Worker Valuation of Retirement Benefits*

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Abstract

How do workers value retirement benefits relative to wages and what impact do these benefits have on firm hiring? We find that dollars paid in employer contributions to 401(k) plans have nearly double the effect on a firm's recruiting success than dollars paid in wages. However, there is significant heterogeneity in the effect of employer contributions across the income and age distribution: the effect is driven primarily by high-income and higher-age occupations. Since firms endogenously select their compensation bundles to attract their desired workers, we use two novel instruments to identify the results: 1) IRS mandated non-discrimination testing of retirement plans and 2) corporate policies of national wage setting. We then develop and estimate an on-the-job search model which shows that the average worker requires only a 0.25 percentage point increase in employer contribution dollars to offset a 1% decrease in wages. Moreover, moving from a job with no retirement plan to a job with a plan increases valuations by the same magnitude as 2% increase in wages. Again, retirement valuations are positively correlated with salary. We confirm the channel in an online survey setting: participants are willing to give up total pay to get a higher employer match to get a non-matching employer-sponsored 401(k). The results imply that 80% of firms could improve their probability of a job offer being accepted by increasing 401(k) contributions.

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1 Introduction

From 2010-2019, employers in the United States spent an aggregate 1.3 trillion dollars on contributions into defined contribution (DC) retirement plans such as 401(k) and 403(b) accounts. Defined contribution plans are important determinants of household disposable income and consumption over the life-cycle, and the wealth accumulated in these accounts is an increasingly important source of household funds for retirement. According to the 2016 Survey of Consumer Finance, the median household holds 76 percent of their total (non-real estate) wealth in DC retirement accounts. Given the importance of DC plans for households savings, wealth accumulation, and firm costs, a large body of research has focused on how employees save and invest in DC retirement plans.[1]

There is less understanding of how employees value the plan as a job feature and how DC retirement plans affect equilibrium labor market behavior. Several studies have shown that many 401(k) participants do not take full advantage of employer matches (Mitchell et al. (2007), Engelhardt and Kumar (2007), Choukhmane et al. (2022)). On the other hand, there is conventional wisdom amongst human resource professionals that retirement benefits are an essential tool to attract talent.[2] Moreover, policymakers and regulators value these plans substantially, as revealed by the increasingly large tax expenditure that these plans represent.

In this paper we measure both how workers value a dollar of retirement contributions, relative to a dollar of wages, and the impact of retirement contributions on labor market flows. First, we use a revealed-preference approach and instruments for exogenous wage and benefit changes to measure how wages and retirement benefits affect a firm's recruiting success. We use data on worker transitions across firms to show that – for the average job – one dollar increase in employer contributions to DC retirement accounts has nearly twice the effect on recruiting success as a one dollar increase in wages. Second, we design and conduct an online survey experiment to show that, consistent with the results in part one, most workers are willing to take a lower-paying job when it offers either higher employer contributions to its DC plan or when it offers a DC plan at all. Third, we develop and estimate on on-the-job search model in which we confirm that – at the equilibrium – the majority of workers are willing to give up some total compensation to get a larger share of

[1]For these various issues, see Gomes et al. (2018), Autor et al. (2020), Sialm et al. (2015), Parker et al. (2022), Carroll (2000), Bernheim et al. (2015), Choukhmane (2019), Choi et al. (2004).

[2]See Wasick (2016), Weber (2022), Whalen and Tergensen (2022), Miller-Merrell (2013)

compensation as a retirement benefit. We also show in a counterfactual exercise that 80 percent of firms in our sample could have improved their recruiting outcomes if they increased retirement contributions, consistent both with the steady increase in benefits over the period studied and also with regulatory constraints on benefit plan equality that make changes to retirement plans costly. In the following paragraphs, we lay out our data, methods, and findings in more detail.

In the first part of the paper, we measure the effect of wages and retirement benefits on firm recruiting success. To do so, we construct a novel data set which merges 1) 30 million online job postings from Lightcast (formerly Burning Glass Technologies), 2) 83 million online resumes, also from Lightcast, and 3) detailed financials on retirement plans from regulatory filing Form 5500 for every U.S. company with a retirement plan. Together, these data link information typically only available through proprietary or administrative access: information on a firm's hiring success (inferred from the resumes, which enable us to see whether a posted vacancy is filled), a job's posted wage (from the online job postings), and the retirement benefits available to workers in each job (from the regulatory filings). The final estimation sample represents over half a million worker transitions to 24,000 firms and 150,000 occupation by CBSA groups from 2010-2019.

Ideally, one could regress job choices on a measure of wages, retirement, and other benefits and estimate directly worker preferences for each type of compensation. However, both wage setting and benefit policy suffer from an endogeneity concern: the way that firms set wages and retirement contributions is likely to be correlated with unobservable firm characteristics that may also be correlated with how attractive the firm is to job-seeking workers.[3] We address this concern using two novel instruments.

First, we use IRS mandated non-discrimination testing (NDT) as an instrument for firm retirement policy. Each year, firms that offer DC retirement plans must undergo this test to show that their plan does not disproportionately favor "highly-compensated employees." We confirm that, following failure, plans increase their effective contribution rate by approximately half a percentage point relative to non-failers who are similar on observables.The identifying assumption is that, conditional on observables, NDT failure is orthogonal to changes in the firm's recruiting ability over time. Consistent with this assumption, we show that firms that fail NDT do not adjust their wages, healthcare benefits, or the composition of their targeted hires in job postings following failure.

[3] See for example, Sockin (2021), Sorkin (2018), Maestas et al. (2018).

The second instrument is the corporate policy of national wage setting. This policy induces exogenous variation in wages at the occupation and geographical level. First documented by Hazell et al. (2022), approximately 30-40 percent of firms follow a policy of setting occupational wages nationally. That is, rather than tailoring wages to local labor market conditions, they offer the same wage to all workers within an occupation across the country. Firms that follow this policy have 1-3 percent higher wages on average.[4] For the firms that follow this policy, we construct an instrument that measures how much an occupation by CBSA specific wage is pushed up, relative to the CBSA and occupation average, due the firm being a national wage setter. The identifying assumption is that national wage setters' other job features that attract workers are not affected by year to year deviations in the wage offered due to national wage setting. Consistent with this assumption, national wage setting is uncorrelated with most observable firm characteristics. Moreover, healthcare and retirement benefits are not significantly correlated with national wage setting.

The instrumented results show that within a firm and occupation by CBSA job market, on average, an extra dollar of retirement contributions has twice the effect on the likelihood of a firm successfully filling a position than an extra dollar of wage. Specifically, We find that a one percent increase in wages increases recruiting success by 1.4 percent while an equivalent dollar increase in employer retirement contributions increases recruiting success by 2.7 percent. This large value of benefits is driven primarily by workers in high-income and higher-age occupations. An equivalent dollar increase in retirement contributions has nearly three times the effect on the recruiting success of a firm when looking only at the higher income and older occupations. For lower age occupations, retirement dollars have one-third the effect of wages. Occupations which are female-dominated have a similar sensitivity to retirement relative to wages as those that are male-dominated.

Following this first portion of the paper that infers workers' valuation of retirement benefits by revealed preference, in the second part of the paper, we use on-line survey experiments to directly measure workers' reported choices and infer from these their valuation of retirement benefits. We find that the stated preferences imply valuations that are consistent with those implied by revealed preferences. We recruit 1,600 online survey participants and measure their willingness to pay

[4]The pattern of higher wages holds at the firm level, controlling for industry fixed effects, and at the occupation by CBSA level, controlling for industry by occupation by CBSA fixed effects.

for varying levels of retirement benefits. To measure willingness to pay, we show participants side-by-side job offers which are identical other than the level of wages and retirement benefits offered.[5] The discrete choice framework allows us to flexibly estimate the distribution of willingness to pay measures using maximum likelihood estimation. We also design the survey to show choices that are strictly dominated, thus we can measure and correct for inattention. We test six retirement related conditions in total, which measure the willingness to pay both for the availability of a 401(k) plan at the job (the extensive margin) and for different levels of employer matching contributions (the intensive margin).[6]

The survey results show that the majority of workers, 50 to 80 percent, depending on the condition, will choose a job that offers better retirement benefits, even when that job pays lower total compensation, *inclusive of the match* and *net of tax differences*. In the conditions that test the intensive margin, or how large of a dollar match the company offered (versus a plan with no match), participants were willing to give up approximately half a percent in total compensation for each percentage point increase in the employer match. The implied willingness to pay is 1.5 percent of total compensation to get a 401(k) with a 3 percent match. In the condition that tested the extensive margin, or whether or not the job offered a 401(k) plan at all, participants were willing to pay about 3.4 percent of total compensation to get a plan, even when it offered no match. These results are consistent with the finding of our first main analysis of actual job flows which implies that most job-seekers value retirement dollars roughly two times as much as they value wage dollars.

In order to understand how these valuations of retirement contributions affect where people choose to work, in the third part of the paper we develop and estimate an on-the-job search model. Similar to Burdett and Mortensen (1998), we assume workers make binary choices over two jobs that offer different wages and different idiosyncratic firm-worker specific match values. As in Sorkin (2018), Bonhomme and Jolivet (2009) and Hall and Mueller (2018) compensation includes non-wage benefits, and we further allow non-wage benefits to be valued differently from wages on both the intensive and extensive margins. Workers have indirect utility over wages, retirement, healthcare, other amenities, and their idiosyncratic match values. We use the search model to estimate retirement valuations (for a subset of workers) from their revealed preference and then

[5]The experimental design is similar to Mas and Pallais (2017).

[6]We also test one condition that elicits willingness to pay for remote working capability, in order to compare with other estimates of worker valuation of flexibility, such as Mas and Pallais (2017) and Wiswall and Zafar (2018).

show how retirement benefits affect where people choose to work, relative to wages and other benefits. The model is identified from the net flows of workers between firms and measurable wage, healthcare and retirement differentials between firm pairs.

The average worker in the estimation sample is willing to give up one percent of wage (550 dollars on average) to get just a 0.25 percentage point increase employer in retirement contributions (110 dollars on average). Strikingly, about 75 percent of the distribution of workers is willing to give up some of total compensation to get a higher retirement benefit. The remaining 25 percent, who also tend to be lower income, need larger compensating differentials; total compensation must increase if the wage decreases for those workers. On the extensive margin, the average worker is willing to give up about 2 percent of wages to get a 401(k) plan, which is close in magnitude to the survey estimates. This estimate is also increasing in income, though 90% of workers place a positive value on the availability of the plan.

The model differs from the revealed preference results in two distinct ways, yet produces remarkably similar results to the revealed preference estimation. First, the model is estimated on a specific subset of job-switchers whose compensating differentials are primarily driven by firm-specific characteristics. Specifically, we estimate the model only on transitions within occupation, CBSA, and industry. This eliminates drivers of job change due to career or location changes. Second, the model estimation allows us to directly estimate the weight workers place on retirement and other non-retirement, non-healthcare benefits *separately*. While the instrumental variables estimates are at the firm-level, the model is estimated from observable compensation differences *between firm pairs*. Combining information on hundreds of firm pairs within an industry by occupation group, the average weight placed on each part of compensation as well as the residual or "amenity" difference between firms for workers in that group are each separately identified. We also validate the model by using the NDT instrument. We show that firms that fail NDT change their retirement following the failure, but that the average difference in amenity valuations in the industry by occupation group does not change. Hence, the estimated amenities term is not picking up changes in retirement contributions.

The results have implications for both firm compensation setting policy and regulation of DC retirement plans. First, our results indicate that 80 percent of firms in the estimation sample could have improved their average recruiting success (across all occupations) if they shifted compensation from wages to employer contributions to DC plans. We obtain these results by conducting a counterfactual exercise in which one firm a time increases either wages or retirement contribution dollars by one percent and then calculate their new unconditional probability of having an offer accepted based on the corresponding estimated valuation weights for each type of worker they are trying to hire. This exercise also shows that all firms that do not offer retirement plans (30 percent in-sample) could improve their recruiting success if they offered a 401(k) plan, holding everything else constant. Ignoring for now the regulatory and set-up costs associated with increasing retirement contributions, dollar for dollar, increases in retirement contributions have two to three times the effect on recruiting success as wages, depending on the estimate used. In other words, it would take a two to three percent increase in wage dollars to induce that same change in recruiting success as a one percent change in employer contribution dollars.[7] However, the regulatory constraint of non-discrimination testing makes increasing retirement contribution prohibitively costly for most firms.

Changes in firm retirement policy would have disparate effect on workers across the income distribution. Because higher-income workers place a higher value on retirement contributions, more generous retirement offerings provide larger gains to higher income workers while doing relatively little for workers on the lower end of the income distribution. Due to the structure of NDT, retirement benefits cannot vary across workers; firms must offer the same policy of contributions to everyone. Hence NDT places a binding constraint on any firm that employs workers with differing valuations of retirement. Firms are unable to tailor these benefits to worker preferences and must cater to the majority, which, holding the income distribution constant, shapes compensation in a way that tends to favor higher income workers. In ongoing work, we use the model and framework to assess the welfare implications of non-discrimination testing on worker valuations.

Contribution: This paper has three main contributions. First, we document new empirical facts about worker valuation of defined contribution retirement plans. Relatively little academic literature has studied how DC retirement plans contribute to worker labor market decisions. We show that 1) workers value retirement plans as a job feature, despite the existing evidence that retirement plans are underused by savers 2) DC retirement plans and contributions are a significant driver

[7] Due to the wide distribution of retirement valuations, this varies based on the type of worker a firm is targeting. If a firm in particular wants to hire in an occupation with lower retirement valuations, it would be better off increasing wages. But given the distribution of workers at most firms, increasing retirement contributions has a larger effect on average.

of compensating differentials between firms. Our findings suggest that workers value retirement plans above and beyond just the dollars paid. Qualitative survey responses suggest that 401(k)s and matching provide value as both a signal of firm quality and a commitment device, but more research is needed to fully understand why workers have strong preferences for the plan at the outset of a job. We also introduce a novel instrument in non-discrimination testing, which shows that firms change their plan design due to regulatory constraints. The variation induced by this testing has many potential applications across both corporate and household finance research agendas. Second, we expand on the class of search models in which workers have values over job features by adding taste for retirement benefits on both the extensive and intensive margin. Moreover, we construct a novel data set that links employers and employees in order to estimate the model. Third, we document how DC plan regulations favor firm compensation policy that disproportionately benefits higher income workers. Few papers have examined why firms structure DC plans the way they do; this paper shows that regulatory constraints have a significant effect on plan design. The following paragraphs discuss in more detail how the paper relates and adds to the existing literature.

Relation to Literature: A large literature has studied the importance of compensating differentials in labor markets. Originating with Rosen (1986) household finance and labor economics have long been interested in understanding what job features make up for differences in wages. Miller (2004) and Sheiner (1999) showed that healthcare benefits are typically passed of into lower wages and valued by workers by as much 10 percent of wages. Simon and Kaestner (2003) shows that offering pensions does not crowd out wages. More recently, several papers have shown that workers place a high value on non-wage, non-retirement and non-health benefits, such as remote-work, working conditions, or job flexibility (Maestas et al. (2018), Mas and Pallais (2017), Wiswall and Zafar (2018)). There is mixed evidence as to whether or not firms with higher wages offer better (Sockin (2021), Becker (2011)) or worse (Lamadon et al. (2022)) amenities. Most studies conclude that non-wage job features make up a large part of job valuation, explaining as much as half of the variance of job valuations (Taber and Vejlin (2020), Sorkin (2018)). Moreover, non-wage characteristics are thought to contribute more to inequality both within and between firms (Kristal et al. (2020), Azar et al. (2022), Ouimet and Tate (2022)).

Also related is a series of papers using structural estimation of on-the-job search models to estimate compensating differentials. Burdett and Mortensen (1998) develops the originating on-the-job random search model; this model generates wage dispersion but does not address non-wage valuations. Others have since expanded upon the model to include worker valuation of non-wage benefits. Bonhomme and Jolivet (2009) shows that workers have strong preferences for non-wage job features, such as job security. Sorkin (2018) find that non-wage features account for over half the firm component of the variance of earnings. Several other papers have shown that that non-wage compensation significantly contributes to worker valuation differences across jobs (Becker (2011), Sullivan and To (2014), Hall and Mueller (2018)).

We contribute to this strand of the literature in two ways. First, we build a data set that connects wages, retirement, and healthcare benefits. Most previous studies lack detailed data on benefits, especially retirement, and thus are only able to measure the non-wage portion of valuations in aggregate. Our merged data set of posted wages and regulatory filing with benefit financials allows us to separately identify the direct effect of retirement alone on worker valuations. Second, we focus specifically on retirement. Studies that have used data with information on benefits have focused primarily on healthcare or general amenities, not retirement. We build on this class of models by adding explicitly taste for retirement on the extensive and the intensive margin.

A smaller literature has studied the effect of retirement plans on worker mobility, primarily focusing on defined benefit, or DB (pension), plans, which differ significantly from DC plans. As most employers shifted from DB to DC plans in the 2000s and 2010s, there was concern over the loss of DBs leading to higher turnover (Johnson (2013)), because DBs typically required much longer vesting periods than DCs to receive full benefits. This fear was largely shown to be unfounded (Goldhaber et al. (2017), Gustman and Steinmeier (2002), Gustman et al. (1994), Goda et al. (2017)). A few studies have looked more generally at how benefits correlate with turnover and have found a positive association (Johnson (2013), Bennett et al. (1993), Lee et al. (2006)).

We add to this literature by updating the findings on mobility for the modern retirement landscape. Currently, 60 percent of workers have access to a DC while only 25 percent have access to a DB, thus making the findings about DBs' effect on mobility less relevant for the modern worker. While we focus on recruitment, rather than turnover, our findings shows that variation between DCs and whether or not a DC is offered are important drivers of job valuation.

Very few papers in finance and economics have analyzed how or why employers design retirement plans. Two exceptions are Bubb et al. (2015) and Bubb and Warren (2020). These papers show that, theoretically, employers design plans to take advantage of the myopia of participants by offering generous matching that they know won't be taken advantage of. This paper complements their findings and together, the findings explain the puzzle of why workers value the plan but often do not use it. Workers value DC plans when choosing jobs perhaps because they plan to use them, but just as employers anticipate, many workers don't end up using them, thus saving the firm costs. Arnoud et al. (2021) documents the current landscape of plan design in the U.S., but it is beyond the scope of that paper to analyze the drivers of plan design. Fadlon et al. (2016) uses a tax reform in Denmark to show that employers adjust their contributions to be consistent with worker preferences.

This paper offers new insights into employer's motivations and incentives for DC plan design. While we cannot measure the mechanism directly, we offer empirical evidence that supports two pieces of motivation. First, at least a subset of (higher income) workers highly values DC retirement plans, so offering such benefits can help firms to more effectively recruit those workers. Second, non-discrimination testing limits a firm's ability to cater plans to individual worker preferences. Thus firms must choose a plan that they think will appeal to either the largest cross-section of workers or the workers they most want to attract. Only one other paper, to our knowledge, has examined the effects of NDT on firm compensation. Ouimet and Tate (2022) show that firms with more high-wage workers also tend to offer higher benefits, which has spill-over effect on lower-income employees. This is consistent with our finding that higher-income workers place higher-value on retirement benefits. This paper shows directly that high-wage workers value retirement benefits more than low-wage workers, which complements the findings in Ouimet and Tate (2022).

The paper proceeds as follows. In section 2, we outline the research design of our instrumental variables approach and the data used for this approach. Next, in Section 3, we describe the instrumental variables results. In Section 4 we describe the survey design and the sample of participants. In Section 5, we describe the survey results. Section 6 describes the on-the-job search model. Section 7 describes the implication of the results for firm policy and worker valuations. Section 8 concludes.

2 Instrumental Variables Approach

In this section, we detail our first method for estimating the impact of retirement benefits on recruiting success and worker's valuations of retirement benefits. In Section 2.1, we detail the empirical specification of our instrumental variables approach. In sections 2.1.1 and 2.1.2, we describe the two instruments that we use to induce exogenous variation in retirement and wage setting policy: non-discrimination testing and the national wage setting, respectively. In section 2.2, we describe our data and its sample representativeness.

2.1 Method

It is well documented that workers place value on many different parts of compensation, other than just wages (Sorkin (2018), Mas and Pallais (2017), Wiswall and Zafar (2018), Bonhomme and Jolivet (2009), Taber and Vejlin (2020)). Imagine a simple indirect utility function from working at firm j for worker i:

$$V_{i,j} = \alpha w_{i,j,} + \beta r_j + \gamma h_j + \delta a_j + \epsilon_{i,j} \tag{1}$$

Worker i values the wage, $w_{i,j,}$, the retirement, r_j, the healthcare h_j, other benefits or amenities, a_j and there is an additional firm worker specific match component that can affect valuation. Note that the wage can be worker specific, but benefits cannot.[8] Normalize $\alpha = 1$ so that all other terms in (12) are in wage-equivalent units.

The primary objective of this paper is to measure β, the worker's sensitivity to the retirement contributions, relative to his sensitivity to wages. There are several empirical challenges to estimating this. First, one does not observe directly worker valuations of benefits and wages. Second, data on wages, retirement, healthcare, and other amenities is not readily available and is difficult to collect. Third, the way firms set their compensation and benefit policies is likely to be correlated with each other *and* correlated with unobservable characteristics that also increase worker valuations. In other words, wages and retirement benefits are endogenous.

To deal with the first issue, we use a firm-level measure of recruiting success to infer worker valuations by revealed preference. Although we cannot measure worker valuations directly, we can

[8]This restriction mimics the equality regulation on benefit plans, such as non-discrimination testing.

observe where people choose to work. Comparing the firms chosen to other choices with different compensation bundles reveals which components of compensation workers place higher value on. We construct the recruiting success measure by comparing job postings to the resume data and thus see when and if a posted job is filled.

To deal with the second issue, we have built a data set that contains detailed information on the first three terms in equation (12): wages retirement, and healthcare. We describe the data in more detail in Section 2.2. This dataset allows us to measure the three largest dollar parts of compensation, but not amenities. Lack of data on amenities contributes to the third challenge described above, an issue we address in the following paragraphs.

