ERP are $E(m) - r\widetilde{b} - c(1 - G(0))$, which are lower than the profits without an ERP of $E(m) - c(1 - G(0))$.

It is also easily seen that there cannot be a separating equilibrium where the worker believes the firm chooses $ERP = 1 - t$. When $t = 0$, the firm believes there is no retention benefit to having an ERP, because selfish workers don't care about being esteemed. The firm has that $\pi(ERP = 1) = E(m) - r\widetilde{b} - c(1 - G(0))$, which is less than $\pi(ERP = 0) = E(m) - c(1 - G(0))$. We now turn to showing the five predictions.

Prediction 1. *Higher referral bonuses will increase referrals.*

Given the firm launches an ERP program with the bonus value $\widetilde{b}$, the employee utility functions will be as follows:

$$U^I(R = 1) = (1 - \sigma)b + \sigma(m + q) + B(\sigma) \tag{7}$$

$$U^I(R = 0) = B(\sigma) = B(\sigma) \tag{8}$$

Thus, the probability, r, that the employee will refer their friend is equal to:

$$r = Pr(U^I(R = 1) > U^I(R = 0)) = Pr((1 - \sigma)b + \sigma(m + q) > 0) = 1 - F(m^*),$$

where $m^* = -\frac{1-\sigma}{\sigma}b - q$. To analyze how bonuses affect the share of referral made, we have:

$$\frac{\partial r}{\partial b} = f(m^*) \cdot \frac{1 - \sigma}{\sigma}$$

which is positive.

Prediction 2. *Referrals will be of higher quality than non-referrals. However, as referral bonuses increase, the quality of referrals decreases.*

The average match quality of a referred worker is equal to $H^r \equiv E[m|m > m^*]$, whereas the average match quality of a non-referred worker is $E[m]$. Thus, $H^r \geq E[m]$ for any m^* in support of $F(\cdot)$. Because $\frac{\partial m^*}{\partial b} = -\frac{1-\sigma}{\sigma} < 0$, we have $\frac{\partial H^r}{\partial b} < 0$. Intuitively, as b increases, E is willing to refer someone who is less suitable for the job, and average referral quality decreases.

Prediction 3. *Having an ERP increases retention. This should occur even in store where no referrals are made.*

We separately consider the retention of incumbent and new workers. As a result of having an ERP, the incumbent worker believes the firm believes that $\Sigma = \sigma$. Thus, they become more likely to stay. This occurs even in stores where no referrals are made because the mechanism involves respect, not referrals. Specifically, the probability of an incumbent worker staying is $G(B(\hat{\Sigma}))$, which is increasing in $\hat{\Sigma}$. Turning to the new worker, no referrals occur without an ERP, and an ERP generates positive referrals because m is continuous. Thus, since referrals are of higher than non-referrals (Proposition 2), having an

ERP increases retention among the new worker. Since workers are either an incumbent or a new worker, overall retention increases.

Prediction 4. *As long as the referral bonus is not too large, having an ERP increases firm profits. The relationship between referral bonuses and firm profits from hiring referrals (vs. hiring non-referrals) is ambiguous.*

We begin with proving the second sentence first. In the Prediction 3, we have shown that an ERP increases retention, thus it has positive indirect effect on the firm's profit. The direct effect is positive, $H^r - \widetilde{b} > E[m]$, as long as the referral bonus, $\widetilde{b}$ is sufficiently small. To analyze how the size of the referral bonus affects profits from referrals we have:

$$\frac{\partial \pi}{\partial \widetilde{b}} = \frac{\partial r}{\partial \widetilde{b}} \left(H^r - \widetilde{b} - E[m] \right) + r \left(\frac{\partial H^r}{\partial \widetilde{b}} - 1 \right), \tag{9}$$

where the first term is positive (provided $\widetilde{b}$ is relatively small), and the second term is negative.