If one has perfect data, including information on firm amenities, the third challenge described above is mitigated. For example, firms that offer better healthcare may also offer better parental leave, both of which add value for workers. If one could observe and control for the parental leave, then one could estimate the worker's true valuation of healthcare alone. However most firm-level data does not indicate how good a firm's parental leave policy is. The parental leave example is one that deals with an amenity that is, at least in theory, measurable. However, there are other amenities that would not be measurable even if perfect data did exist. For example, a firm that offers better retirement benefits may also have more financially savvy employees, from which there is a positive spillover to other employees who work there. This type of amenity is unmeasurable to the econometrician. In sum, the fact that our data does not have information on non-retirement and non-wage amenities, and that some amenities are unmeasurable, means that the endogeneity issues remains.

We address this in two ways. First, our specification includes a firm by occupation by CBSA fixed effect. Thus, we compare firms to themselves in prior years, within the same CBSA and occupation (or market) as their wages or benefits in that market change. This helps reduce bias in the estimates due to endogeneity so long as we believe that changes in within firm amenities over time are smaller than differences in between firm amenities.[9] The empirical specification is thus:

$$HireSuccess_{j,t,l} = \alpha w_{j,t,l} + \beta r_{j,t} + \gamma h_{j,t} + X_{j,t} + \delta_{j,l} + \delta_t + \epsilon_{j,t,l} \tag{2}$$

[9] This assumption is supported by other work, such as Ouimet and Tate (2022) and Kristal et al. (2020).

Where HireSuccess is a dummy variable equal to one if the firm successfully filled a job in that market, measured at the firm, occupation, CBSA and year level. $w_{j,t,l}$ is the posted wage at firm j in year t for occupation and CBSA (market) l. $r_{j,t}$ is the employer contribution rate offered by firm j in year t; note that this does not vary by occupation as this policy must be constant within firm. Similarly $h_{j,t}$ is the healthcare benefits offered by firm j in year t and does not vary across occupations. $\delta_{j,l}$ is a firm by market fixed effect and δ_t is a year fixed effect. $X_{j,t}$ is an additional control for time varying firm characteristics not captured by the firm fixed effect. The specification thus measures how much hiring success changes within a firm and occupation by CBSA market as wages and retirement and healthcare change, controlling for yearly trends in the hire success rate and other observed firm characteristics.

The fixed effects are however, not sufficient to fully address the endogeneity concern. It is possible that firms change other unobservable amenities over time. To further address the issue, we use two instrumental variables to estimate (2). The first, non-discrimination testing, has a direct effect on retirement contributions. The second, national wage setting, has a direct affect on wages. we describe the instruments in detail in the following subsections.

2.1.1 Non-discrimination Testing of Defined Contribution Plans

Each year, about 60 percent of firms with retirement plans must undergo IRS mandated non-discrimination testing (NDT).[10] The purpose of the test is for employers to show that their plan does not disproportionately favor "highly compensated employees" or HCEs. As of 2022, these are employees who make over 135,000 dollars per year.[11] There are various steps to the test, but the main objective is to show that HCEs do not have a significantly higher contribution rate than non-HCEs, inclusive of the employer match.[12]

When a plan fails, there are two options for correction. First, they can give more contributions to their non-HCES to raise that group's effective contribution rate. Second, they can take contributions

[10]Firms that choose a safe harbour contribution schedule are exempt from testing. Arnoud et al. (2021) estimate that about 40 percent of all firms choose safe harbor plans. The three available safe harbor provisions are: 1) Non elective safe harbor: the employer contributes 3% of salary to all employees which is immediately vested, regardless of how much the employee contributes to the plan; 2) Basic safe harbor match: the employer matches 100% of the first 3% of the employee's contribution and 50% of the next 2%; 3) Enhanced safe harbor match: the employer matches 100% of the first 4% of each employee's contribution.

[11]See https://www.irs.gov/retirement-plans/plan-participant-employee/definitions for details on the definition of an HCE.

[12]See Appendix Table A.1 for a concrete example of how NDT is implemented.

back from HCEs and distribute them as income, which is now taxable. Either method presents costs for the firms. The first method is costly in dollar terms: the firm must make payouts to some or all of their employees who make less than $130,000. The second method, while not financially costly, presents a significant administrative burden and likely disgruntles HCEs who now have more taxable income than expected. If firms do not correct the failure within 3 months of the end of the filing year, they must pay 10% excise tax on the corrective distribution amount. If they don't correct it within a year, they must enter an IRS corrective program and are at risk of losing their qualified status as a plan.

Despite the cost, we find that failure is not uncommon. Based on corrective distributions paid, which is observable in the regulatory filings we use for our retirement plan financial data, roughly 5% of all firms (or 8.5% of the firms that must test) fail each year (Figure 1). About 10-12% of firms pay some corrective distributions each year.[13] This can include small penalties for other plan mistakes, so we assume that a firm failed NDT testing only if its corrective distributions per person are in the top 10% of the distribution that year. This is likely a conservative definition of NDT failure, as the majority of corrective distributions paid are due to NDT failure. Figure 1b shows that about 10% of firms in our main estimation sample fail NDT each year.

Due to the cost and administrative hassle of failure, it is natural to think that most firms that fail want to avoid failing again. Indeed, we observe that less than 10% of firms that fail fail more than once. While we do not directly observe if a plan chooses a safe harbor provision that would exempt them from future testing, our conversations with benefit administrators indicate that the most common policy change after failure is to either elect into safe harbor or introduce auto-enrollment (if the firm did not already use auto-enrollment). More often that not, this results in the firm having a more generous contribution overall. All three safe harbors have an effective contribution rate of 3-4% (see footnote 10), which is typically an improvement over what non-safe harbor plans offer. We drop any failing firms that had an effective contribution rate of higher than 4% prior to the NDT failure in order to ensure that the monotonicity condition of the instrumental variable is met (Imbens and Angrist, 1994). Without this restriction, it could be the case that higher income employees who were previously maxing out on a high employer match would receive a lower

[13] Appendix Figure A.1 shows that while large firm ($>$ 100 employees) are more likely to pay some corrective distributions, they are not more likely to fail NDT. The median dollar amount in corrective distributions paid, conditional on paying some is around $400 per person in our sample period. Larger firms pay higher dollar amounts per person.

match after the failure if the firm switched to a safe harbor. This restriction applies only to about 10% of the firms that failed.

Indeed, we find that retirement plans in our main estimation sample that fail NDT in a given year increase their ratio of contributions by 2.5% , and their contribution rate by approximately .5% in the three years immediately following the failure. Figure 2 show the parallel trends comparing failers to non-failers, controlling for year by industry fixed effects, log number of employees, and log dollars of assets in the retirement plans. Table 1 shows the corresponding regressions. The specification compares those that failed to those that did not fail, starting three years prior to failure and ending three years after failure.[14] For the control group, the comparative year zero is taken as the median year the firm appears in the sample. Robust standard errors are clustered at the firm level. Note that we do not find a significant effect of NDT failure on autoenrollment for firms in our sample, indicating that these firms do not typically use autoenrollment as a way to remediate NDT failure.

Over the same time period, NDT-failers do not significantly change wages. The event study plot is shown in Figure 3. They also do not significantly change how many jobs they post, their experience requirements for a job, or their spending on healthcare (Table 2). We do observe that NDT failers slightly increase their number of new hires after failure; this is consistent with the finding that workers find better retirement benefits to be an attractive feature.

A few notable differences between firms that fail and those that do not are present. In particular, firms that fail have ex-ante lower contribution rates. This is consistent with the fact that they ultimately fail the NDT. Moreover, these firms tend to have higher salaries, more job postings, and more new hires. Controlling for industry and size reduces these differences, but does not eliminate them entirely. Hence, there is reason to believe that NDT failing firms are somehow different from firms that don't fail, in a way that might by correlated with recruiting outcomes. This is further motivation for using a firm fixed effect in our estimating equation. Because these firms appear different on several dimensions, comparing them only to themselves in prior years is likely to reduce the endogeneity concern that unobservable firm characteristics are correlated with the firms'

[14] In unreported robustness checks, we find the results are similar using two alternate controls groups. First, we limit the control group to be only firms that do not fail, but have a high probability of failing based on a predictive regression of failing on firm characteristics. Second, we limit the control group to firms that will fail in the future, but compare them to failing firms in the years before the control group actually failed.

attractiveness to workers. The identifying variation from the NDT instrument represents *time series variation* within firm when they switch from non-failing to failing. Thus, the instrumental variable estimates capture the firm's change in recruiting success in a specific occupation by CBSA market that is due only to the retirement plan changing at that firm.

The exclusion restriction is that, conditional on observables, NDT failure is orthogonal to the firm's recruiting ability. With a firm and occupation by CBSA fixed effect, this means that the NDT failure does not affect other firm characteristics (like amenities) that may also contribute to recruiting outcomes. While we don't directly observe other amenities, we do observe that healthcare and wages do not change around NDT failure, implying that the firms at least do not adjust on those margins. In addition, we find that hiring slightly increases following NDT failure at failing firms, thus there is no indication that these firms try to decrease hiring after failing the test. Moreover NDT is a relatively unknown institutional procedure that potential employees are not likely to know about and it should only affect job choice by how it changes retirement benefits.

2.1.2 National Wage Setting

The second instrument we use to induce exogenous variation in wages is corporate policy of national wage setting. First documented by Hazell et al. (2022), approximately 30-40% of occupation have their wages set nationally by the firm, rather than tailoring wages to local labor market conditions. For example, if a firm employs one accountant in New York City and one in Santa Fe, it pays the two employees the same salary, despite the differing labor market conditions between the two cities. Firms that follows this policy sometimes do so for only select occupations or sometimes they do so for the majority of their workforce. Figure 4 shows that in our estimation sample, about 20-25 percent of firms predominately set wages nationally, meaning they do so for at least 75% of their occupations. Around 15% of occupations have the wage set nationally.[15]

National wage setters also pay a wage premium: on average, nationally identical jobs pay 1-3% percent more than other comparable jobs within their markets. Table 3 shows that this wage premium holds both at the firm level, controlling for industry by year fixed effects, and at the market level, controlling for CBSA by occupation by industry and year fixed effects.

[15] Note that the incidence of national wage setting declines significantly in 2018 and 2019 as Lightcast significantly expanded its coverage of postings,

We construct an instrument in which national wage setting is interacted with the difference between an occupation and CBSA specific wage and the predicted occupation and CBSA specific wage for non-national wage setters in that CBSA. The instrument is:

$$Instrument = \begin{cases} [ln(\widehat{Sal_{j,t,l}}) - ln(Sal_{t,l})] & \text{If Wage set Nationally} \\ 0 \quad \text{If Wage not Set Nationally} \end{cases}$$

where $Sal_{j,t,l}$ is the salary for firm j for occupation and CBSA l in year t, $\widehat{Sal_{t,l}}$ is the predicted wage for that same occupation and CBSA in year t, estimated only for non-national wage setters.[16] The instrument thus measures a firm's difference from the predicted value for non-national wage setters in that same occupation and geography. It is a measure of how much the wage deviates from the predicted value due to national wage setting. Appendix Figure A.2 shows the median value of the instrument across various geographical and firm characteristics (including only occupations for which the wage is set nationally). Wages are pushed up the most by national wage setting in lower-population and lower cost of living areas and at at larger firms.

National wage setters differ from other firms on several dimension. First, by definition, they must have multiple establishments and thus tend to be larger firms. However, when compared to other multi-establishment firms, they are actually slightly smaller by employment size. Correspondingly, they also have fewer job postings and hire fewer new employees on average when compared to other multi-establishment firms. Table 4 documents these results.

Most importantly for our setting, however, national wage setters do not differ significantly on measures of turnover, retirement contributions, or healthcare benefits (see Table 4). This indicates that nationally wage setting firms do not offer substantially different benefits or amenities than other firms. Hazell et al. (2022) provide further evidence that national wage setting firms appear similar to non-national wage setting firms, and that the decision to set wages nationally is typically related to organizational structure and concentration, but not benefits.

The identifying variation of this instrument comes from time series variation within firm and market. The instrument measures how much a firm's wage is being pushed up or down in a given

[16] We estimate the predicted wage by regressing the average posted salary on CBSA, 6-digit SOC code occupation, and year fixed effects, including only jobs for which the wage is not set nationally.

year relative to the local average for that occupation and CBSA due to being a national wage setter. A firm may increase wages in some CBSA and occupation for reasons unrelated to local conditions if they decide to increase the national wage. With firm and market fixed effects, it measures how much wages are being pushed up or down in a given market due to being a national wage setter, relative to the same firm and market in previous years. So long as firms that set wages nationally do not change their other benefits or amenities (at the occupation and CBSA level) when the nationally set wage changes, then the instrument captures changes in the firm's recruiting success that are due only to the changing wage.

How the Instruments Work Together

The effects that we identify in our instrumental variables specification apply only to the sample of treated firms (Imbens and Angrist (1994)). We estimate the effect of wages and the employer contribution rate on recruiting success for firms that 1) have recently failed a non-discrimination test and 2) set wages nationally.

Table 5 shows summary statistics for firms that are affected by each instrumental variable separately, the two IVs together, and the full sample. Firms that are affected by either NDT Failure or being a National Wage Setter tend to be larger than the average (or median) firm, both in terms of plan assets and number of employees. As expected, firms that fail NDT test tend to have lower contribution rates and levels of employer contributions. Firms to which both IVs apply are by definition, multi-establishment firms, versus only 41 percent of firms in the full sample. In the sample affected by both instrumental variables, there are 588 firms with 55,786 unique jobs and 66,938 transitions from 2010-2019.

Figure 5 shows the geographic, industry, and occupational composition of the firms affected by the instrumental variables and the full sample. Each group has broad representation across geographies and sectors. In the main results, we include only firms that both have DC plans and that have greater than two establishments.

2.2 Data

This paper uses a panel data set of posted wages at the firm by occupation by CBSA level, individual (worker) level resume data with detailed job information, and firm-level retirement plan financials. We aggregate each source to the yearly level from 2010-2019 and merge all three sources to combine information on wages, new worker transitions, and retirement plans at the firm-level. The resume and posted wage data are from Lightcast (formerly Burning Glass Technologies) and the retirement plan financial data are from regulatory filing Form-5500. In the following subsections, we describe each data source in detail. In Section 2.2.3, We describe how we construct the estimation sample and compare the sample to the average U.S. firm.

2.2.1 Lightcast

Job Postings Data The Lightcast data on posted wages contains the near universe of online job postings. The postings are collected from over 40,000 distinct sources including company websites and online job boards, with no more than 5% of vacancies from any one source (Hazell and Taska (2020), Schubert et al. (2020)). Azar et al. (2020) shows that in 2016, the Lightcast job-posting database captured around 85% of all job vacancies, including offline jobs. So, while Lightcast likely omits job-postings in certain occupations where offline or informal postings are more common, it does capture the majority of posted jobs. Schubert et al. (2020) finds that particularly underrepresented occupations include low-wage food service jobs, cleaners, home health aides, laborer and cashiers. Thus, our estimates should be interpreted while keeping in mind that some occupations, particularly low-income ones, are underrepresented.

The main data we extract from the job postings is the posted wage. This is available for about 20% of postings, which equates to around 40 million postings from 2010-2019 with non-missing posted wages. The wage can appear either as single number or a range; when it is a range, we take the median as the posted wage. The data also include pay frequency, i.e. whether pay is hourly or annual, the type of salary (base or bonus pay), thus we can aggregate all wages up to an annual level. Appendix Table A.2 shows that the posted wages in Lightcast match well the wages in the Occupational Employment Statistics (OES).[17]

The final sample of posted wages also only includes jobs for which the SOC code, industry, and location information are available. We then collapse wages to the 5-digit SOC code, CBSA, year, and firm level. The final posted wage data set, prior to matching with the other data sources, has posted wages for over 8 million jobs at 1.2 million distinct firms. 437 out of 459 possible 5-digit SOC

[17]We collapse wages at the 5-digit SOC code by CBSA by year level and regress the OES salary (or hourly wage) on the Lightcast salary (or hourly wage), using the within-occupation and CBSA, medians, means, and within-occupation quantiles.

codes and 929 out of and 939 possible CBSAs are represented. The average annual salary is $50,247, the median $29,205. Appendix Table A.3 shows summary statistics of this sample.

One may be concerned about how well the postings data with wage information represents all jobs in the United States. Hazell and Taska (2020) show that the postings data, limited to postings with wages and job information are largely representative of the population of U.S. employment. Compared to data from the Bureau of Labor Statistics (BLS) and the Occupation Employment Statistics (OES), the data match the regional and occupation distribution of actual posted jobs well. Compared to Dun & Bradstreet data, the Lightcast data also represents the population of establishments well, based on industry classification and establishment age. we discuss the representativeness of the final estimation sample in more detail in Section 2.2.3.

Resume Data The next data set we use to construct the final estimation sample is a collection of resumes taken from online sources, also constructed by Lightcast. Resumes were sourced from a variety of Lightcast partners, including recruitment and staffing agencies, workforce agencies, job boards and social media. The resumes form a longitudinal data set, since we observe all jobs that an individual lists on their resume.[18]

In total, the data represent 83 million unique resumes with non-missing current job info. In 2010, the Lightcast resumes capture 26% of the total workforce; in 2019, this figure increases to 35% (see Appendix Figure A.3). Appendix Table A.4 shows high-level summary statistics for the sample. Across the 83 million resumes, there are 106 million transitions to new jobs, 65 million of which are to a new firm. Each resume has an average of 2.5 jobs represented with 1.6 transitions to a new job. The median job length is three years, compared to about four years in the BLS. The mean span of years observed on the resume is 15 years.

While the data represents a large percentage of the total U.S. workforce, it is not completely representative of the average U.S. worker. Appendix Figure A.4a shows that the average worker in Lightcast is younger than the average worker in the U.S., with about 75% of workers in Lightcast being under the age of 45.[19] The average worker in Lightcast also has a higher education level than the average worker in the BLS data (Appendix Figure A.4b). About half of all the Lightcast resumes

[18]A job here means a firm by occupation pair.

[19]We impute age by using education information on the resume. If the resume gives a year of high school or college graduation, We assume the individual was 18 at the time of high school graduation and 23 for college graduation and use that year to calculate the worker's current age.

have non-missing education information. Using only that information, around 75% of workers in Lightcast have a college degree or more, versus only about 38% in the BLS data. However, if we assume that missing education info indicates that the worker did not receive education beyond college, then roughly 33% have greater than a college education, which matches the BLS much more closely. Some occupations are over-represented in Lightcast: management, business and finance, computer and mathematical, engineering, and arts and design (Appendix Figure A.4c). Others are underrepresented, such as office and administrative support, sales, food preparation, and healthcare. The Lightcast data matches the geographical distribution of all workers in the BLS at the state level quite well (Appendix Figure A.4d). In general, while the resume data captures a significant portion of the labor force, our results should be interpreted with the caveat they they apply to a younger, higher educated sample which works in typically higher-income occupations.

2.2.2 Form 5500

Our final data source is regulatory filing Form 5500, which contains detailed financial information on retirement and health plans for all U.S. firms. This is publicly available data, published by the Department of Labor.[20] Form 5500 is required yearly of all retirement plans which have qualified status under the Employee Retirement Income Security Act (ERISA). The form contains detailed information about their benefit plans, including what type of plan it is, financial information about inflows and outflows, how the funds are invested, the number of participants covered in the plan, and some information about plan features.

There are two version of Form-5500, one for large plans (those with greater than 100 participants) and one for small plans (those with less than 100 participants). The version required for large plans is significantly more detailed than the version required for small plans. However, small plans make up approximately three-quarters of all plans. Thus, we elect to include small plans in our final merge across all data sets in order to preserve sample size. The form for small plans provides enough information to 1) back out the effective employer contribution rate and 2) know whether or not the firm offers a healthcare plan and thus is sufficient for our analysis.

The administrative data do not include information about the specific default contribution rate or the structure of employer contributions offered in the plan. However, Schedule H of the Form

[20] https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/public-disclosure/foia/form-5500-datasets

5500 for large plans and Schedule SF for small plans gives the amount in dollars that the employer contributes to the plan each year. It also gives the amount in dollars that participants contribute to the plan each year.

Form-5500 also contains details about healthcare plans. The main Form 5500 for large plans and Schedule SF for small plans have indicators as to whether or not the firm has a health plan. Schedule A of Form 5500 has specific information about health plans, including the insurance carrier and dollars paid by the plans on claims and total plan expenses, but this is available only for large plans.

Appendix Table A.5 shows summary statitics for all DC plans in Form 5500 from 2010-2019. Appendix Figure A.5 shows how the firms with retirement plans in Form-5500 compare to all U.S. firms, as measured by the Bureau of Labor Statistics. Roughly two-thirds of firms offer retirement plans, thus Form 5500 is representative only of those firms. Appendix Figure A.5a shows the distribution of industry (2-digit NAICS code) in each data set by number of firms, Firms with retirement plans are more likely to be in the Healthcare or Professional/Scientific/Technical industry than other U.S. firms. They are also less likely to be in Construction, Trade, and Service Industries. Appendix Figure A.5b compares firms in Form 5500 to the BLS by employment size. Firms with retirement plans are larger, with firms with more than 20 employees representing about one-third of all firms amongst firms with retirement, versus less than 10% in the BLS. Moreover, only about 20% of firms have 1-4 employees in Form 5500, versus about 61% in the BLS.

2.2.3 Variable Construction and Estimation Sample

Our final data set is a merged panel of posted wages, new-hire transitions and retirement plan information from the three combined data sets. We first merge the wage data with the resume data at the firm by occupation by CBSA level. That is, from the 65 million between-firm transitions with full job information in the posted resumes, We match the new workplace of the person changing jobs with the 8 million job-level posted wages, at the firm by occupation by CBSA level. Then, we merge in the retirement plan information from Form 5500 at the firm-level. All three data sources are matched through fuzzy merging on firm name, as the firm name may vary slightly between the three data sources.

The final estimation sample represents over half a million worker transitions to 24,000 firms in 486,000 unique CBSA by occupation jobs. Figure 6 shows how the main estimation sample compares to all firms in the U.S. The sample over-represents firms in the Professional/Scientific/Technical industry, as well as firms in Finance and Insurance, Information, and Healthcare. This is expected given the representativeness of both firms that have retirement plans (see Figure A.5a) and firms that are represented in the Lightcast data (see Hershbein and Kahn (2018) and Schubert et al. (2020)).

By size, the matched sample over-represents large firms, with about 18% of sample firms having over 500 employees, compared to less than 1% of firms in the BLS. This is driven by both the distribution of firms that have retirement plans, as these firms skew larger (see Figure A.5b) and due to the matching process, which is more likely to pick-up larger firms.

At the occupation level, we compare the distribution of all workers by occupation to the distribution of transitions in the Lightcast resume data. New workers in the sample over-represent those in Management, Business/Finance, Computer and Engineering occupations. This is consistent with the distribution of all resumes in Lightcast shown in Appendix Figure A.4c.

In Section 2.2.1 we showed that the posted wage in Lightcast closely matches the wage in the BLS's Occupational Employment Statistics. Table 6 compares the distribution of wages in the OES with that of the matched sample. The means and median wage in the sample are slightly lower than that in the BLS. But the 90th percentile is significantly higher; this is expected given the skew toward higher income occupations and industries. However, the distribution of wages in the sample matches that of the OES reasonably well.

Table 7 shows the main summary statistics for the matched sample. In the following paragraphs, we describe how we construct the variables needed for our analysis.

Employer Contribution Rate: Form 5500 does not directly disclose the employer's matching formula or contribution rate. Instead, we use the combined Form 5500 with the Lightcast wages to calculate an "effective" employer contribution rate. Schedule H of Form 5500 (or Schedule SF for small plans), gives the total dollars that the employer contributes to the plan each year. Then, from the Lightcast job postings data, we calculate the average wage at the firm. From the average wage and the number of employees at the firm (from Form 5500), we calculate total wages paid. Then, we divide the employer contribution by total wages paid to infer an effective employer contribution rate. While this measure does not capture the exact matching formula, it does serve as a measure of the generosity of the employer's plans. The average effective contribution rate at firms in our sample is 5.12%. This aligns well with the descriptive evidence in Arnoud et al. (2021), which finds that the majority of plans offer at least 3% and 40% of plans offer matching contributions up to 6% of salary.

There are two alternative measures of plan generosity used in robustness checks. First is the employer contributions in dollar per person, which is directly from Form 5500. Second is the employer's ratio of all contributions, relative to contributions from the employer and the participants summed together, which is also directly from Form 5500. All three variables give similar results.

Hiring Success: Hiring success at the firm, occupation, and CBSA level is the main outcome variable for our instrumental variables specification. We measure this by comparing the resume data with the postings data. When we see a job postings in the postings data, We can then see if it is filled within the year in the resume data. The average hire success in our matched sample is 11%. The average percentage of employees captured in the resume data, using Form 5500 as the true number of employees, is 42%. Given that the resume data do not capture all employees, its is likely that our estimates of hire success is downward biased for many firms.

3 Effect of Wages and Retirement on Firm Recruiting

In this section we describe the results of the instrumental variable approach to measuring the effect of wages and retirement contributions on firm hiring success outlined in Section 2. The empirical specification is shown in equation (2). The sample studied in this section is the 24,000 firms and 486,000 unique firm by CBSA by occupation jobs for which we matched data on posted wages, new worker flows, and retirement plans. Summary statistics for the sample are shown in Table 7.

3.1 Instrumental Variable Results

Table 8 shows the results from the main estimating equation in (2) on the full sample of firms. We find that a one percentage point increase in the employer contribution rate increases the likelihood of filling a position in each CBSA by occupation in which a firm recruits by 2.7%. A 1% increase in wages has an effect of half the magnitude: 1.4%. Note that these unit increases for the independent variable are roughly equivalent in dollar terms, as a one percentage point increase in the employer contribution rate has the same effect as a 1% increase in salary.[21,22] The average hire success in the sample is 11%, so these are large effects. The estimation sample is limited to those that both have at least two establishments and have a DC plan, as those are the firms to which the instruments are applicable. The specification has firm by CBSA by occupation fixed effects and controls for log employment size by year, log assets in the DC plan by year and whether or not the firm has a healthcare plan.

Comparing the OLS and IV results (columns (3) and (4) of Table 8) suggests that there is a significant correlation between retirement and unobserved characteristics that affect hiring success and that the OLS coefficients are indeed biased. There is a very large difference between the two coefficients on the employer contribution rate. However, there is not a large difference between the coefficients on log salary. Consistent with the discussion of endogeneity in Section 2, the OLS coefficient on the employer contribution rate fails to pick up employee valuation of retirement contributions.

These results suggest that, by revealed preference, workers value a dollar of retirement contributions roughly double what they value a dollar of wages. In other words, the average worker in this sample values a dollar of employer contributions to his DC account nearly twice as much as an extra dollar of annual salary. The results applies to this sample of workers, who are higher income and working in selected occupations and industries. Moreover, the effects are measured for those who went to work at firms affected by both national wage setting and failure of non-discrimination tests.

The specification has strong first-stages, with an F-statistic of 136. As outlined in Sections 2.1.1-2.1.2, national wage setting has a positive effect on salary and NDT failure has a positive effect on the employer contribution rate. Within firm, employer contribution rates increase by .33 percentage points following NDT failure. With the firm-fixed effect, national wage setting does appear to have an effect on contribution rates (unlike in the difference-in-difference results shown in Section 2.1.2, in which national wage setting was not correlated with contribution rates). However, the negative effect of national wage setting is smaller in magnitude than the effect of NDT, so the net effect is still positive. The national wage setting instrument measures how much the firm's wage

[21]For example, with a salary of $100,000 going from a 2% to a 3% employer matching rate means going from $2,000 to $3,000 in employer contributions, or a $1,000 increase. This is equivalent to a 1% increase in the $100,000 salary.

[22]We say roughly equivalent because these calculation do not account for taxes or non-linear matching formulas.

is being pushed up due to national wage setting. Thus, it is natural that employer contributions might decrease within firm in years when there is more upward wage pressure in order to even out costs.

3.1.1 Heterogeneity by Income

Table 9 shows that the effect of the employer contribution rate is driven primarily by high-income occupations. In the high-income sample (column (8)), recruiting success increases by 6.03% for a one percentage point increase in employer contribution rate, relative to a 2.03% increase for a 1% increase in salary. In contrast, the low-income occupations (column (4)) are roughly equally effected by similar dollar increases in wages and employer contribution rate; hiring success increases by 1.87% and 1.60%, respectively. These results are consistent with standard lifecycle saving and consumption theory that higher income individuals tend to save more, and would therefore value these contributions more highly (Gourinchas and Parker (2002), Parker et al. (2022), Carroll (2000)).

These estimates come after re-estimating (2) on sub-samples of occupations, partitioned by salary levels. We take the median annual salary of all industry by occupation groups and designate low-income occupations as those below the median ($44,508) and high-income occupations as those above the median.[23] Thus, the partitioning is based on occupational salaries, not individual job salaries, so that we still compare jobs within the same occupation.

As before, both instruments have a strong first stage in each of these subsamples. The F-statistics are 140.67 for the low-income occupations and 23.00 for the high-income occupations. The national wage setting instrument has a positive association with salary and employer contribution rates increase following NDT failure in both subsamples.

3.1.2 Heterogeneity by Age

Table 10 shows that the powerful effect of employer contribution rates on recruiting success is also increasing in age.[24] In high-age occupations, a one percentage point increase in employer

[23]After creating these subsamples, the low-income group has a median (mean) annual salary of 31,000 ($33,484). The high-income group has a median (mean) annual salary of $63,585 ($70,470).

[24]We partition the sample by median age in the occupation, as measured by the BLS's Occupational Employment Statistics. Occupations with an median age of greater (less) than 42 are "older" ("younger") occupations. The highest-age occupations are: motor vehicle operators (other than taxi drivers, chauffeurs, truck drivers and bus drivers), crossing guards and agricultural managers. The lowest-age occupations are: lifeguards, restaurant hosts and hostesses, and

contribution rates increases recruitment success by 7.2%. A 1% increase in wage increases recruiting success by only 2.36%. On the other hand, recruiting success in low-age occupations is much more affected by wages than by retirement. A 1% increase in wages improves recruiting outcomes by 2.05%; a one percentage point increase in contribution rates has no statistically significant effect on recruiting outcomes in this sample. This finding is consistent with lifecycle theory of saving and consumption (Gourinchas and Parker (2002), Scholz et al. (2006)) in that older people would be expected to save more and thus would value retirement contributions more highly. Again, both instruments have a strong first stage in the expected direction in each of the sub-samples.

3.1.3 Heterogeneity by Gender

Table 11 shows that the effect of retirement and wages on recruiting success in similar across occupations with differing gender compositions. In both male-dominated and female dominated occupations, a one percentage point increase in the employer contribution rate increases hiring success by between 3% and 4%. A one percent increase in annual salary increases hiring success by between 1.4% and 2% for both groups.[25]

In sum, for the average firm in our estimation sample, a one percentage point increase in contribution rates has nearly twice the effect on recruiting success as a 1% increase in wages. By revealed preference, this suggests that job-switchers in this sample value retirement contributions nearly twice as much as wages. The results are identified by comparing within firm, CBSA and occupation across years when wages and benefits change due to national wage setting and failure of NDT, respectively.

4 Eliciting Willingness to Pay in a Survey

In this section, we outline our second method of measuring employees valuations of retirement benefits: an online experimental survey that directly measures valuations by eliciting willingness to pay (WTP) for various levels of retirement benefits. We first discuss the method of eliciting WTP

counter attendants at cafeterias, concession shops and coffee shops.

[25] We divide occupations into two groups: majority female or majority male, as measured by the BLS's Occupational Employment Statistics. The most female occupation are: skincare specialists, preschool and kindergarten teachers, and executive administrative assistants. The most male occupations are: cement masons, concrete finishers, and terrazzo workers, extraction workers, and electrical power line installers and repairers.

and then the sample of participants who completed the survey experiment.

4.1 Method

In each survey question, we show participants two similar job offers in which only the wage and the retirement vary slightly. Showing different combinations across many participants allows us to estimate the complete distribution of willingness to pay for the retirement benefits, similar to Mas and Pallais (2017).

In each question, the participant was shown two job offers. One of these was always a "baseline" job offer that has no retirement, which is stated explicitly. Then, the salary was varied in downward increments (randomly) across participants for the second offer, while adding a retirement benefit. Figure 7 shows two example questions. Note that participants were told explicitly what the difference in take home pay would be between the two jobs. They were also told, prior to seeing each condition, that the two jobs they were choosing between were exactly the same, other than what was observed in the table. Vacation, healthcare, and remote work were always exactly the same between the two choices in which retirement varied.

We tested 5 conditions in total[26]:

1. Willingness to pay for a 401(k) with a 3% match versus no 401(k)
2. Willingness to pay for a 401(k) with a 5% match versus no 401(k)
3. Willingness to pay for a 401(k) with no match versus no 401(k)
4. Willingness to pay for a 401(k) with a 3% match versus a 401(k) with no match
5. Willingness to pay for working remotely for 2 days a week, versus no days of remote work

The first two conditions simultaneously measure the willingness to pay for both the intensive and the extensive margin of retirement benefits. The third measures only the extensive margin. The fourth measures only the intensive margin. The last measures willingness to pay for a non-monetary amenity, remote work, in order to compare the estimates from our sample to other estimates in the literature.

[26]Appendix Figure A.6 shows example questions for each condition

We follow the procedure in Mas and Pallais (2017), using a discrete choice framework to estimate willingness to pay. Imagine individual i is shown two jobs with wage difference $w_1 - w_0 = \Delta_w$ where job 1 offers the better retirement (R_i) than job 0. Then her willingness to pay (WTP_i) if she is fully attentive for the (better) retirement benefit is:

$$P_{\Delta w} = \Pr(WTP_i > -\Delta w) \tag{3}$$

However, some survey participants are likely to be inattentive. Those participants are equally likely to choose either job. Imagine 2α percent of participants are inattentive; then α of them will choose a dominated option by chance. Then, the probability that that an individual chooses the job with the better retirement benefit is:

$$\begin{aligned} Pr(R_i = 1|\Delta w) =& P_{\Delta w}(1-\alpha) + (1 - P_{\Delta w})\alpha & (4) \\ =& F(b\Delta w + c; \mu, \sigma)(1-\alpha) + \alpha & (5) \end{aligned}$$

where μ is the population mean willingness to pay, while σ is the population standard deviation. Equation (5) is a mixture model that can be estimated by maximum likelihood. We assume the distribution follows a logistic distribution and bootstrap the standard error. Although the fraction of inattentive participants, α, is identified in (5), we estimate it directly through an attention check. A fraction of participants in each condition view a dominated condition - that is the job offers higher pay and the better retirement benefit. We use the fraction which do not choose this job to estimate α directly. We find that only a small number (2.5%) of participants are inattentive.

Testing each of the conditions across hundreds of participants means that we can flexibly estimate the full distribution of the willingness to pay in the population of survey participants. We thus can estimate willingness to pay for higher retirement benefits both on the intensive and extensive margin.

4.2 Data and Sample

For our survey sample, we recruited 1,600 online participants via Prolific. Prolific is an online platform on which participants are paid to take part in survey research.[27] We limited our sample to only those who live in the U.S., speak English as a first language, and were currently working or looking for work. We also balanced the sample equally between non-college graduates and those with a college degree or more. Figure 8 shows summary statistics for the survey participants. The average age is 34 (median 32). The sample is equally balanced on gender. The majority (75%) of participants are white.

5 Survey Results

In Section 3, we showed that, by revealed preference, workers place nearly double the value on retirement contributions than on wages when selecting between two otherwise similar jobs. In this section, we show that workers place about 1.5 times the value on employer contributions to 401(k)s than on wages when comparing between similar jobs. We measure this by eliciting valuations of retirement benefits directly in an online experimental survey setting. The method of eliciting willingness to pay and the sample of participants are described in Section 4.

First, we start by measuring the value of additional retirement benefits on the intensive margin by varying the dollar value given in contributions by the employer conditional on having a retirement plan (a 401(k)). These results are most directly comparable to the revealed preference results of Section 3. Specifically, we asked participants if they would prefer a job with a 401(k) with no match or a 401(k) with a 3% match (see Figure 7a). The wage was higher in the condition with no match and varied in downward increments randomly across participants for the job offering the 3% match.[28]

The first finding is that a majority of participants (80%), exhibit some willingness to pay for the 3% match. This is shown in the black line in Figure 9, with corresponding summary statistics in Table 12, Column (1). The plot shows the fraction of the participants who chose the job with the

[27] Prolific is similar to MTurk, which has been more commonly used in Economics and Finance studies. However, several studies from other fields have shown that Prolific produces higher data quality than MTurk (Peer et al. (2017), Péer et al. (2021)).

[28] In some conditions, the job with the 3% match offered a higher wage in order to test for inattention.

3% match against the total compensation gap.[29] 80% chose the job with the 3% match when the total compensation difference was $0, indicating that only 20% of participants place no value on the employer match. Moreover, 55% of participants chose the job with the 3% match even when it paid less overall.

Focusing now on the participants to the left of the black line, who saw conditions in which the job with the match paid less overall, their implied willingness to pay in total compensation is $748, or 1.5% of compensation offered in the higher-paying job. Net of taxes, the willingness to pay is $258.[30] In terms of wages, rather than total compensation, the willingness to pay is $2,226, or 4.3% of the annual salary offered by the job without the match.

Next, we show that the distribution estimated by maximum likelihood and corrected for inattention implies an even higher willingness to pay: $909 or 1.8% of total compensation. The top panel of Table 13 shows the results. Participants at the 25th percentile of the willingness to pay distribution are willing to give up only $60 in annual pay to get the 3% match. The top 25% of workers are willing to give up at least $1757, or 3% of total compensation to get the employer match. Hence, there is significant heterogeneity across workers in the valuation of this benefit; but the majority of workers are willing to pay for the 3% match, relative to a 401(k) with no match. These results come from estimating the inattention rate using the procedure described above in Section 4; the inattention-corrected shares are plotted in the red dotted line in 9a, along with the inattention corrected maximum likelihood estimates, plotted in a blue dashed line.[31]

Relative to the revealed preference results in Section 3, the relevant comparison here is how many dollars in wage participants are willing to give up for each dollar in match. The willingness to pay estimates suggest that workers will give up about 1.4% of wages for each one percentage point increase in the match. This is less than the near two to one trade-off estimated in the instrumental variables specification on the full sample, but directionally consistent in that it implies a higher valuation of employer contribution dollars than wage dollars when comparing amongst similar jobs.

[29]The total compensation gap includes the dollar value of the employer match.

[30]The tax calculation accounts for the difference in taxes paid because the job with the 3% match offers a lower wage and the match dollars are not taxable at the time they are paid out. It does not account for future taxation of the employer contributions.

[31]Note that the inattention correction changes the distribution only slightly, as we found very few participants to be inattentive in the sample.

Next, we show the results for the condition that tested for the WTP for the extensive margin of retirement benefits, or whether or not the job offers a 401(k) at all. In this condition, participants were given the choice between a job with a 401(k) that has no match or a job with no 401(k) (see Figure 7b).

Starting with the raw share of participants that chose the job with the 401(k), 80% chose the 401(k) job when it paid only $500 less, implying that less than 20% of participant have no willingness to pay for the 401(k).[32] Figure 9b shows the results; corresponding summary statistic are in Column (2) of Table 12. Moreover, 49% chose the job with the 401(k), even when it paid less. When the compensation premium is less than $2000, this figure increases to 60%.

This implies that the majority of participants have some willingness to pay for the 401(k), even when it offers no match. Focusing on the participants to the left of the black line, who saw conditions in which the job with the 401(k) paid less overall, their implied willingness to pay for the 401(k) is $1,775 or 3.4% of total pay. Note that the willingness to pay in wages and total compensation are the same in the condition, as there is no added dollar value from a match. Net of taxes, the willingness to pay is $1,345.[33]

As in the intensive margin condition, the estimation of the distribution by maximum likelihood results in an even higher mean estimated willingness to pay - $2,268 or 4.4% of total pay. The bottom panel of Table 13 shows the estimated distribution from the maximum likelihood procedure. The 25th percentile is $823 or 1.5% of total pay. The 75th percentile is $3,711, meaning that 25% of participants are willing to pay at least 7.2% of total pay to get a 401(k).

The test for the extensive margin is not directly comparable to the revealed preference results from Section 3, as the specification in that analysis included only firms with a DC plan. However, the survey results show that, when accounting for the match dollars, job-seekers are willing to pay even more just to get a 401(k), even when it offer no match, than they are to get an employer match, conditional on having a plan. The average willingness to pay for the 401(k) alone is about three times the willingness to pay for the 3% match (4.4% of total pay versus 1.5% of total pay). This suggests that workers value DC retirement plans beyond the dollars offered and that the plan itself

[32]There is no condition that had an exact $0 difference in compensation in this case, but the closest is that in which the total compensation difference is only $500

[33]In this condition, the inattention correction (red dashed line) does very little to change the estimates as inattention was not prevalent in the sample. The attention-corrected maximum likelihood estimates (blue dashed line) smooths out the distribution and slightly alters the tails, but does not significantly change the median.

provides value to employees even when it does not offer any dollar matching from the employer.

In Appendix Figure A.6 and Tables A.6-A.7,we show the results for the remaining conditions that we tested. Two conditions tested simultaneously for the intensive and extensive margin of benefits, offering participants a choice of a job with a 401(k) with 3% or 5% match versus a job with no 401(k). The final condition tested the willingness to pay for the ability to work remotely for two days per week, versus no remote work option. The willingness to pay for the extensive and intensive margin simultaneously aligns with the results that test each condition separately; the WTP for both is higher than the WTP for each separately. comparing the 3% conditions, the estimated average willingness to pay for a 401(k) and a 3% match separately is around $3,200 versus $3,600 for both the 401(k) and the 3% match simultaneously.. For the remote work condition, We find an average willingness to pay of $2,935 in annual salary for two days of remote work per week. This aligns well with the finding from Mas and Pallais (2017) who estimate and average willingness to pay of $2,533 in annual salary.[34]

Reasons for Valuing Retirement: In a sub-sample of participants ($N = 600$) who were tested for the extensive margin condition, we asked why they chose the selected job. One-half were given multiple choice options and one-half were given a text box in which they could write freely. For the multiple choice options, participants could choose between the following:

1. Chosen job has a higher wage
2. Chosen job has higher total compensation
3. Chosen job has a retirement plan
4. Chosen job is a better job

For those choosing between a 401(k) or no 401(k) when the job with the 401(k) paid less, the overwhelming majority (91%) say they chose it because of retirement plan, as opposed to only 5% who chose is because it's a "better job".[35] This indicates that participants value the retirement plan itself for some reasons besides the dollar value, and not that they see it as signal of employer quality.

[34]Mas and Pallais (2017) find an average willingness to pay of $1.33 per hour for the option to work from home, which we scale up to an annual salary assuming full time work of 1,920 hours per year.

[35]The remaining 4% erroneously said they chose the job because it had higher total compensation, when it fact did not. They may have considered the 401(k) to be part of compensation, but there was no dollar value associated with it. See Appendix Figure A.7.

In the open text-box responses, participants who chose the 401(k) job when it paid less almost unanimously said that they chose the job because of the 401(k) or the job having better benefits. 4% mentioned the tax advantages and 5% mentioned the importance of saving for the future. A few selected answers below capture the qualitative nature of the majority of the responses:

- "Because it had a retirement plan, even though it didn't have an employer match."
- "$83 lower income per month is nothing compared to the long-term benefit of having money set aside for retirement. "
- "The company sponsored 401(k) instead on $1000 annually seems like a good deal."
- "Retirement benefits are always good."

6 On-the-job Search Model with Retirement Benefits

In Sections 3 and 5, we showed across two distinct empirical settings that job-seekers place approximately 1.4-2 times the value on retirement contributions than on wages when comparing between two otherwise similar jobs. Moreover, the survey results show that most workers also exhibit willingness to pay for having a DC retirement plan at all. Motivated by these facts, in this section, we develop a random on-the-job search model, similar to Burdett and Mortensen (1998) and Sorkin (2018), in which workers value retirement benefits (on both the intensive and the extensive margin.) and the other non-wage portions of compensation separately. The model allows us to both directly estimate worker valuations and show the effect of retirement policy on labor market outcomes. We first describe the model setup and how it is estimated in our data. Then we describe the results and a validation exercise using the non-discrimination testing exercise.

6.1 Model Setup

The model is an on-the-job random search model, in the category of Burdett and Mortensen (1998), The model is partial equilibrium in the sense that wages and firm behavior are exogenous. Employers post contracts in which they are willing to pay workers a (exogenous) wage premium, proportional to the worker's skills and match value with the firm and exogenous benefits. Workers make binary choices over job offers, based on their valuation of the wage, benefits, and idiosyncratic features offered by the job. We focus only on transitions within industry, occupation and CBSA, to highlight job changes that are directly related to firm differences, rather than career or location changes.