Now consider the overall impact of an ERP on firm profits. That is, compare $r\big(E[m|m > m^*] - \widetilde{b}\big) + (1-r)E[m] - c(1-G(\sigma))$ with $E(m) - c(1-G(0))$. Here, $c(1-G(\sigma)) < c(1-G(0))$ and $r\big(E[m|m > m^*] - \widetilde{b}\big) + (1-r)E[m] > E[m]$ provided that $\widetilde{b}$ is sufficiently small. Therefore, having an ERP increases firm profits.

Prediction 5. *More referrals will be made for attractive jobs than for less attractive jobs. Suppose that $f'(m^*) < 0$, which occurs if referrals are few. Then, the more attractive the job, the more responsive are referrals to bonuses.*

To analyze the relevance of job attractiveness for the decision to refer, note that $\frac{\partial r}{\partial q} = f(m^*)$, which is positive because people value their friends and to refer them for better jobs. To see how job quality affects the responsiveness of referrals to bonuses, note that $\frac{\partial^2 r}{\partial b \partial q} = -f'(m^*)\frac{1-\sigma}{\sigma}$. Thus, if $f'(m^*) < 0$, then $sgn\big(\frac{\partial^2 r}{\partial b \partial q}\big) = -sgn(f') = +$. This seems likely to hold if only a minority of workers make referrals.[20]

D.3 Discussion of Model Assumptions

The model simplifies many aspects of reality. This subsection discusses our model assumptions.

The referral bonus is paid upon hire. In reality, the referral bonus is only paid partially upon hire, with most of the bonus paid only if the referrer and referral stay five months. If this encourages both parties to stay, this will only further accentuate the prediction that referrals stay longer, as well as that incumbent workers stay longer under ERPs. The model also is static, whereas reality is dynamic. Thus, m should be interpreted as outcomes over time at the firm instead of outcomes at one time. Thus, referral and non-referral hires also become incumbents capable of making referrals, so our predictions on the retention of incumbents actually cover the retention of all workers.

[20] E.g., if m has a normal (or log-normal) distribution, if the quality cutoff m^* is above the argmax of f, then $f' < 0$.

The incumbent has social preferences toward their friend, not toward the firm. We assume that the incumbent worker only has potential social preferences toward their friend, not toward the firm. If the worker had potential social preferences toward the firm, all predictions of the mode would be the same. The key feature of the model is that having an ERP involves delegating the hiring decision to the incumbent worker, and doing so is only valuable if the worker cares about the match quality of a referred worker. The incumbent worker may do so because they care about their friend (and the firm also happens to benefit from higher match quality) or because they directly care about the firm. In our model, the firm also has zero outside information outside of potential referrals.[21] Also, while we assume that the friend and firm equally benefit from match quality for simplicity, this assumption is not required.

The level of the referral bonus and respect. We assume that a worker's true social preferences can only take two values, and we do not analyze the worker updating their sense of respect in reflection of the particular value of $\widetilde{b}$. If worker social preferences can take many values, then choosing higher values of $\widetilde{b}$ could communicate that the firm has a particularly high belief about the value of altruism for a worker. On the other hand, outside our model, choosing a very high value of $\widetilde{b}$ could communicate other messages, such as that making referrals is an unpleasant task (Bénabou & Tirole, 2003). Thus, because of these competing effects, we set this aspect aside. One can also examine empirically whether larger referral bonuses tend to have larger impacts on incumbent workers. Conditional on having a referral bonus, we do not observe a clear relation between the level of the bonus and incumbent retention effect.

Worker's perception of firm belief updating. The incumbent worker believes that the firm initially believes that the worker has $\Sigma = 0$ for sure. After seeing the ERP, the incumbent worker recognizes that the firm would not have the ERP unless the firm recognized that $\Sigma = \sigma$. Such belief updating is not consistent with Bayes' Rule, since a Bayesian will never update if they believe that the initial value of some event occurring is 0. This assumption is made entirely for simplicity of the model. One could alternatively assume that the worker believes that the firm believes that the worker has $\Sigma = \sigma$ with a 50% probability, and that seeing the ERP leads the worker to update to believe that the firm believes that $\Sigma = \sigma$ for sure.