Firms: There are J firms in the economy. Each firm employs workers in L_j unique occupation by industry by CBSA markets (henceforth, markets), indexed by $l_j = 1_j, ..., L_j$. Each firm is characterized by the tuple: $\mathbf{j_j}, r_j, \mathbb{1}_{r_j}, \mathbb{1}_{h_j}, \mathbf{g_j}, \mathbf{f_j}, \mathbf{a_j}$ with

- $\mathbf{j_j}$: a $1xL_j$ vector in which each element is the log wage premium paid by firm j to all workers in a market l equally
- r_j: the firm's employer contribution rate, a constant within firm
- $\mathbb{1}_{r_j}$ an indicator equal to one if the firm offers a retirement plan
- $\mathbb{1}_{h_j}$: an indicator equal to one if the firm offers a healthcare plan
- $\mathbf{g_j}$: $1xL_j$ vector in which each element is the number of employees in market l at firm j. Denote $\sum_{l=1}^{L} g_j = G_j$ where G_j is the total number of employees working at firm j.
- $\mathbf{f_j}$ a $(J-1)xL_j$ vector of firm j's recruiting intensities, where each element $f_{j,k,l}$ is the intensity with which firm j makes offer to employees of firm k in market l.
- $\mathbf{a_j}$: a $1xL_j$ vector in which each element is the non-wage, non-healthcare, non-retirement amenities offered by the firm to workers in market l.

To fix notation consider an example firm, Amazon, in the retail trade industry. Denote Amazon as firm 1. Amazon operates in the Retail Trade industry and employs workers in many occupations and cities. Denote marketing managers in San Jose as occupation $l_1 = 1_1$, marketing managers in New York City as $l_1 = 2_1$ and human resource managers in San Jose as $l_1 = 3_1$. The $\mathbf{j_1}$, $\mathbf{g_1}$ and $\mathbf{a_1}$ vectors thus contain the corresponding values to each of the markets for Amazon's workers (log wage premium, number of employees, and amenities, respectively). $\mathbb{1}_{h_j}$, $\mathbb{1}_{r_j}$, r_j are constants for all employees. Each row of $\mathbf{f_1}$ contains all the recruiting intensities of Amazon for the corresponding market in the Retail Trade Industry, For example, the first row of $\mathbf{f_1}$ contains the recruiting intensity of Amazon toward marketing managers in San Jose at all other firms in the Retail Trade industry, etc.

Workers: M workers are characterized by $m_{i,l}$ which encompasses their skill-level, labor market experience and other factors for which they will be compensated equally by all employers while working in market (occupation, industry and CBSA) l. A worker's indirect utility from working at firm j is a linear combination of his log wage, $w_{i,j,l}$ plus the value of having a health plan, the log dollars of retirement benefits $r_{j,l}$, the value of having a retirement plan, the log-dollar value he places on the amenities at firm j, denoted $ln(\bar{a_{i,j}})$, and his idiosyncratic valuation for working at j:

$$\begin{aligned} V_{i,j,l} &= \gamma_{i,l} ln(w_{i,j,l}) + (1-\gamma_{i,l}) ln(w_{i,j,l}(1+r_j)) + \beta_{i,l}\mathbb{1}_{r_j} + \alpha_{i,l}\mathbb{1}_{h_j} + ln(\bar{a_{i,j}}) + \epsilon_{i,j,l} \\ &= \gamma_{i,l} ln(w_{i,j,l}) + (1-\gamma_{i,l}) ln(w_{i,j,l}) + (1-\gamma_{i,l}) ln(1+r_j) + \beta_{i,l}\mathbb{1}_{r_j} + \alpha_{i,l}\mathbb{1}_{h_j} + ln(\bar{a_{i,j}}) + \epsilon_{i,j,l} \\ &= ln(w_{i,j,l}) + (1-\gamma_{i,l}) ln(1+r_j) + \beta_{i,l}\mathbb{1}_{r_j} + \alpha_{i,l}\mathbb{1}_{h_j} + ln(\bar{a_{i,j}}) + \epsilon_{i,j,l} \end{aligned} \tag{6}$$

Note that the wage is individual specific, due to the individual's skill level, but the retirement is not: firms must pay the same retirement (as a fraction of salary) to all workers. $\gamma_{i,l}$ is the weight worker i in market l places on wages, (1-$\gamma_{i,l}$) is the weight placed on total dollar compensation (wages + employer retirement contributions) by worker i when working in market l. $\beta_{i,l}$, and $\alpha_{i,l}$ are the weights placed on the firm having a retirement plan and healthcare dollars, respectively. In the modeling framework, weights are individual and market specific. That is, workers can value the distinct parts of compensation differently than other workers and individual workers may value compensation components differently when they are working in different markets. Assume $\epsilon_{i,j,l} \sim N(0, \sigma_l^2)$. Note that the distribution of the idiosyncratic match-value is market specific. This log-additive form of indirect utility is supported by findings in Maestas et al. (2018) and Mas and Pallais (2017).

Search and Transitions: Employed workers receive job offers sequentially (one at a time) from other employers randomly. Offers are received at an exogenous rate, λ.[36] When another offer is received, workers make a binary choice over the two jobs. Firms offer:

$$ln(w_{i,j,,l}) = m_{i,l} + \tilde{\eta}_{j,l} + \varphi_{i,j,l} \tag{7}$$

where $\varphi_{i,j,l}$ is a random draw from a mean zero distribution and $\tilde{\eta}_{j,l} = \eta_{j,l} - E[\varphi_{i,j,l}|$ Offer Accepted]

[36] Note that λ depends on the $\mathbf{f_j}$s of other firms in the market, but the functional form is not crucial for the subsequent analysis.

is the pay premium j offers to workers in market l adjusted for the fact that those with a higher match value are more likely to be accepted. By offering $\tilde{\eta}_{j,l}$, the firm ensures that the actual average log-wage premium paid to workers is $\eta_{j,l}$.

If a worker is employed at firm j and receives an offer from firm k, he makes a binary choice over the two jobs. He will leave his current job if $V_{i,k,l} > V_{i,j,l}$ which occurs with probability:

$$P(V_{i,k,l} > V_{i,j,l})$$

$$= P(\gamma_{i,l} ln(w_{i,k,l}) + (1-\gamma_{i,l}) ln(w_{i,k,l}(1+r_k)) + \beta_{i,l}\mathbb{1}_{r_k} + \alpha_{i,l}\mathbb{1}_{h_k} + ln(a_{i,k}) + \epsilon_{i,k,l} \tag{8}$$

$$> \gamma_{i,l} ln(w_{i,j,l}) + (1-\gamma_{i,l}) ln(w_{i,j,l}(1+r_j)) + \beta_{i,,l}\mathbb{1}_{r_j} + \alpha_{i,l}\mathbb{1}_{h_j} + ln(a_{i,j}) + \epsilon_{i,j,l})$$

$$\begin{aligned} &= \Phi[\gamma_{i,l}(ln(w_{i,k,l}) - ln(w_{i,j,l})) + (1-\gamma_{i,l})(ln(w_{i,k,l}(1+r_k)) - ln(w_{i,j,l}(1+r_j))) \\ &+ \beta_{i,l}(\mathbb{1}_{r_k} - \mathbb{1}_{r_j}) + \alpha_l(\mathbb{1}_{h_k} - \mathbb{1}_{h_j}) + (ln(a_{i,k}) - ln(a_{i,j}))] \end{aligned} \tag{9}$$

where Φ is the normal CDF $\sim N(0, 2\sigma_l^2)$.

Let $\Omega_l = ([j,k,\Delta ln(w_l)]_1, ..., [j,k,\Delta ln(w_l)]_{Sl})$ be the set of all S employer-to-employer transitions within market l. The joint likelihood of observing all such transitions, conditional on offers being made, is:

$$\mathbb{L}_l = \Pi_{s=1}^{S\in l}\Phi[V_{i,k,l} - V_{i,j,l}] \tag{10}$$

$$\begin{aligned} &= \Pi_{s=1}^{S\in l}\Phi[\gamma_{i,l}(ln(w_{i,k,l}) - ln(w_{i,j,l})) + (1-\gamma_{i,l})(ln(w_{i,k,l})(1+r_k)) - ln(w_{i,j,l}(1+r_j))) \\ &+ \beta_{i,l}(\mathbb{1}_{r_k} - \mathbb{1}_{r_j}) + \alpha_l(\mathbb{1}_{h_k} - \mathbb{1}_{h_j}) + (ln(a_{i,k}) - ln(a_{i,j}))] \end{aligned} \tag{11}$$

In words, the likelihood of the given transitions occurring is the product of the likelihood of each individual transition.

6.2 Estimation of Random Search Model

The main estimating equation from the model, (10), is a likelihood function and can be estimated by standard maximum likelihood techniques. With an ideal data set which contains all information about wages, healthcare, retirement, amenities and all offers from outside employers, one could estimate each of the weights and the amenities term in (10). However, two challenges prevent us from directly estimating these parameters. First, our data set does not have information on amenities.

Second, we do not observe rejected offers, only accepted ones. In the following paragraphs, we detail how we deal with each of these issues in the model estimation.

First, to address the lack of data on amenities, we move from estimating individual worker level weights to estimating weights at the occupation by industry level. That is, instead of the indirect utility function in (6), we have[37]:

$$V_{i,j,l} = \gamma_l ln(w_{j,l}) + (1-\gamma_l) ln(w_{j,l}(1+r_j)) + \beta_l \mathbb{1}_{r_j} + \alpha_l \mathbb{1}_{h_j} + ln(\bar{a}_j) + \epsilon_{i,j,l} \tag{12}$$

Estimating $\gamma_{i,l}$, $\beta_{i,l}$ and $ln(a_{i,j})$ from the likelihood function in (10) is not possible because the parameters are not identified. Even with data on transitions across many firm-to-firm pairs, the individual worker's weights cannot be pinned down without data on multiple transitions for the same worker. However, when the weights and the amenities term are averaged across all workers in an occupation by industry group, the parameters γ_l, β_l, and the mean of $ln(a_j) - ln(a_k)$ for all firm to firm pairs in S are clearly identified. This is because the measured retirement, wage and healthcare differentials across firms, plus an unobserved difference in amenities must explain the observed probability of workers moving between firms. Using the observed transition probabilities for all workers moving between firms in the industry by occupation group gives sufficient degrees of freedom and variation to estimate the average value of the parameters for all workers.

The variation that identifies the weight workers place on retirement benefits and the amenities term is driven by the net flows of workers between employers. The estimation results in three main outcomes of interest: 1) a unique weight on the intensive margin of retirement contributions for each occupation by industry group, 2) a unique weight on the extensive margin of having a DC retirement plan for each occupation by industry group, 3) a residual term that corresponds to the amenities term in equation (10). This term explains other job features that are not captured by wages, healthcare, retirement, occupation, industry, or CBSA differences but that drive transitions between employers. In this estimation method, the estimated amenities term represents an average difference in amenities across all firm-to-firm pairs in that industry by occupation group.

To address the second issue, that we do not observe rejected offers, we borrow from Sorkin (2018) and Bonhomme and Jolivet (2009) and make an assumption about offer intensities at the firm

[37]Note also that the i subscript on wages has been dropped, as we only observe occupation wages, not worker-specific wages.

by market-level. We assume that firms make offers to unemployed workers in that market at the same rate as they do to employed workers in that market and that unemployed workers never reject offers, that is $f_{k\to j,l} = f^{NE}_{j,l}\ \forall j \neq k \in J$. Thus, we use observed transitions out of unemployment to measure offer intensity ($f_{j,l}$).[38] This allows us to convert the conditional (on receiving an offer) probabilities of transition that we observe to unconditional probabilities of transition.

Normalizing $\gamma = 1$ so that all all other terms in the worker's valuation function are in log-wage equivalent units, the empirical counterpart of (10) is :

$$\mathbb{L}_{n,l} = \Pi_{s=1}^{S\in l}\Phi[V_{i,j,l} - V_{i,k,l}]^{\frac{1}{f^{NE}_{j,l}}\frac{1}{g_k}} \tag{13}$$

$$\begin{aligned} &= \Pi_{s=1}^{S\in l}\Phi[((ln(w_{k,l}) - ln(w_{j,l})) + \hat{\gamma}_l(ln(w_{k,l}(1+r_k)) - ln(w_{j,l}(1+r_j))) \\ &+ \hat{\beta}_l(\mathbb{1}_{r_k} - \mathbb{1}_{r_j}) + \hat{\alpha}_l(\mathbb{1}_{h_k} - \mathbb{1}_{h_j}) + \Delta(\widehat{ln(a_l)})]^{\frac{1}{f^{NE}_{j,l}}\frac{1}{g_k}} \end{aligned} \tag{14}$$

This is simply the likelihood function, weighted by both the inverse of the joining firm's offer intensity and the leaving firm's size. These estimation weights account for flows observed in the data that are due to firm size and recruiting efforts, but not the valuation of job qualities. This likelihood is estimated separately for each industry and occupation to get distinct weights on retirement benefits by worker type. Table 14 details the definitions of each component of the model.

Another step in the estimation of the search model is to limit the estimation sample to job-transitions that occur within industry, within occupation, and within CBSA. The motivation for doing so is two-fold. First, this choice eliminates variation in job-choice that comes from career or location switches. In this model framework, those differences would be picked up as "amenities." However, the preferences that drive these kinds of switches may not be directly comparable to wage and benefit levels. So, eliminating this variation makes the estimates of the different component valuations more directly comparable. Second, both the revealed preference results in Section 3 and the survey results in Section 5 relied on job-switchers who chose between very similar jobs. In the instrumental variables setting, the effect is measured within a firm, CBSA, and occupation, in which the wage does not vary drastically over time. In the survey setting, the wage difference between the

[38] We measure unemployment from gaps in employment on an individual's resume. If a person has a gap of at least 6 months between two jobs on their resume, we assume they were unemployed.

jobs offered was only about $2,000, on average and the other benefits (besides retirement), were always exactly the same. Hence, these methods are measuring the willingness to pay for retirement benefits when choosing amongst jobs with relatively similar wage levels and other benefits and job features. The choice to only keep this specific type of job-switcher creates a similar setting, in which the choice to move is not driven by large differences in the wage or other job characteristics that are specific to an occupation and CBSA.

As a final step before estimating the model, we also discount the dollar value of retirement contributions at the firm level by the participation rate in the plan. The participation rate can be calculated directly form Form 5500, by dividing the number of actively contributing employees by the number of eligible participants. This step is necessary because if we assumed that all employees participated in the plan, then that would lead to an over-valuation of benefits. Rather, we assume that a smaller number of employees (only the participating ones) are getting the benefit. The average participation rate in DC plans in the estimation sample is 75%, which is lightly higher than but close to the BLS estimate of 68%.[39]

Summary statistics for the estimation sample are shown in Table 15. This sample represents about 35,000 transitions to 9,500 firms, relative to the half a million transitions to 24,000 firms in the instrumental variables results.[40] Moreover, this sample represents a higher-income group of workers - the mean salary is $56,000, versus $49,554 in the main sample; the median is $50,000 versus $41,000 in the main sample. Firms in the estimation sample are also significantly larger: the average (median) number of employees is 3,800 (856), compared to 400 (66) in the main sample. Table 16 shows the input values from the sample corresponding to the terms in equation (14).

The main parameters of interest are $\hat{\gamma}_l = \frac{1-\gamma_l}{\gamma_l}$ and $\hat{\beta}_l$, which are measured at the industry by occupation level. $\hat{\gamma}_l$ is the weight on log total dollar compensation, relative to a weight of one on log wages only. $\hat{\beta}_l$ is the weight on having a retirement plan relative to a weight of one on log wages. While we could directly estimate $\hat{\alpha}_l$, the weight on having a health plan, we choose instead to calibrate it in order to preserve degrees of freedom and focus on estimating retirement-related parameters.

To understand the interpretation of the coefficients, note that the coefficient $\hat{\gamma}_l = \frac{1-\gamma_l}{\gamma_l}$ is the

[39]More details on: https://www.bls.gov/ncs/

[40]See Appendix Table A.9 to see how transitions change when each of the criteria are added.

ratio of the weight on log total pay to the weight on log wages. Consider two jobs at firms j and k that offer an agent the same indirect utility. For simplicity assume both firms have retirement plans, healthcare plans, and the same valuation of amenities by workers. It must be that:

$$ln(w_{k,l}) + \hat{\gamma}_l(ln(w_{k,l}(1+r_k))) = ln(w_{j,l}) + \hat{\gamma}_l(ln(w_{j,l}(1+r_j))) \tag{15}$$

$$\implies \hat{\gamma}_l = \frac{ln(w_{k,l}) - ln(w_{j,l})}{ln(w_{j,l}(1+r_j)) - ln(w_{k,l}(1+r_k))} \tag{16}$$

$$= \frac{\text{-\% change in wage}}{\text{\% change in total compensation}} \tag{17}$$

$\hat{\gamma}_l$ thus measures what percentage change in total compensation is necessary to compensate a worker for a 1% decrease in wage (or vice versa). Note the following ranges of interest for $\hat{\gamma}_l$:

- $\hat{\gamma}_l < -1$: workers place a higher weight on total compensation than on wages. A 1% decrease in wage must be compensated by some smaller increase in retirement. The worker can get the same utility at a lower level of total compensation, so long as retirement has increased.
- $\hat{\gamma}_l > 0$: workers place some weight on wages, but less than on total compensation. A 1% decrease in wages must be compensated by a larger increase in total compensation, meaning retirement must increase[41]

6.3 Estimates of Retirement Valuations

Table 17 shows the main results following the estimation of (14), The mean weight on wages is -2.83 and the corresponding mean weight on total compensation is 3.83. This implies an elasticity of wages to total pay of -0.74, meaning that a 1% decrease in wages can be compensated for by an increase in retirement that results in a -0.74% decrease in total compensation. The median is similar to the mean. Industry by occupation groups at the 10th percentile of the wage valuation

[41] Special cases:

- When γ_l , the non-normalized weight on wages is greater than one, then $-1 \leq \hat{\gamma}_l \leq 0$: this means that workers care about wages more than total compensation and a decrease in wages can never be compensated for by an increase in total pay.
- When γ_l, the non-normalized weight on wages, is equal to zero, then workers only care about total compensation. Any decrease in wages must be compensated for exactly (dollar for dollar) in total compensation.

distribution have an elasticity of -0.88, meaning that they require a smaller compensating differential in retirement contributions than those at the mean. At the 90th percentile of the distribution, workers have $\gamma_l = .83$. This means that workers place a higher value on wages than on total pay. Approximately 25% of the industry by occupation groups has $\gamma_l > 0$, and thus places a higher weight on only the wage portion of compensation versus the total compensation (See Appendix Figure A.8). The remaining 75% would be willing to give up some total compensation to get a higher employer contribution to their DC plan.

The estimates of β_l, the weight placed on the extensive margin of having a plan, show an average valuation of .02, meaning that the average occupation by industry group of workers is willing to give up 2% of total pay to get a DC plan. The 10th percentile of the distribution is slightly above 0, but still positive, indicating that most workers are willing to pay for this benefit. The 90th percentile of the distribution of β_l estimates value the DC plan as 4% of wages. These estimates align well with the survey estimated value of 3.4% of wages to get a 401(k).

The results also show that workers in higher income industry by occupation groups place a higher value on DC retirement plans. Figure 10 shows the relationship between retirement valuations and salary. Figure 10a shows a binscatter of the weight on total pay $(1 - \gamma_l)$ versus the average salary in the occupation by industry group. There is a strong positive correlation, with a coefficient of .38 and p-value of .009. Figure 10b shows a binscatter of the weight on having a DC plan (β_l) versus the average salary in the occupation by industry group. Again, there is a positive correlation, with a coefficient of .002 and p-value of .026, though the slope is much smaller than in the case of the intensive margin valuations. The willingness to pay for having the plan applies to almost all workers, while a significant portion of the distribution of workers (25%) has no willingness to pay for higher dollar contributions to the plan.

Compensating Differentials: In the following paragraphs, we detail what the model estimates imply about compensating differentials in retirement contribution dollars. Table 18 shows the results from an exercise which supposes that wages were reduced by 1%. What compensating differential in retirement contribution would be required to give worker the same valuation as before the wage reduction, holding all other benefits constant? We split the sample by income groups to show how the valuation of retirement contributions varies with the income distribution.

The first column of Table 18 shows the results for the 10th-25th percentile income group in the estimation sample. The average salary in these occupation by industry groups is $41,618. A 1% loss in wage is equivalent to a loss of about $414. For workers to get the same valuation from retirement contribution after this wage reduction, they need retirement contributions to increase by $2,240. Thus, total compensation must increase by $1,825 or 4.1%. This groups places a higher value on wages than on total pay, and thus needs large compensating differential to be made indifferent between the two compensation bundles. The increase in retirement needed is equivalent to the employer increasing their contribution rate by 5.48 percentage points (i.e. the employer goes from offering a 2% contribution rate to a 7.48% contribution rate).

Moving to the second column, we show the results for the middle 10% of the income distribution. This group has an average salary of $57,000, so a 1% decrease in wages is equivalent to a lost of about $567. To be made indifferent, this group only needs retirement to increase by $108, meaning thy will accept a total pay cut of $460, or 0.75%. This group of workers requires the employer contribution rate to increase by only 0.28 percentage points (i.e. the employer goes from offering a 2% contribution rate to a 2.28% contribution rate). This group values total pay more than wages, so they will accept a wage cut to get a slightly higher retirement contribution.

Similar to the middle income group, the high income group also values total pay more than wages. A 1% pay cut is equivalent to a loss of around $740 for this group. They require only a $130 increase in retirement contributions to get the same valuation as before the pay cut. So, this group will accept a total pay cut of about .77% so long as the employer contribution rate increases by .25 percentage points.

The instrumental variable estimates, the survey results, and the results from this structural model all show that most workers are willing to take less total compensation in return for a greater share of compensation as retirement benefits. The instrumental variables estimates and the structural model imply quite similar willingness to pay for higher income households. The instrumental variable results indicated by revealed preference that the average work values a dollar of retirement contribution nearly twice as much as a dollar of wage, while high-income workers value it nearly three times a much as a dollar of wage. In the estimated search model, the trade-off is 3-4 dollars of retirement for one dollar of wage amongst higher income workers; thus the estimates are fairly comparable in magnitude. Recall that the estimation sample for the model captures more high-income workers and occupations, thus it is expected that the results match more closely to the high-income only results from the instrumental variables analysis.

In the survey of hypothetical job choices, workers were willing to give up about 1.4% of wages for each one percentage point increase in the match - this is less than the trade-off estimated in the models. In terms of the extensive margin, survey participants were willing to give up 3.4% of wages to get a 401(k), versus about 2% on average here. Around 80% of participants had some willingness to pay for the 401(k) plan in this survey; about 90% of workers do according to the model estimates. Survey participants were 50% college graduates, compared to 75% in the Lightcast resume data. Survey participants had a median age of 32 versus about 40 in the Lightcast resume data. These differences could explain the higher valuation on retirement values found in the model estimation, as older and higher income workers seem to value retirement more.

6.4 Model Validation

While the total pay and amenity terms are separately identified in (14), one may still be concerned that the weights pick up variation from the amenities term and vice versa. That is, it could be that the preference for retirement is reflective of the fact that firms with better retirement also have better amenities. To address this, we use non-discrimination testing to show that firm-level amenity valuations do not change around NDT testing.

To complete this exercise, we must estimate *firm-level* valuations, rather than industry by occupation average weights. In the main modeling framework, we elect to estimate weights at the occupation by industry level for two main reasons. First, we are interested in estimating a worker-level quantity, not a firm-level one. Ideally, we could estimate these quantities at the individual level, but as discussed above, this is not possible in our data. Hence, the occupation by industry averages are a way to estimate a proxy for the desired parameter (worker-level weights on retirement) that is possible in our data. Second, we have data on retirement contributions and plans. Most papers that estimate firm-level valuations (Sorkin (2018), Lehmann (2022), Bonhomme and Jolivet (2009)) do not have such data, and thus estimate the valuation of all benefits at the firm-level. We have data on benefits (retirement and healthcare), and thus can estimate worker valuations for each component separately, using variation across workers in the same industry by occupation group.

This estimation method results in an industry by occupation average amenity difference, denoted $\Delta\widehat{ln(a_l)}$ above, which represents the average amenity difference between each firm pair in the industry-by-occupation group. This does not reveal firm-level amenity valuation. As a validation exercise of the model, we estimate firm-level amenity valuations, net of the estimated retirement valuations and show that the amenity valuations do not change around NDT failure for the subset of firms who failed in our estimation sample. The likelihood function to estimate firm-level valuations is:

$$\mathbb{L}_{n,l} = \Pi_{s=1}^{S\in n,l}\Phi[(\gamma[ln(w_{j,l}) - ln(w_{k,l})] + ln(\bar{a_{j,l}}) - ln(\bar{a_{k,l}})]^{\frac{1}{f_{j,l}^{NE}}\frac{1}{g_k}} \tag{18}$$

Note that in this method, we no longer use any data on retirement or healthcare. We estimate firm-level valuations for all amenities, inclusive of retirement, healthcare, and any other benefits. As before, we normalize $\gamma = 1$ so that the amenities term is in log-wage equivalent units. Each firm's valuation is estimated against a base-firm, that is $\bar{a_{k,l}}$ is normalized to zero for some firm k, which we select to be the firm with the most transitions in the estimation sample.

We have shown in Sections 2.1.1 and 3 that the shock of NDT failure induces changes in the measured retirement contributions. Thus, NDT failure can be used to test the model by showing that the firm-level amenity term, net of implied retirement valuations, does not change around NDT failure. That is, $[ln(\bar{a}_j) - ln(\bar{a}_k)] - (1-\gamma_l)(w_{j,l}r_j)$, should not change following a firm's NDT failure.

Figure 11 shows the results of a difference and difference regression for this estimated quantity around NDT failure. There is no significant different in amenity valuation, net of the implied valuation on retirement contributions, for NDT failing firms after NDT failure. In the model estimation sample, around 800 firms fail NDT at some point from 2010-2019. The regression controls for year by industry fixed effects, log number of employees, and log dollars of assets in the retirement plan. Hence, firm-level amenity valuations do not change around NDT failure. The results of this test indicate that the estimated weights on retirement contributions in Section 6.3 indeed are measuring the valuation of retirement, not other amenities.

7 Firm Policy Implications

In this section, we assess whether or not firms could improve recruiting outcomes with changes in compensation structure in partial equilibrium under the constraint that retirement benefits are common across workers and firms hire workers across the income distribution who value retirement benefits heterogeneously. We consider the distribution of workers in our data – not just new hires – and measure the differential impact on worker well-being across the income distribution.

7.1 Setup

The search model estimates yield a value for γ_l in each industry by occupation group, which reveals how much workers value a 1% increase in retirement contributions relative to a 1% increase in salary.

Let $\Omega_{j,n,l} = ([j, 1, \Delta ln(w_l)], ..., [j, k, \Delta ln(w_l)]_J)$ be the set of all possible transitions of workers in market l to firm j from all other firms in the same industry employing workers in the same market. When looking at all such transitions, there is an average probability that workers who are offered jobs at firm j will accept the offer. The probability that j offers a greater value than a given firm, k is:

$$\begin{aligned} Pr(V_{i,j,l} > V_{i,k,l}) = \Phi[&\gamma_{i,l}(ln(w_{k,l}) - ln(w_{j,l})) + (1-\gamma_{i,l})(ln(w_{k,l}(1+r_k)) - ln(w_{j,l}(1+r_j))) \\ &+ \beta_{i,l}(\mathbb{1}_{r_k} - \mathbb{1}_{r_j}) + \alpha_l(\mathbb{1}_{h_k} - \mathbb{1}_{h_j}) + (ln(a_{i,k}) - ln(a_{i,j}))] \end{aligned} \tag{19}$$

Denote this probability as $\phi_{j,k,l}$. Thus the expected probability that any offer from firm j to a worker in market l is accepted (unconditional of the worker's current employer) is:

$$\phi_{j,l} = \frac{\sum_{k=1}^{J_n} \phi_{j,k,l} g_{k,l}}{\sum_{k=1}^{J_n} g_{k,l}} \tag{20}$$

which is the weighted average of the probability of transitions from each possible leaving firm, weighted by the leaving firms' sizes. This means that firm j will hire

$$g_{j,l,new} = \phi_{j,l} \times f_{j,l} \times (g_l - g_{j,l}) \tag{21}$$

new workers in market l in a given time period. This is the probability of acceptance, times the offer intensity of firm j to all other firms in occupation l times the number of workers in occupation l at other firms.

Consider the case where firm j increases its wages in occupation l by 1%. This also implies that $r_{j,l}$ increases by 1%, assuming that retirement is a percentage of compensation. Holding wages and retirement at all other firms constant, this necessarily increases $\phi_{j,l}$ and $g_{j,l.new}$. The magnitude of the increase depends on the magnitude of the wage and retirement differential between j and all other firms employing workers in occupation l, the size of those competitor firms, the size of γ_l, and the standard deviation of the individual to firm match component, σ_l^2. Denote the new number of new workers for firm j in market l as $\hat{g}_{j,l,new} = Ag_{j,l,new}$ where A is some constant > 1.

Now consider the case where firm j raises its employer contribution by one percentage point. Holding wages and retirement at all other firms constant, this also necessarily increases $\phi_{j,l}$ and $g_{j,l,new}$. Again, the magnitude of the increase depends on the other terms in (19) and (20). Denote this new number of new workers as $\tilde{g}_{j,l,new} = Bg_{j,l,new}$ where B is some constant > 1.

The total net cost of increasing wages by 1% in occupation l is exactly:

$$(w_{j,l}(1 + r_j)) \times .01 \times g_{j,l,new} \tag{22}$$

.

The net cost for new workers of increasing retirement to occupation l by 1% is:

$$w_{j,l}(r_j + .01) \times (g_{j,l} + g_{j,l,new}) \tag{23}$$

However, recall that due to NDT regulations, the firm must increase the employer contribution rate for all occupations if it does so for one occupation. The total cost, inclusive of increasing contributions of existing employees, is:

$$\sum_{l=1}^{L_j} w_{j,l}(r_{j,l} + .01) \times (g_{j,l} + g_{j,l,new}) \tag{24}$$

When increasing retirement contributions, the firm must do so for all employees and thus pays a cost that is summed across all occupations and all existing and new employees. If the firm increases wages, the cost is limited to new workers in that occupation. For a given firm that wants to increase its hiring efficiency in occupation l, it has two options each of which have different costs. It can increase wages at a cost of

$$\frac{(w_{j,l}(1 + r_j)) \times g_{j,l,new}}{A g_{j,l,new}} \tag{25}$$

per new worker in market l. Or it can increase retirement at cost:

$$\frac{\sum_{l=1}^{L_j} w_{j,l}(r_{j,l} + .01) \times (g_{j,l} + g_{j,l,new})}{B g_{j,l,new}} \tag{26}$$

per new worker in market l. This trade-off will vary by occupation and depending on the firm's set of competitors and its worker composition.

7.2 Effect on Firm Recruiting

Table 19 shows the results from the counterfactual exercise of firms increasing their wages by 1% or their contribution rate by one percentage point.[42] The exercise is partial equilibrium; we assume that each firm increases its wage, one at a time, that other firms do not respond, and that firms do not change their recruiting intensity. The top panel shows the results for a 1% increase in wage. On average, firms would improve their recruiting success (the likelihood of a job offer being accepted) by 0.16% if they increased wages by 1% in all occupations. The average cost of doing so per one new worker is about \$543. Spreading the total cost for all of the net new workers hired over all employees results in a cost of just 6 cents per employee to increase wages by 1% across the board

[42]Note that these unit increases for the wage and retirement are roughly equivalent in dollar terms, as a one percentage point increase in the employer contribution rate has the same effect as a 1% increase in salary. For example, with a salary of \$100,000 going from a 2% to a 3% employer matching rate means going from \$2,000 to \$3,000 in employer contributions, or a \$1,000 increase. This is equivalent to a 1% increase in the \$100,000 salary.

for new hires. So, the increase has relatively small effect on recruiting outcomes but it is also not very costly.

The bottom panel show the effect on recruiting success and cost of increasing the employer contribution rate by one percentage point. First, we explain the costs per new worker, which is more directly comparable to the exercise of increasing wages, as those costs apply only to new hires. A one percentage point increase in the employer contribution rate leads to an average .41% increase in the recruiting success rate. This is about 2.5 times the effect of the equivalent dollar increase in wages. The cost per one new hire is roughly similar to the wage exercise: $503. The cost is slightly lower for increasing retirement contributions because of tax considerations; firms do not have to pay payroll taxes on the retirement portion of compensation. The net cost of the new hires spread across all employees is 10 cents per worker. This is slightly higher than the wage cost per worker because increasing retirement contributions gets the firms more new workers. Thus, on a per new worker basis, increasing retirement contributions has about 2.5 times the effect on recruiting success as increasing wages at a slightly lower cost.

However, the retirement exercise explained above ignores the constraint of non-discrimination testing. As described in Section 2.1.1, firms must offer equitable retirement contributions across all workers. Thus, increasing retirement contributions only for new workers is not an option. The last two rows of Table 19 shows the cost of increasing the employer contribution rate by one percentage point for all workers, including existing workers. The cost per one new worker increases nearly 17 fold to $8,282. Spread across all existing workers, the cost of hiring the new workers brought on by this change is about $35 per worker. So, while firms might like to use retirement contributions to attract workers, as doing so has a larger effect on success, regulations make it prohibitively costly.[43]

The top panel of Appendix Table A.10 shows the equivalent increase in wages that would be required to get the same effect on recruiting success as the one percentage point increase in retirement. To increase the probability of offer acceptance by .41%, the average firm needs to increase wages by 2.7%, which has a net cost of $1,480 per new worker, or 17 cents per existing worker. Thus, if one considers the cost of increasing retirement contributions for all workers at the firm (not just the costs per new worker), increasing wages to get the same effect is still significantly

[43]It is likely also challenging for firms to increase wages only for new hires. This is not for regulatory reasons, but rather because of workplace organization and bargaining dynamics (Grigsby et al. (2021), Galuscak et al. (2012)). We abstract from this issue here, but note that our estimates on the cost of increasing wages are a lower-bound.

cheaper, about one-eighth the cost, than increasing retirement per one new worker hired.

The bottom panel of Appendix Table A.10 shows the effect of increasing wages at roughly the same cost as increasing retirement, inclusive of the costs for existing workers. For the increase in wages to cost roughly $8,200 per new worker, the firms would need to increase wages for new hires by 14%. This will results in nearly a 2% increase in new hires, at a net cost of just 92 cents per existing worker.

There are three main takeaways from this exercise. First, retirement contributions, dollar for dollar have a about 2.5 times the effect on the recruiting success of new hires. If considering only the cost per new hire, increasing retirement contributions is a much more effective way to recruit in this sample of job-switchers. Second, the equity regulations on retirement plans make increasing retirement contributions for new hires extremely costly. When considering the cost of increasing contribution for all workers, rather than just new hires, the cost per new worker increases nearly 17 fold. Thus, although firms may want to use DC retirement contributions as a recruiting tool, doing so may be prohibitively costly. Lastly, increases in wages and retirement have a relatively small effect on recruiting success, even in this specific sample of switchers.

7.3 Effect on Worker Valuations

The previous section discussed the effect of changing compensation policy on firm outcomes and concluded that while increasing retirement contributions is more effective for most firms, increasing wages is often cheaper, due to regulatory constraints. But what effect would these changes have on worker job valuations? This section discusses the effects of changing the different types of worker compensation on worker valuations.

This counterfactual exercise involves increasing either wage by 1% or the employer contribution rate by one percentage point, one firm at a time. Then, we calculate the new valuation a worker would get from that job, from the worker's indirect utility function (6). Thus, this valuation change represents a potential valuation change if the worker were to move to the firm that changed its policy. The valuation increase should thus be thought of as an increase to the worker's outside option, or valuation at potential employers, not a valuation increase they get immediately at their current job.[44] As above, the exercise is partial equilibrium in the sense that only one firm changes

[44]Note that changes to the retirement contribution would impact workers at their current job because of the NDT

its policy at a time, other firms do not react, and firms change nothing else about their hiring or compensation.

Table 20 shows the effect on worker valuations from either changing the employer contribution rate by one percentage point or increasing the wage by 1%, split by how much the group values retirement contributions. Starting with the top 10th percentile, or those who value retirement the most and whose average income is $70,000, we see that a one percentage point change in the contribution rate of a potential employer increases those workers' potential valuations by 43%. In contrast, a 1% increase in the wages of a potential employer increase their potential valuation by only 4%. For the middle 10th percentile of retirement valuations, whose average income is $67,000, the effects are 11% and 3%, respectively. So, for the majority of the distribution, the retirement increase has a much larger (3-10 times) effect on outside options. However, for the bottom 10th percentile of retirement valuers, who are also lower income (average=$57,000), the retirement increase increases outside options by only .69%. In contrast, the 1% wage increase increase outside options by over 10 times as much: 8%.

This exercise demonstrates how the potential valuation differences between workers are due to the heterogeneous preferences for retirement. The workers who place the most value on the employer contributions get large positive effects to their outside options if firms offer higher contribution rates; this thus helps firms to recruit these workers more so than an increase in wages would. However, because the employer contribution rate must change for everybody, due to NDT regulations, this has a negative spillover on lower-income workers. Rather than getting a wage increase, which would provide them with a greater valuation increase, they would be offered higher retirement contributions, which do little to affect their valuations.

8 Conclusion

Defined contribution (DC) retirement accounts, such as 401(k) and 403(b) accounts, and employer contributions to these accounts are an increasingly important part of both household wealth accumulation and corporate labor costs. In this paper, we study both how workers value these plans as well their effect on labor market outcomes. We show across three distinct methods that most

regulation. We abstract from that in this exercise.

workers exhibit willingness to pay for both the intensive and extensive margin of DC retirement plans.

Our first finding, focusing on plausibly exogenous variation in firm-level retirement plans and posted wages, is that the average worker values a dollar of retirement contributions nearly twice as much as a dollar of wage when choosing between similar jobs. This ratio increases to 3:1 when focusing on high-income or older workers. The variation in wages and retirement plans is driven by changes induced by non-discrimination testing and firms that set common wages nationally for each given job type.

Second, we design and conduct an online experimental survey that uses hypothetical choices to measure how much potential workers are willing to give up in total compensation in order to get a 401(k) plan and to get higher employer contributions. Workers in the survey are willing to give up 3.4% of total pay to get a job with a 401(k) and 1.4% of wages for each one percentage point increase in the employer match. The majority of participants exhibit willingness to pay for both the intensive and extensive margin of the DC plans.

Lastly, we build and estimate an on-the-job search model which estimates worker valuations and allows us to conduct counterfactual analyses on firm compensation policy. Consistent with the instrumental variable results and the direct estimation of valuations in the survey, we show that the majority of workers (75%) are willing to give up some total pay to get a higher employer contribution. The valuation of retirement contributions increases with income, as in the revealed preference results. Moreover, 90% of workers are willing to give up some of total pay just get a 401(k). The results suggest increasing retirement contributions has a much larger (2.5 times) effect on firm recruiting success than increasing wages. However, doing so disproportionately benefits higher income workers who place a higher value on these contributions.

In future work, using the framework and data developed here, we plan to study the impact that non-discrimination testing has on worker welfare. Given the higher valuation placed on retirement benefits for higher-income workers, firms are incentivized to design plans to attract these workers. This could have spill-over effects on the wages of lower-income workers who don't value the retirement. Another natural follow-up is to study how retirement benefits affect retention. Many DC retirement contributions are vested and require workers to stay at the firm for some amount of time to reap the full benefits of employer matching. This paper focused on hiring, but the employer contributions and vesting schedules likely have an affect on retention; understanding this would improve our understanding of how DC plans affect equilibrium labor market outcomes. We would also like to study further the mechanism that leads to the high valuations of retirement benefits that we find. There are three prevailing theories to explain the high valuation 1) the signaling power of retirement benefits 2) retirement accounts are valuable as a commitment device 3) the valuation can be explained by a combination of taxes and discount rates. Combining both empirical methods and experiments, we plan to look for evidence of these theories in future work.

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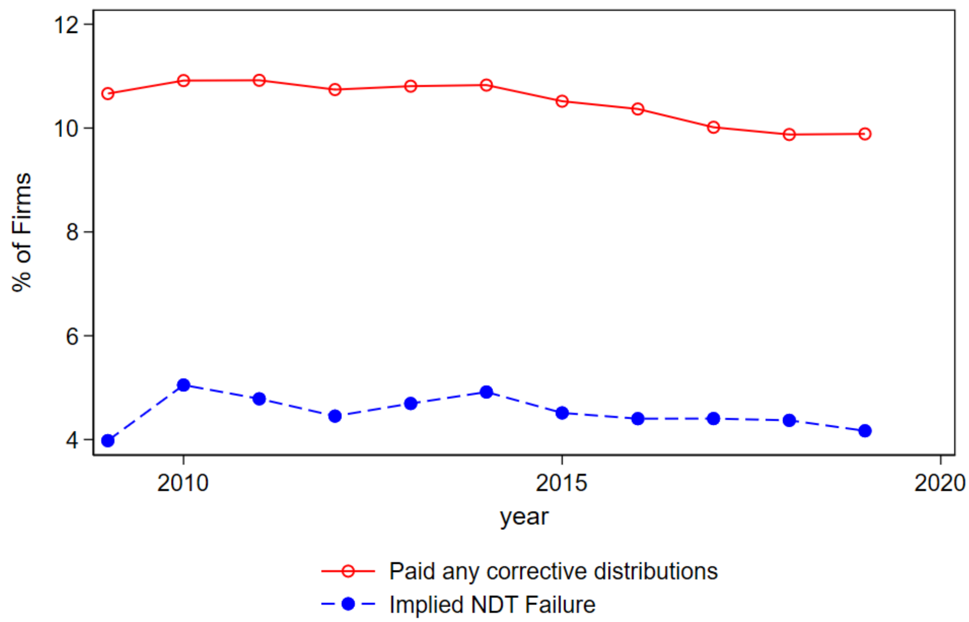
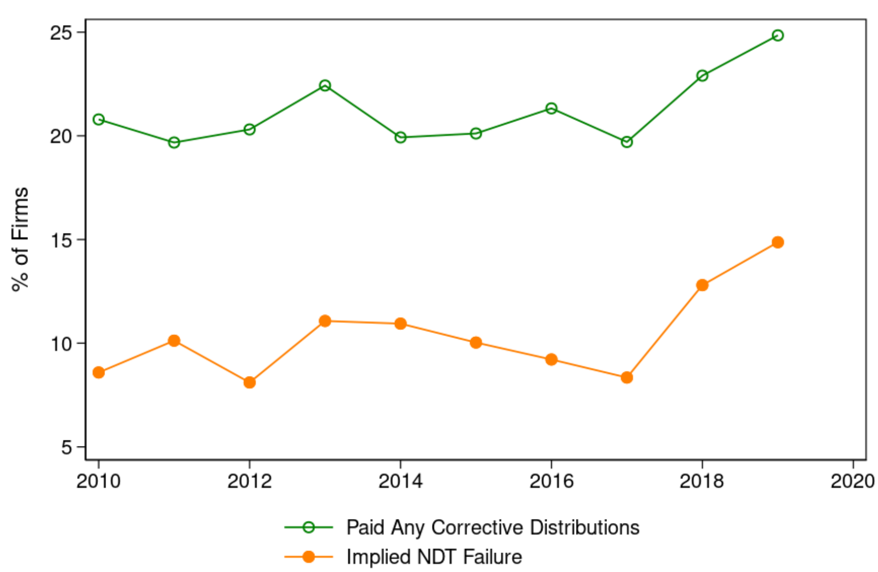
Figures

Figure 1: NDT Failure over Time

(a) % of DC Plans with a Corrective Distribution or NDT Failure



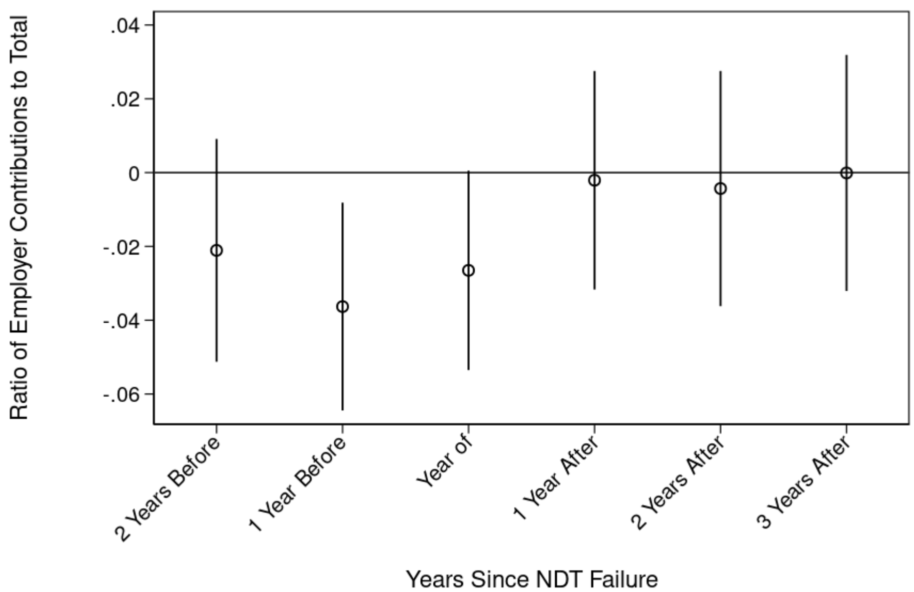
(b) Estimation Sample: % of DC Plans with a Corrective Distribution or NDT Failure



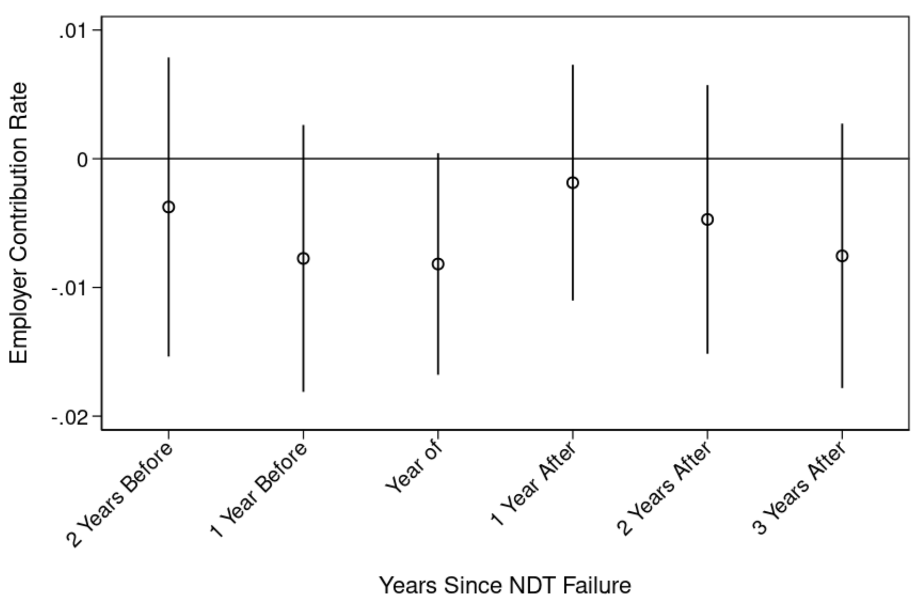
Notes: Authors' calculations from the Form-5500 data, 2010-2019. Includes only DC plans. The top panel shows the entire universe of form-5500 filers. The bottom panel shows only firms in our estimation sample.