Appendix E Documents Used in the RCT and in the Firmwide ERP Rollout

We first present the letters given to workers in the RCT. These are followed by Figure E1, which shows the posters that were used in the 2017 firmwide ERP rollout. The only information redacted in these documents is firm identifiers (i.e., firm name or logo); the name of the country where the firm operates; and employee names and contact information.

[21] Because of this, the decision to fully delegate hiring to incumbent workers via referrals is a prediction of the model, not an assumption.

[FIRM logo]

Dear Employee,

Over the last couple of years, FIRM has dedicated a lot of its attention and resources to ensuring the quality of its products and services, as well as investing in the development and renovation of its stores. We believe that we are on the right path to becoming one of the best and most appealing grocery stores in COUNTRY!

In order to become a market leader, we continuously seek out the best employees, who can become permanent members of our large team. Right now, we also invite you to join our recruitment process and to recommend a friend, a relative, or an acquaintance for a job at one of our FIRM stores.

How can I recommend my friend, relative, or acquaintance?

1. Find a candidate who, in your opinion, would fit a vacant position in your or any other stores in which we are looking for employees (information on new positions available will be provided by your store manager).
2. Call and register* your recommended candidate.
   *register by calling us at XXX (YYY, regional human resources manager)
3. Send your recommended candidate to a store where positions are available.

We believe that together with your help we can find professional employees and create a friendly work environment for every one of you!

Best wishes,
[FIRM logo]

Notes: This is a translated and redacted version of the letter employees received in the R0 group during the RCT.

[FIRM logo]

Dear Employee,

Over the last couple of years, FIRM has dedicated a lot of its attention and resources to ensuring the quality of its products and services, as well as investing in the development and renovation of its stores. We believe that we are on the right path to becoming one of the best and most appealing grocery stores in COUNTRY!

In order to become a market leader, we continuously seek out the best employees, who can become permanent members of our large team. Right now, we also invite you to join our recruitment process and to recommend a friend, a relative, or an acquaintance for a job at one of our FIRM stores. If they get hired, the person who recommended them (you) will receive a **bonus!**

How can I recommend my friend, relative, or acquaintance?

1. Find a candidate who, in your opinion, would be suitable for a vacant position in your or any other stores in which we are looking for employees (information on new positions available will be provided by your store manager).
2. Call and register* your recommended candidate.
   *register by calling us at XXX (YYY, regional human resources manager)
3. Send your recommended candidate to a store where positions are available.
4. **If your recommended candidate:**
   - Fits the requirements of a position
   - Is hired and stays in employment for at least 5 months

We will award you a bonus €ABC! (after tax)

IMPORTANT!

- The bonus is awarded after taxes are deducted. A part of this bonus – **€**15 – you will receive after your candidate gets hired (included in your next month's salary), while the rest of this bonus will be given 5 months after you and your recommended employee have worked through that period (5 months) at our company.
- Please be aware that the whole bonus will be paid out only if your recommended candidate is hired and only after they have completed 5 months of employment at our company.
- The bonus and its payouts will be organized directly by the Human Resources department; therefore, it is very important to call and register your candidate before you send them to a store.

We believe that together with your help we can find professional employees and create a friendly work environment for every one of you!

Best wishes,
[FIRM logo]

Notes: This is a translated and redacted version of the letter employees received in the R50, R90, and R120 groups during the RCT. The amount ABC was 50, 90, or 120 euros depending on treatment.

Figure E1: Posters Used during the 2017 Firmwide ERP Rollout

Notes: This is a translated and version of the posters during the 2017 firmwide ERP rollout (with identifying firm information redacted). From left to right, the posters are for grocery store workers, logistics workers, and food production workers, respectively. Except for the different pictures, the posters are the same.

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