Figure 2: Employer Retirement Contributions Before and After NDT Failure: Event Study Plots

(a) Employer's Ratio of all Contributions

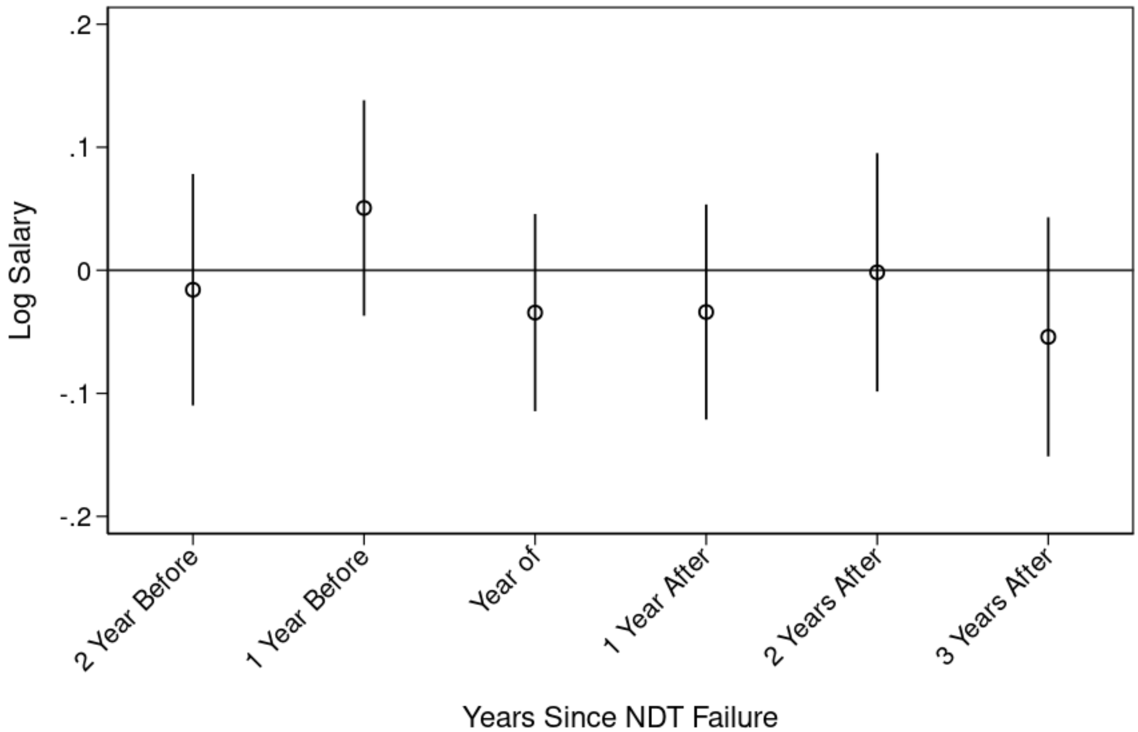


(b) Employer Contribution Rate



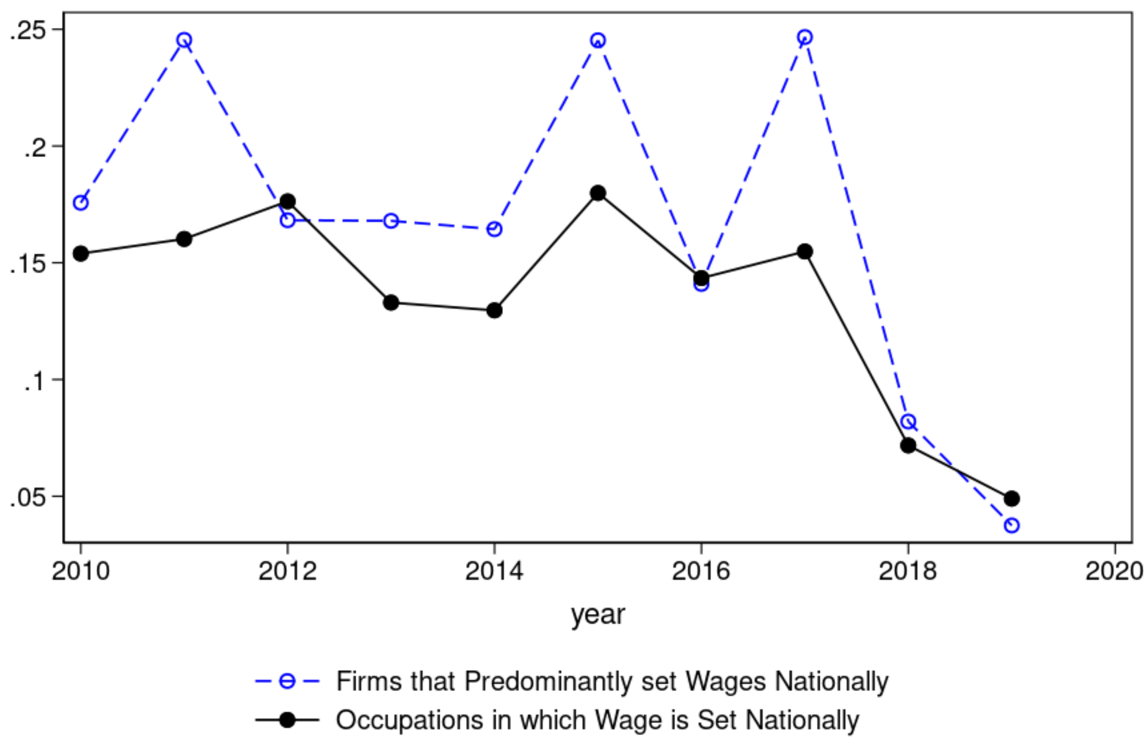
Notes: Control group is firms that do not fail NDT with the median year taken as year zero. Treated firms are those that fail in year zero. Regressions include industry by year fixed effects and controls for log number of employees and log dollars in assets in the retirement plan.Robust standard errors are clustered at the firm level. Confidence intervals are at the 95% significance level.

Figure 3: Average Annual Salary Before and After NDT Failure



Notes: Control group is firms that do not fail NDT with the median year taken as year zero. Treated firms are those that fail in year zero. Regressions include industry by year fixed effects and controls for log number of employees and log dollars in assets in the retirement plan.Robust standard errors are clustered at the firm level. Confidence intervals are at the 95% significance level.

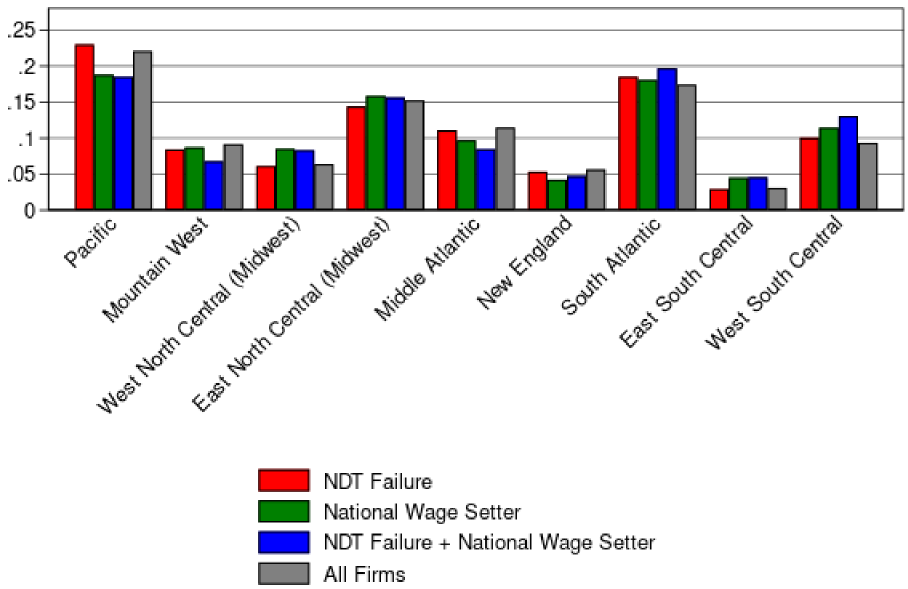
Figure 4: Percentage of Firms that are National Wage Setters



Notes: This figure shows the percentage of firms that set wages nationally in the matched sample of Lightcast wages, resumes and Form 5500. "% of Firms that Predominantly Set Wages Nationally" refers to firms that set at least 75% of their occupations across geographies at the same level. " of Occupations in which Wages are set Nationally" refers to the any occupation for which a firm sets wages identically across geographies.

Figure 5: Comparison of IV Estimation Samples

(a) Geographical Distribution



(b) Industry Distribution

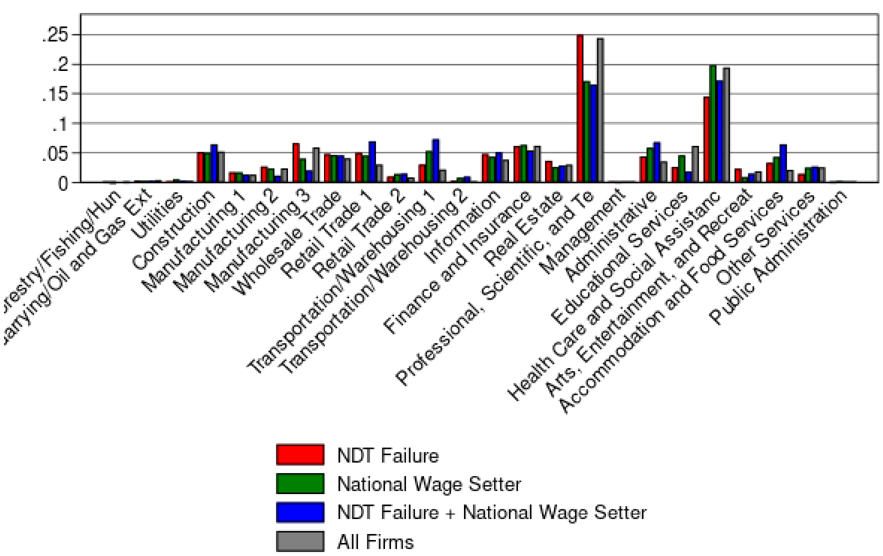
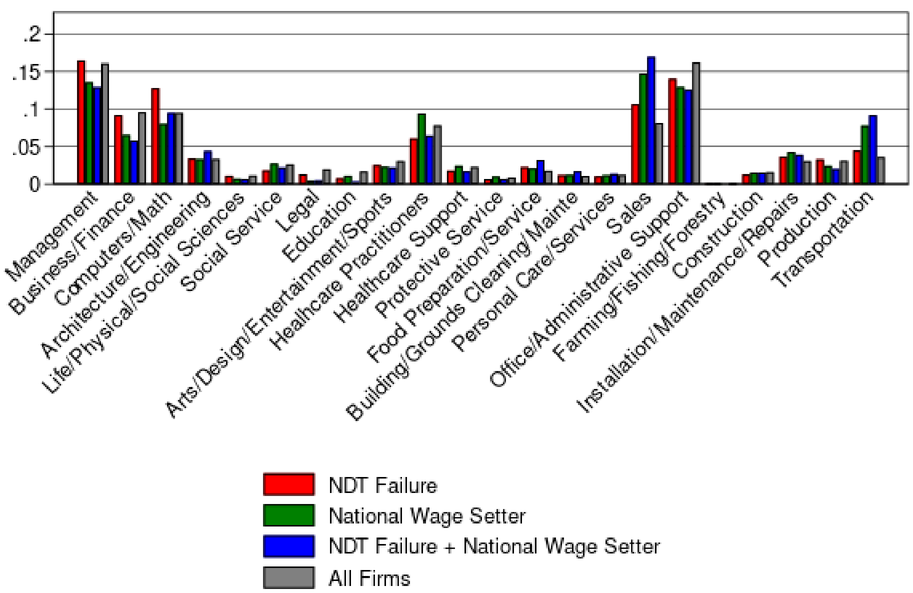


Figure 5: Comparison of IV Estimation Samples (continued)

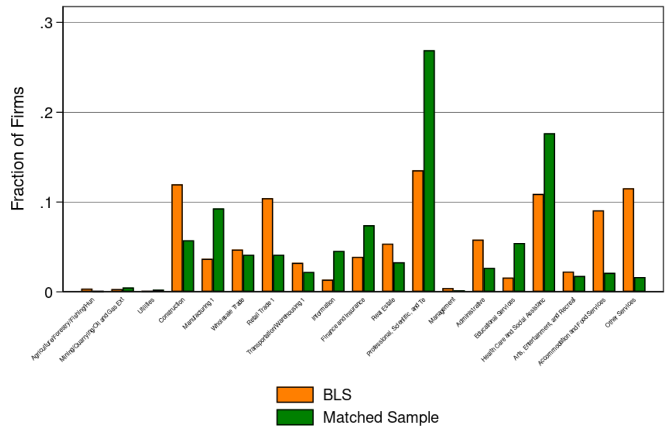
(c) Occupation Distribution



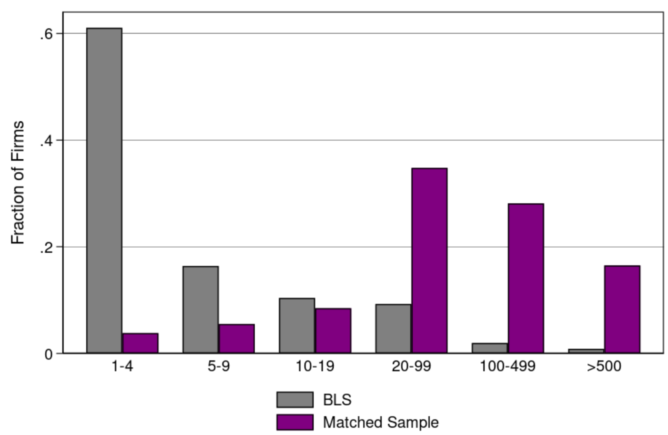
Notes: These figures compare the geographic, industry, and occupational distribution of firm in our estimation sample, split by firms affected by each of the instrumental variables.

Figure 6: Matched Sample Characteristics versus BLS

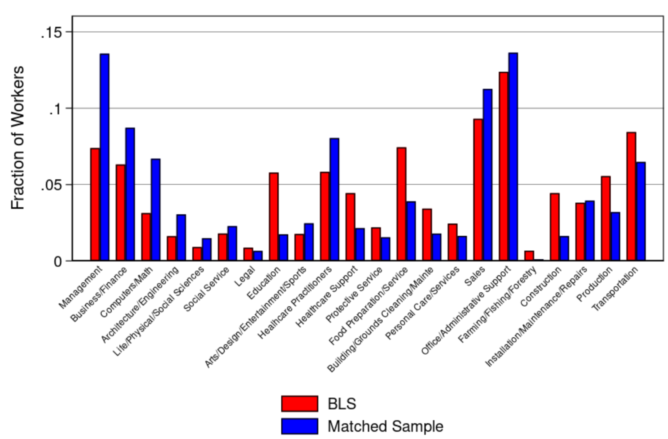
(a) Industry by Number of Firms



(b) Firm Size by Number of Firms



(c) Occupation by Number of Employees



Notes: These figures shows the distribution of firms and employment by industry, firm size and occupation in the main sample versus the BLS. The main sample is all firms in the merged sample of Lightcast posted wage, Lightcast, resumes, and Form 5500. The BLS sample is from the Bureau of Labor Statistics database.

Figure 7: Example Survey Question

(a) 401(k) with a 3% match versus 401(k) with no match

Scenario 5

	Job 1	Job 2
Annual Earnings when working full time:	$51,500	$49,000
Retirement benefits:	Company sponsored 401(k) (no employer match)	Company sponsored 401(k) with matching of 100% up to 3% (for a total possible match of $1,470 per year)
Healthcare benefits:	No	No
Vacation:	10 days of paid vacation	10 days of paid vacation
Work flexibility:	2 days of remote work per week	2 days of remote work per week

Note that with Job 2, your pre-tax take home pay will be $2,500 lower annually, or approximately $208 lower per month.

Select which you would be more likely to accept.

Job 1

Job 2

(b) 401(k) with no match versus no 401(k)

Scenario 3

	Job 1	Job 2
Annual Earnings when working full time:	$49,500	$51,500
Retirement benefits:	Company sponsored 401(k) (no employer match)	None
Healthcare benefits:	Yes	Yes
Vacation:	20 days of paid vacation	20 days of paid vacation
Work flexibility:	2 days of remote work per week	2 days of remote work per week

Note that with Job 1, your pre-tax take home pay will be $2,000 lower annually, or approximately $167 lower per month.

Select which you would be more likely to accept.

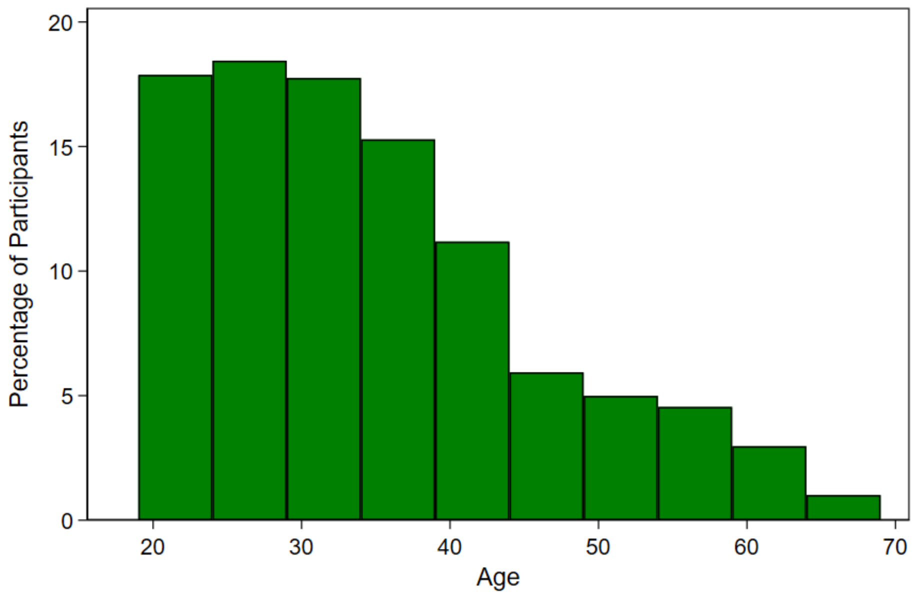
Job 1

Job 2

Notes: These figures show example question from the survey.

Figure 8: Demographic Characteristics of Survey Participants

(a) Age



(b) Gender

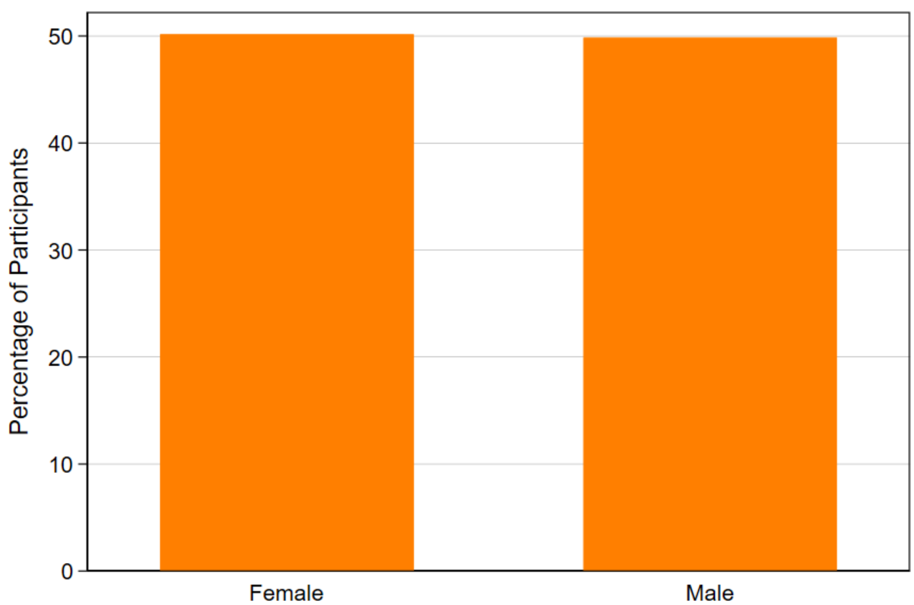
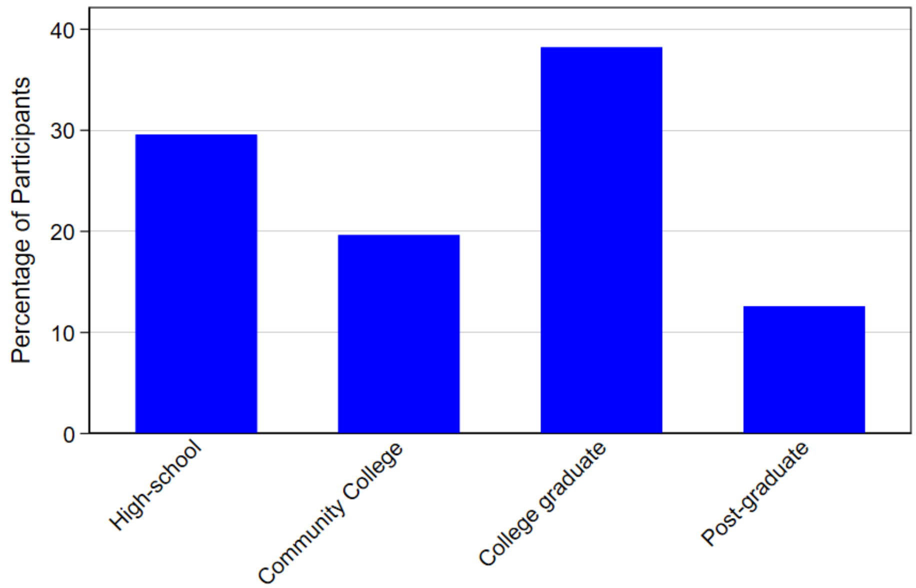
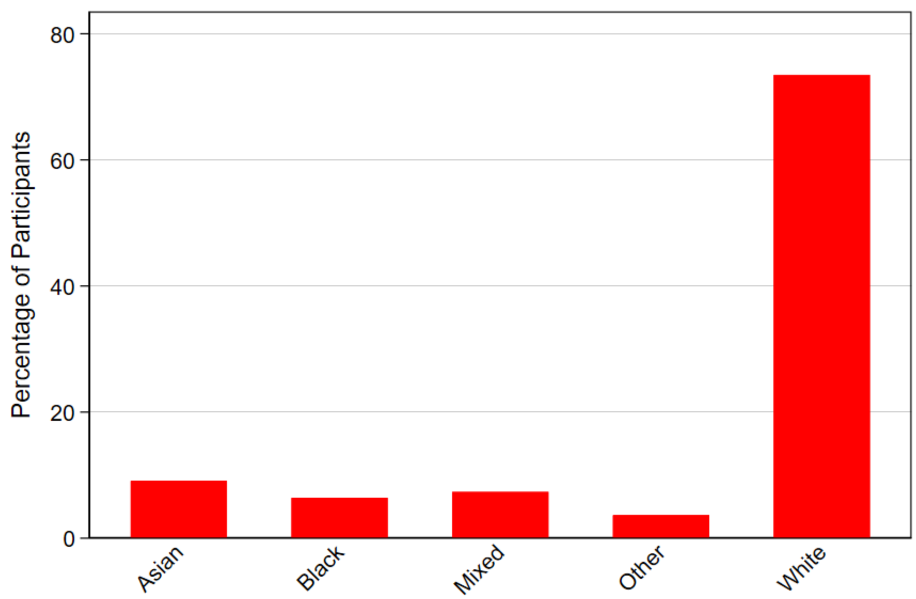


Figure 8: Demographic Characteristics of Survey Participants (continued)

(c) Education



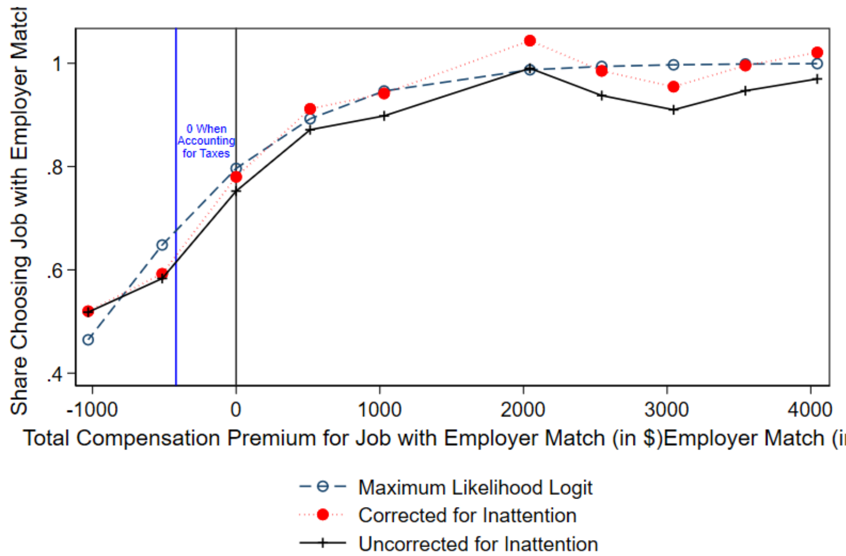
(d) Ethnicity



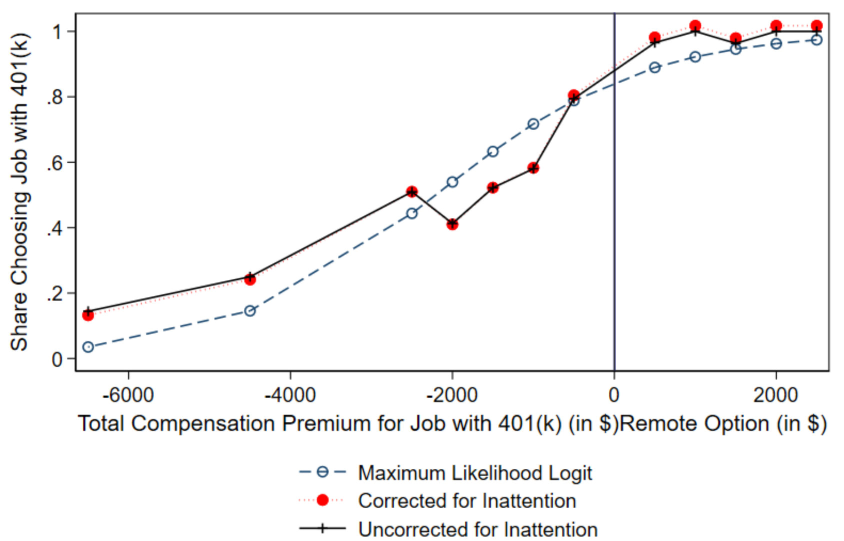
Notes: These figures show characteristics of the 1,600 survey participants recruited on Prolific. All participants are living in the U.S., speak English as a first language and are either working full-time or seeking work.

Figure 9: Willingness to Pay for Retirement Benefits

(a) Intensive Margin: Has 401(k) with 3% Match versus 401(k) with no match



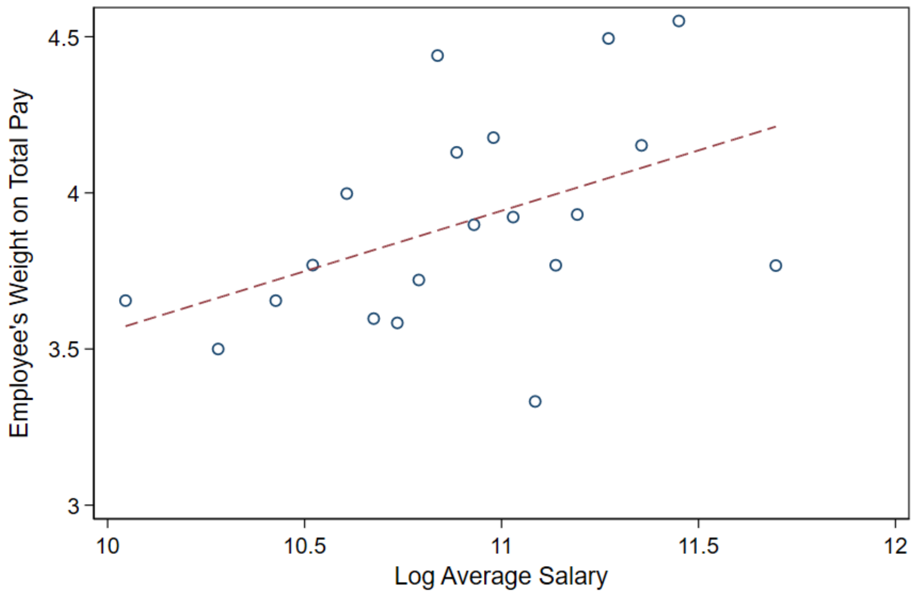
(b) Extensive Margin: Has 401(k) with no match versus no 401(k)



Notes: These plots show the fraction of participants who chose the job with the better retirement benefit plotted against the difference in total compensation. The total compensation gap is the total compensation for the job with the 401(k) in panel (b) and the job with the match in panel (a) minus the the total compensation for the job with no retirement in panel (b) or the job with no match in panel (a). Based on a a survey with 1,629 participants. The black line shows the raw data. The red dotted line shows the distribution corrected for inattention. The blue dashed line shows the distribution estimated by maximum likelihood.

Figure 10: Retirement Weights versus Salaries

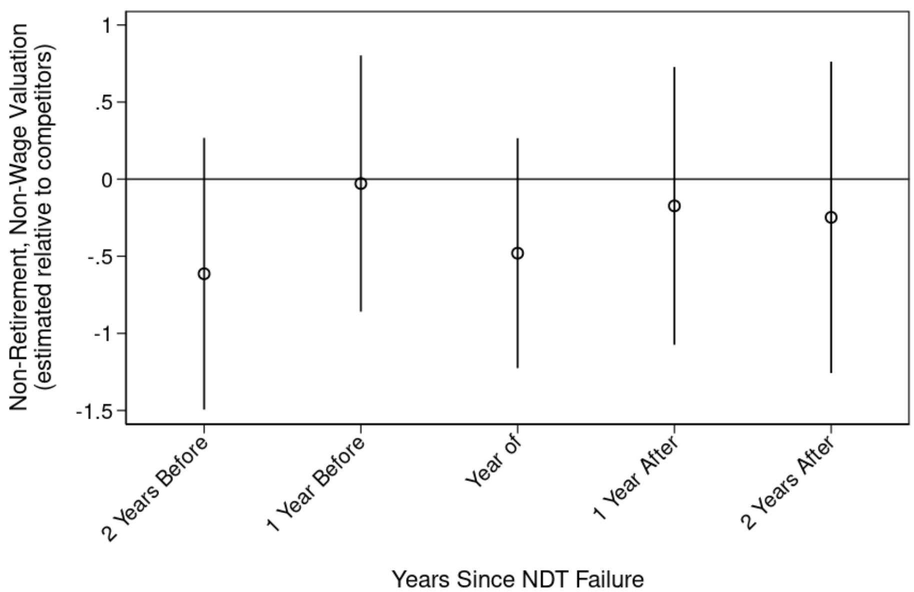
(a) Intensive Margin of DC Plan



(b) Extensive Margin of DC Plan

Notes: These figures show binscatters of the average log salary in an industry by occupation group against a) the estimated weight on total pay $(1 - \gamma_l)$ and b) the weight on the extensive margin of having a retirement plan (β_l). The binscatters control for year fixed effects and are unweighted.

Figure 11: Firm-level Amenities around NDT Failure



Notes: This figure shows difference-in-difference results for firm-level amenity valuations around NDT failure. The control group is firms that do not fail NDT with the median year taken as year zero. Treated firms are those that fail in year zero. Regressions include industry by year fixed effects and controls for log number of employees and log dollars in assets in the retirement plan. Robust standard errors are clustered at the firm level. Confidence intervals are at the 95% significance level.

Tables

Table 1: Difference in Difference Results: Effect of NDT Failure on Plan Features

	(1) Employer Ratio of All Contributions	(2) Employer Contribution Rate	(3) Has Autoenrollment
Time	-0.00987***	-0.00295**	0.0145***
	(0.00244)	(0.000949)	(0.00401)
Treated	-0.0735***	-0.0146***	0.106***
	(0.00343)	(0.00120)	(0.00965)
Time x Treated	0.0240***	0.00407*	-0.0235
	(0.00604)	(0.00204)	(0.0185)
Observations	28043	28350	34952
R^2	0.148	0.161	.152

Standard errors, clustered at the firm level, are in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This regression shows the difference in difference results for firms that failed NDT tests compared to firms that did not. The sample period is 2 years before, the year of, and 3 years after the NDT Failure. The year of is set to the median sample year for non-failing firms. Regressions control for year by industry fixed effects, log number of employees and log dollar assets in the retirement plan. Only firms with DC plans are included.

Table 2: Difference in Difference Results: Effect of NDT Failure on Non-Retirement Firm Characteristics

	(1) Log Salary	(2) Log # of Postings	(3) Log # of New Hires	(4) Log Years of Experience Required	(5) Log Dollars Paid in Healthcare Benefits per Person
Time	0.00946	0.480***	0.256***	0.0219	0.314**
	(0.00616)	(0.0200)	(0.0153)	(0.0340)	(0.106)
Treated	0.0362***	0.145***	0.0521*	0.0935*	0.166
	(0.00854)	(0.0259)	(0.0217)	(0.0470)	(0.160)
Time x Treated	-0.00921	-0.0133	0.101*	-0.0335	0.398
	(0.0179)	(0.0550)	(0.0455)	(0.0910)	(0.334)
Observations	31678	31678	31678	21954	28239
R^2	0.158	0.125	0.272	0.100	.039

Standard errors, clustered at the firm level, are in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This regression shows the difference in difference results for firms that failed NDT tests compared to firms that did not. The sample period is 2 years before, the year of, and 3 years after the NDT Failure. The year of is set to the median sample year for non-failing firms. Regressions control for year by industry fixed effects, log number of employees and log dollar assets in the retirement plan. Only firms with DC plans are included.

Table 3: Wages of National Wage Setters

	Log Average Salary		
	Firm level	Market Level	Market Level, Multi-establishment firms
National Wage Setter	0.0228**	0.0224***	0.0171***
	(0.00779)	(0.00170)	(0.00175)
Observations	47,348	468,011	398,544
R^2	0.151	0.452	0.472

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is log average salary at the firm level (column 1) and the occupation by CBSA level (columns 2 and 3). The independent variable is an indicator equal to one if the firm sets at least 75% of its wages nationally and 0 otherwise. Additional controls include log employment, industry by year fixed effects (column 1) and industry and occupation by CBSA by year fixed effects (column 2). Robust standard errors are clustered at the firm level.

Table 4: Characteristics of National Wage Setters

	(1) Log Employment	(2) Employer Contribution Rate	(3) Log # of New Hires	(4) Turnover	(5) Log $ per Person Spent on Healthcare
National Wage Setter	-0.254***	-0.00116	-0.238***	0.000989	-0.2040
	(0.0413)	(0.00127)	(0.0254)	(0.00248)	(.1666)
Observations	21611	19511	22262	21901	19981
R^2	0.093	0.050	0.137	0.407	0.0240

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Regressions are at the firm level. The independent variable is an indicator equal to one if the firm sets at least 75% of its wages nationally and 0 otherwise. Additional controls include industry by year fixed effects. Only firms with at least 2 establishments are included. Robust standard errors, clustered at the firm level, are in parentheses.

Table 5: Comparison of IV Samples

	NDT Failure	National Wage Setter	NDT Failure + National Wage Setter	All Firms
Employment and Hiring Variables				
# of Job Postings per Year	31.01 (6.00)	166.50 (30.00)	122.17 (33.00)	33.91 (6.00)
# of New Hires per Year	5.38 (2.00)	12.33 (2.00)	11.58 (3.00)	4.72 (1.00)
Hire Success	0.09 (0.00)	0.08 (0.00)	0.07 (0.00)	0.11 (0.00)
Annual Salary	57927.65 (50000.00)	55208.22 (47465.64)	52886.59 (44905.46)	56487.93 (49000.00)
Hourly Wage	27.88 (24.04)	26.61 (22.82)	25.44 (21.59)	27.21 (23.56)
Turnover - Form 5500 Employment	0.24 (0.17)	0.23 (0.14)	0.22 (0.12)	0.24 (0.16)
Tenure (months)	29.64 (26.21)	29.77 (27.15)	29.39 (27.40)	29.59 (25.88)
Total Employees	376.51 (90.00)	1155.29 (103.00)	775.88 (138.50)	397.88 (66.00)
Retirement Plan Variables				
Total Plan Assets (Millions of $s)	30.07 (3.61)	113.27 (3.58)	70.22 (4.81)	37.58 (2.63)
Employer Contribution Rate (%)	3.30 (2.16)	4.34 (2.87)	2.73 (1.88)	5.12 (3.38)
Ratio of Employer Contribution to Total	0.22 (0.22)	0.28 (0.29)	0.21 (0.21)	0.30 (0.30)
Employer Contributions per Participant ($)	1848.11 (1017.00)	985.29 (1427.80)	2110.26 (845.68)	2943.37 (1695.64)
Total # of Plan Participants	777.23 (165.00)	1876.81 (182.00)	1854.79 (332.50)	608.04 (92.00)

Table 5: Comparison of IV Samples (continued)

	NDT Failure	National Wage Setter	NDT Failure + National Wage Setter	All Firms
Other Variables				
% of Employees Captured in Resume Data	44.65	41.36	40.97	41.97
	(39.72)	(35.71)	(35.41)	(35.84)
% of Firms that set Wages Nationally	0.35	0.64	0.63	0.34
	(0.10)	(0.81)	(0.80)	(0.07)
% of Firms with $\geq$ 2 Establishments	0.48	1.00	1.00	0.41
	(0.00)	(1.00)	(1.00)	(0.00)
% of Firms with $\geq$ 4 Establishments	0.21	0.66	0.72	0.15
	(0.00)	(1.00)	(1.00)	(0.00)
# of Unique CBSAs per Firm	7.74	18.30	24.04	4.71
	(2.00)	(6.00)	(8.00)	(1.00)
# of Unique Occupations per Firm	9.52	19.97	19.98	7.44
	(4.00)	(6.00)	(9.00)	(2.00)
# of Unique Years per Firm	2.50	2.73	3.40	1.93
	(2.00)	(2.00)	(2.00)	(1.00)
# of Transitions	144499	264478	66938	555991
# of Unique Jobs	124438	227237	55786	486081
# of Firms	4328	2517	588	24554

Notes: This table shows summary statistics for them matched sample of firms that have job postings data in Lightcast, resume data in Lightcast, and Form 5500 data on health and retirement plans. Summary statistics are calculated at the firm level and averaged over all years the firm appears in the sample. Retirement summary statistics are conditional on having a retirement plan. Sample are split into groups affected by each of the instrumental variables. Medians are in parentheses.

Table 6: Distribution of Wages in the Matched Sample versus BLS

	Mean	P10	P25	P50	P75	P90
Matched Sample	49,554	21,840	27,560	40,951	60,000	90,000
BLS	50,629	24,000	30.970	42,880	61,690	85,570

Notes: This table shows the mean and percentiles for the annual salary in the matched sample of Lightcast job postings, Lightcast resumes, and Form 5500 versus from the Occupation Employment Statistics database for 2015.

Table 7: Summary Statistics for Matched Sample of Wages, Resumes, and Retirement Plans

	All Firms
Employment and Hiring Variables	
# of Job Postings per Year	33.91
	(6.00)
# of New Hires per Year	4.72
	(1.00)
Hire Success	0.11
	(0.00)
Annual Salary	56487.93
	(49000.00)
Turnover - Form 5500 Employment	0.24
	(0.16)
Tenure (months)	29.59
	(25.88)
Total Employees	397.88
	(66.00)
Retirement Plan Variables	
Total Plan Assets (Millions of $s)	37.58
	(2.63)
Employer Contribution Rate (%)	5.12
	(3.38)
Ratio of Employer Contribution to Total	0.30
	(0.30)
Employer Contributions per Participant ($)	2943.37
	(1695.64)
Total # of Plan Participants	608.04
	(92.00)
Other Variables	
% of Employees Captured in Resume Data	41.97
	(35.84)
# of Unique CBSAs per Firm	4.71
	(1.00)
# of Unique Occupations per Firm	7.44
	(2.00)
# of Unique Years per Firm	1.93
	(1.00)
# of Transitions	555991
# of Unique Jobs	486081
# of Firms	24554

Notes: This table shows summary statistics (means and medians) for the matched sample of firms that have both job postings data in Lightcast, resume data in Lightcast, and Form 5500 data on health and retirement plans. Summary statistics are calculated at the firm level and averaged over all years the firm appears in the sample. Retirement summary statistics are conditional on having a match in the Form 5500 data. Medians are in parentheses.

Table 8: IV Results: Effect of Wages and Retirement on Recruiting Success

	(1)	(2)	(3)	(4)
	First Stage		OLS	IV
	Log Salary	Employer Contribution Rate	Successfully Hire	
National Wage Setting Instrument	0.477***	-0.161***		
	(0.0116)	(0.0228)		
After NDT Failure	-0.00967	0.330***		
	(0.00800)	(0.0274)		
Log Salary			0.0141***	0.0142*
			(0.00419)	(0.0079)
Employer Contribution Rate			-0.00198	0.0271**
			(0.00131)	(0.0124)
Observations	124533	124533	124533	124533
Cragg-Donald Wald F-Statistic				136.485
Kleinbergen-Paap rk LM Statistic				190.852
Additional Controls:				
Year by Log Employment	Y	Y	Y	Y
Year by Log Assets	Y	Y	Y	Y
Health Plan Indicator	Y	Y	Y	Y
Fixed Effects:				
Firm by CBSA by Occupation	Y	Y	Y	Y
Year	Y	Y	Y	Y

Standard errors, clustered at the firm-level, are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a dummy equal to one if the firm successfully filled a position in a given occupation and CBSA in the year it was posted. The baseline average hire success rate is 11%. All regressions include firm by CBSA by occupation (5-digit SOC code) fixed effects and year fixed effects. Regressions are weighted by occupation by CBSA employment size. Only firms with at least two establishments and a defined contribution retirement plan are included.

Table 9: IV Results by Income Group: Effect of Wages and Retirement on Recruiting Success

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low-income Occupations				High-income Occupations			
	First Stage		OLS	IV	First Stage		OLS	IV
	Log Salary	Employer Contribution Rate	Successfully Hire		Log Salary	Employer Contribution Rate	Successfully Hire	
National Wage Setting Instrument	0.429***	-0.149***			0.509***	-0.173***		
	(0.0156)	(0.0291)			(0.0164)	(0.0330)		
After NDT Failure	-0.0035	0.388***			0.000732	0.189***		
	(0.00924)	(0.0461)			(0.0132)	(0.0312)		
Log Salary			0.00906	0.0187**			0.0172***	0.0203*
			(0.00577)	(0.0086)			(0.00583)	(0.0113)
Employer Contribution Rate			-0.00383**	0.0160*			-0.000173	0.0603**
			(0.00156)	(0.0097)			(0.00220)	(0.0279)
Observations	65022	65022	65022	65022	59511	59511	59511	59511
Cragg-Donald Wald F-Statistic				140.673				22.997
Kleinbergen-Paap rk LM Statistic				141.212				52.433
Additional Controls:								
Year by Log Employment	Y	Y	Y	Y	Y	Y	Y	Y
Year by Log Assets	Y	Y	Y	Y	Y	Y	Y	Y
Health Plan Indicator	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects:								
Firm by CBSA by Occupation	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors, clustered at the firm-level, are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a dummy equal to one if the firm successfully filled a position in a given occupation and CBSA in the year it was posted. The baseline average hire success rate is 8% for the low-income group and 14% for the high-income group. All regressions include firm by CBSA by occupation (5-digit SOC code) and year fixed effects. Regressions are weighted by occupation by CBSA employment size. Only firms with at least two establishments and a defined contribution retirement plan are included. Low (high) income are occupations below (above) the median income in that year.

Table 10: IV Results by Age: Effect of Wages and Retirement on Recruiting Success

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High-age Occupations				Low-age Occupations			
	First Stage		OLS	IV	First Stage		OLS	IV
	Log Salary	Employer Contribution Rate	Successfully Hire		Log Salary	Employer Contribution Rate	Successfully Hire	
National Wage Setting Instrument	0.469***	-0.125***			0.458***	-0.158***		
	(0.0193)	(0.0446)			(0.0206)	(0.0395)		
After NDT Failure	0.00864	0.296***			-0.0042***	0.326***		
	(0.0112)	(0.0472)			(0.0158)	(0.0594)		
Log Salary			0.00810	0.0236*			0.00989	0.0205*
			(0.00791)	(0.0122)			(0.00768)	(0.0111)
Employer Contribution Rate			-0.00267	0.0720*			-0.00277	0.00638
			(0.00220)	(0.0416)			(0.00269)	(0.0074)
Observations	46159	46159	46159	46159	33009	33009	33009	33009
Cragg-Donald Wald F-Statistic				43.111				30.937
Kleinbergen-Paap rk LM Statistic				55.928				38.738
Additional Controls:								
Year by Log Employment	Y	Y	Y	Y	Y	Y	Y	Y
Year by Log Assets	Y	Y	Y	Y	Y	Y	Y	Y
Health Plan Indicator	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects:								
Firm by CBSA by Occupation	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors, clustered at the firm-level, are in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a dummy equal to one if the firm successfully filled a position in a given occupation and CBSA in the year it was posted. The baseline average hire success rate is 10% for the low age occupations and 11% for the high age occupations. All regressions include firm by CBSA by occupation (5-digit SOC code) and year fixed effects. Regressions are weighted by occupation by CBSA employment size. Only firms with at least two establishments and a defined contribution retirement plan are included. Low (high) age occupations are those for which the median age, as measured by the BLS's Occupational Employment Statistics, is below (above) 42 years.

Table 11: IV Results by Gender: Effect of Wages and Retirement on Recruiting Success

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male-dominated Occupations				Female-dominated Occupations			
	Log Salary	Employer Contribution Rate	Successfully Hire		Log Salary	Employer Contribution Rate	Successfully Hire	
National Wage Setting Instrument	0.502***	-0.181***			0.423***	-0.138***		
	(0.0168)	(0.0304)			(0.0190)	(0.0410)		
After NDT Failure	-0.0248*	0.230***			-0.00734	0.340***		
	(0.0136)	(0.0327)			(0.0115)	(0.0531)		
Log Salary			0.00351	0.0140*			0.00443	0.0198
			(0.00633)	(0.0083)			(0.00825)	(0.0122)
Employer Contribution Rate			-0.00452**	0.0370*			-0.00355	0.0315*
			(0.00180)	(0.0210)			(0.00223)	(0.0189)
Observations	44987	44987	44987	44987	48223	48223	48223	48223
Cragg-Donald Wald F-Statistic				27.462				49.845
Kleinbergen-Paap rk LM Statistic				63.435				54.683
Additional Controls:								
Year by Log Employment	Y	Y	Y	Y	Y	Y	Y	Y
Year by Log Assets	Y	Y	Y	Y	Y	Y	Y	Y
Health Plan Indicator	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects:								
Firm by CBSA by Occupation	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors, clustered at the firm-level, are in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is a dummy equal to one if the firm successfully filled a position in a given occupation and CBSA in the year it was posted. The baseline average hire success rate is 9% for the male-dominated occupations and 12% for the female-dominated occupations. All regressions include firm by CBSA by occupation (5-digit SOC code) and year fixed effects. Regressions are weighted by occupation by CBSA employment size. Only firms with at least two establishments and a defined contribution retirement plan are included. Male (female) dominate occupations are those for which the estimated share of male (female) workers is greater than 50%, as measured by the BLS's Occupational Employment Statistics.

Table 12: Willingness to Pay for Retirement Benefits: Survey Evidence

	Intensive Margin	**Extensive Margin**
	401(k) with no match versus 401(k) with a 3% match	No 401(k) versus 401(k) with no match
Fraction that chose job with better retirement	0.846 (1004)	0.669 (1628)
Conditional on:		
Job with with better retirement having a lower wage	0.711 (478)	0.491 (1036)
Job with better retirement having a higher wage	0.968 (526)	0.980 (592)
Job with better retirement having a lower total comp	0.555 (191)	0.491 (1036)
Job with better retirement having higher total comp	0.942 (724)	0.980 (592)
Job with better retirement having lower total comp, net of taxes	0.555 (1036)	0.491 (191)
Conditional on choosing job with better retirement and lower total comp:		
WTP	2226 (106)	1775 (509)
WTP as a percent of wages	4.3 (106)	3.4 (509)
WTP in total comp	748 (106)	1775 (509)
WTP as a percent of total comp	1.5 (106)	3.4 (509)
WTP in total comp, net of taxes	258 (106)	1385 (509)
Cost of retirement plan to employer (excluding fixed/set-up costs)	1478 (106)	0 (509)

Notes: This table shows summary statistics for the survey conditions that test willingness to pay for the intensive and extensive margin of retirement benefits. The extensive margin condition asks participants to choose between similar jobs, one of which offers a 401(k) with no match and the other offers no 401(k). The intensive margin condition has participants to choose between similar jobs, one or which offers a 401(k) with a 3% match an the other offers a 401(k) with no match. Numbers in parentheses show the number of participants who answered for the relevant condition.

Table 13: Maximum Likelihood Estimates of Willingness to Pay in Survey

Treatment	Mean	SD	P25	P50	P75
Willingness to Pay for the Intensive Margin of Employer Contributions					
401(k) with 3% match versus 401(k) with no match	909.17	1400.26	60.61	909.17	1757.72
	(122.64)	(154.02)	(94.29)	(122.64)	(196.51)
Willingness to Pay for the Extensive Margin of Retirement Plans					
401(k) with no match versus no 401(k)	2267.56	2383.31	823.29	2267.56	3711.84
	(129.99)	(173.83)	(82.303)	(129.99)	(221.84)

Notes: This table shows the distribution of the willingness to pay estimates from the survey. Estimates are from an inattention-corrected maximum likelihood logit model using data from the experiment. Bootstrapped standard errors based on 1000 samples are in parentheses.

Table 14: Model parameters

Parameter	Definition	Source
$w_{i,j,l}$	Wage (in dollars) for individual i at firm j in occupation and CBSA l	Data: Lightcast Job Postings
$\mathbb{1}_{h_j}$	An indicator equal to one if firm j has a healthcare plan	Data: Form 5500
α_l	The weight on the dollar value of healthcare benefits	Calibrated (Baicker and Chandra (2006), Miller (2004))
$f_{j,l}^{NE}$	The recruiting intensity of firm j in CBSA and occupation l to unemployed workers	Data: Lightcast Resumes
$g_{j,l}$	The number of workers at firm j in occupation and CBSA l	Data: Lightcast Resumes
$r_{j,l}$	The retirement benefit (in dollars per person) given to workers at firm j in occupation and CBSA l	Data: Form 5500
$\mathbb{1}_{r_j}$	An indicator equal to one if firm j has a retirement plan	Data: Form 5500
$\hat{\gamma}_l$	The weight employees place on total compensation, relative to a weight of one on wages	**Estimated**
$\hat{\beta}_l$	The weight employees place the presence of a retirement plan	**Estimated**
$\widehat{\Delta ln(a_l)}$	The residual portion of job transitions that is not explained by wages, healthcare, retirement or industry, occupation or CBSA differences - referred to as "amenities"	**Estimated**
σ_l	The standard deviation of the idiosyncratic match value for workers in market l	**Estimated**

Notes: This table defines all of the model parameters and how they are measured or estimated.

Table 15: Summary Statistics of Model Estimation Sample

	mean	p50	p10	p90
Number of Employees	3795.95	856.00	61.00	8278.00
Average Salary	55929.12	50000.00	28500.00	90496.82
# of Job Postings per Year	209.29	14.00	2.00	322.00
Has a Retirement Plan	0.58	1.00	0.00	1.00
Employer Contribution $ per Person	2967.00	2063.91	0.00	6604.01
Participation Rate in Retirement Plan	0.75	0.86	0.43	0.93
Employer Contribution Rate	0.06	0.04	0.00	0.14
Has a Healthcare Plan	0.87	1.00	0.00	1.00
Number of Transitions	34,656			
Number of Industry by Occupation Groups	308			
Number of Firms	9,511			
Number of Unique Jobs	18,751			

Notes: This table shows summary statistics for the estimation sample of the on-the-job search model. The sample is limited from the full matched sample of Lightcast wages, Lightcast resumes and Form 5500 to individuals who transitioned between firms within the same industry, occupation, and CBSA.

Table 16: Inputs to Model Estimation

	Source	Mean	p50	p10	p90
$\Delta(ln(w_{j,l}(1+r_j)))$	Lightcast & Form 5500	0.01	0.01	-0.70	0.73
$\Delta w_{j,l}$ in dollars	Lightcast Job Postings	385.23	149.41	-40000.00	40821.33
$\Delta r_{j,l}$ in dollars	Form 5500	-51.60	48.02	-3774.77	4178.51
$\Delta \mathbb{1}_{h_j}$	Form 5500	0.02	0.00	-1.00	1.00
$\Delta \mathbb{1}_{r_j}$	Form 5500	0.01	0.00	-1.00	1.00
$f_{j,l}^{NE}$	Lightcast Resumes	0.07	0.01	0.00	0.17
$g_{j,l}$	Lightcast Resumes	806.16	82.00	6.00	1384.00
# of Firms		9,511			
# of Industry by Occupation Groups		308			
# of Transitions		34,656			
# of Jobs		28,036			

Notes: This table shows summary statistics for the inputs to the on-the-job random search model.

Table 17: Search Model Parameter Estimates

	mean	p50	p10	p90
γ_I	-2.83	-2.45	-7.37	0.83
$(1-\gamma_I)$	3.83	3.45	8.37	0.17
Elasticity of Total Pay to Wages	-0.74	-0.71	-0.88	4.76
β_I	0.02	0.02	0.00	0.04
Δa_I	0.93	0.76	-0.11	1.67
# of Transitions		34,656		
# of Industry by Occupation Groups		308		
# of Firms		9,511		

Notes: This table shows the estimated parameter values from the on-the-job random search model.

Table 18: Required Compensating Differentials to Make up for 1% Decrease in Wage - by Salary Group

	Estimation Sample Salary Percentile		
	10th-25th%	Middle 10%	75th-90th %
Average Salary	41618.00	57024.73	74649.37
γ_I	0.80	-2.90	-3.35
Dollar Differences:			
Wage ($)	-414.11	-567.41	-742.77
Retirement ($)	2,239,50	107.56	129.69
Total Compensation ($)	1,825.40	-459.85	-613.09
Percentage Differences:			
Total Compensation (%)	4.11	-0.74	-0.77
Employer Contribution Rate (pp)	5.48	0.28	0.25

Notes: Table shows averages. $ values are based on the ex-ante average salary, retirement contributions, and total compensation in the industry by occupation group, weighted by the number of new employees. Each group represents 25-30 industry by occupation groups.

Table 19: Effect of Changing Wages or Retirement on Recruiting Success

	p50	p25	p75
1% Increase in Wages			
% Change in number of new hires	0.16	0.07	0.32
Net cost per one new hire	543.86	387.17	781.67
Net cost per employee	0.06	0.00	1.00
1 pp Increase in Contribution Rates			
% Change in number of new hires	0.41	0.10	1.05
Cost for New Employees Only:			
Net cost per one new hire	502.69	357.86	722.50
Net cost per employee	0.10	0.00	1.68
Cost for All Employees:			
Net cost per one new hire	8282.43	2400.00	36824.67
Net cost per employee	34.79	12.00	91.11

Notes: This table shows the effect of changing wages or retirement contributions by 1% of one percentage point, respectively, on recruiting success. The top panel shows the effect of 1% increase in wage. The bottom panel shows the effect of a one percentage point increase in the employer contribution rate, with costs for only the new hires and costs for all employees. Statistics are at the firm-level.

Table 20: Effect of Increasing Wages or Retirement Contributions on Worker Valuations

	Percentile of Retirement Valuation:		
	Top 10th	Middle 10th	Bottom 10th
Average Salary	70027.95	67144.90	56933.18
γ_I	-7.84	-2.48	0.91
% Increase in Valuation due to:			
1 pp Increase in Contribution Rate	42.94	10.92	0.69
1% Increase in Wages	4.18	2.98	7.93
# of Industry by Occupation Groups	31	32	31
# of Jobs	3,374	5,561	5,520

Notes: This table shows the effect on worker valuations of increasing wages by 1% or increasing the employer contribution rate by 1 percentage point. The effect is averaged amongst all workers in a decile of retirement valuations.

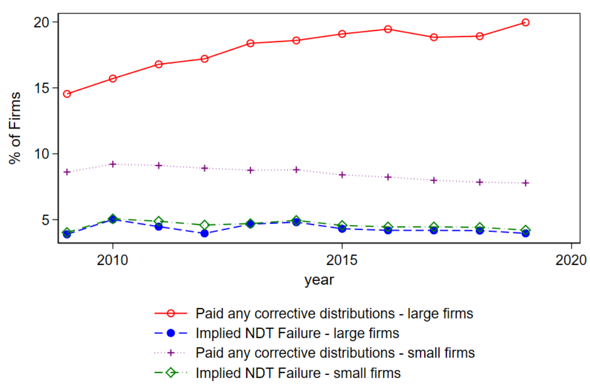
Online Appendix for "Worker Valuation of Retirement Benefits"

April 26, 2023

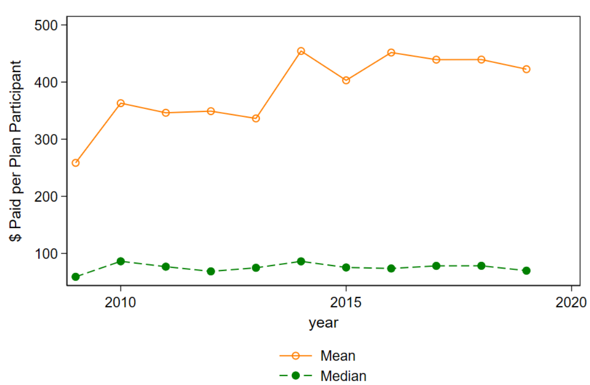
A Appendix Tables and Figures

Figure A.1: NDT Failure over Time

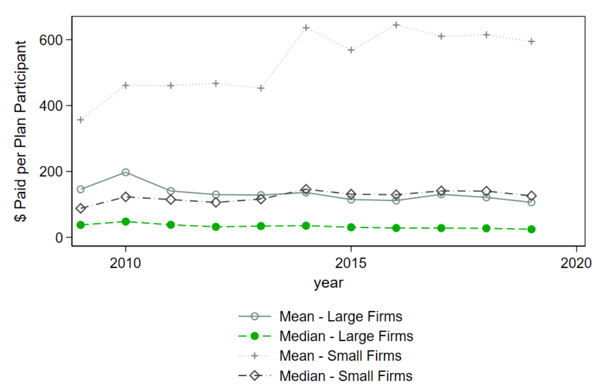
(a) % of DC Plans with a Corrective Distribution or NDT Failure, by Size



(b) $ in Corrective Distributions paid per Participant, Conditional on Paying Any



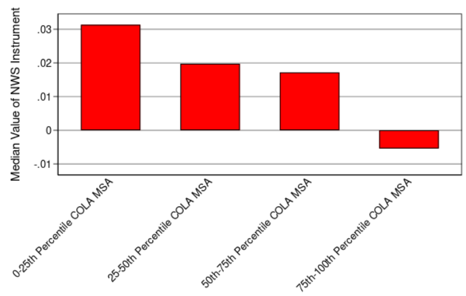
(c) $ in Corrective Distributions paid per Participant, Conditional on Paying Any, by Size



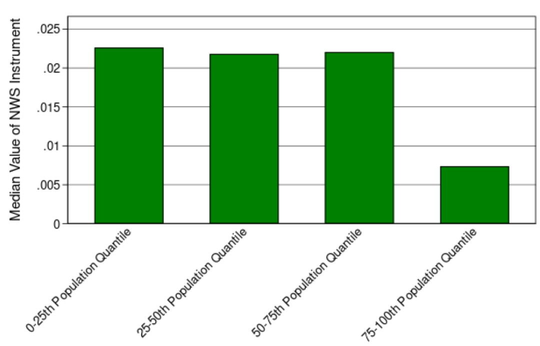
Notes: My calculations from the Form-5500 data, 2010-2019. Includes only DC plans. Dollar amounts in figures c and d are conditional on firms that paid some corrective distributions. Large plans are those with greater than 100 participants.

Figure A.2: National Wage Setting Instrument

(a) By Cost of Living



(b) By Population



(c) By Firm Size

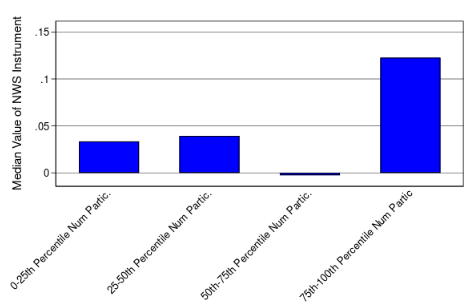
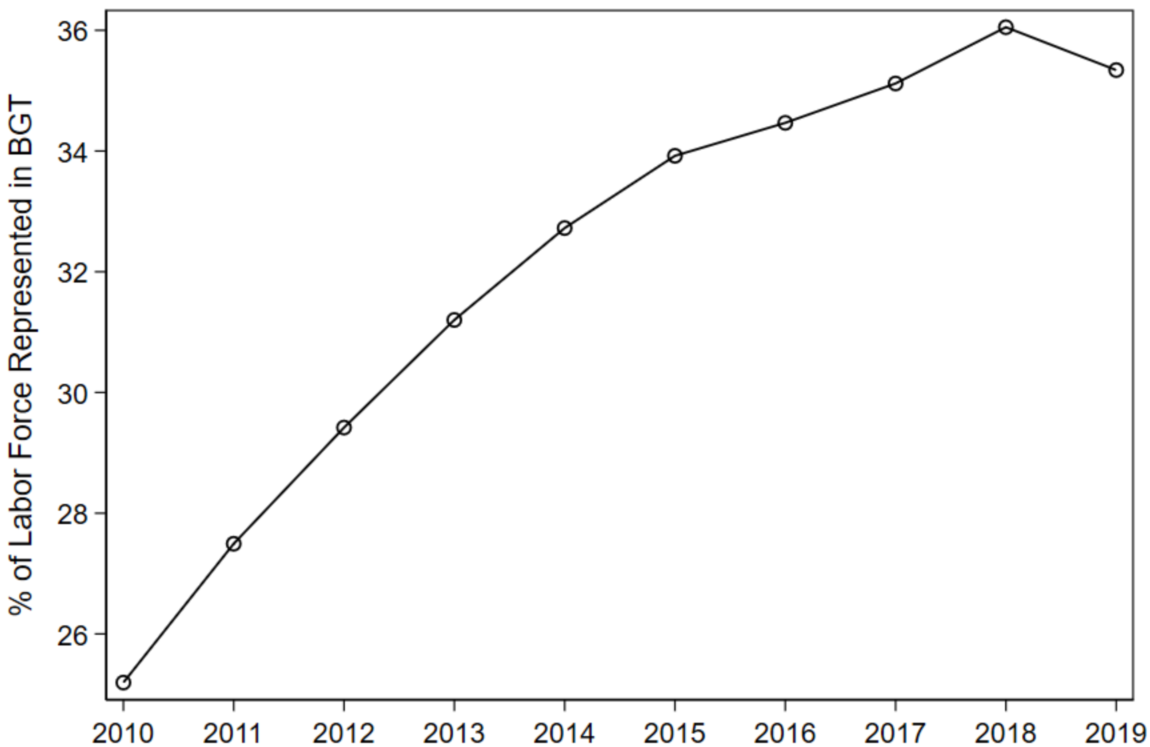


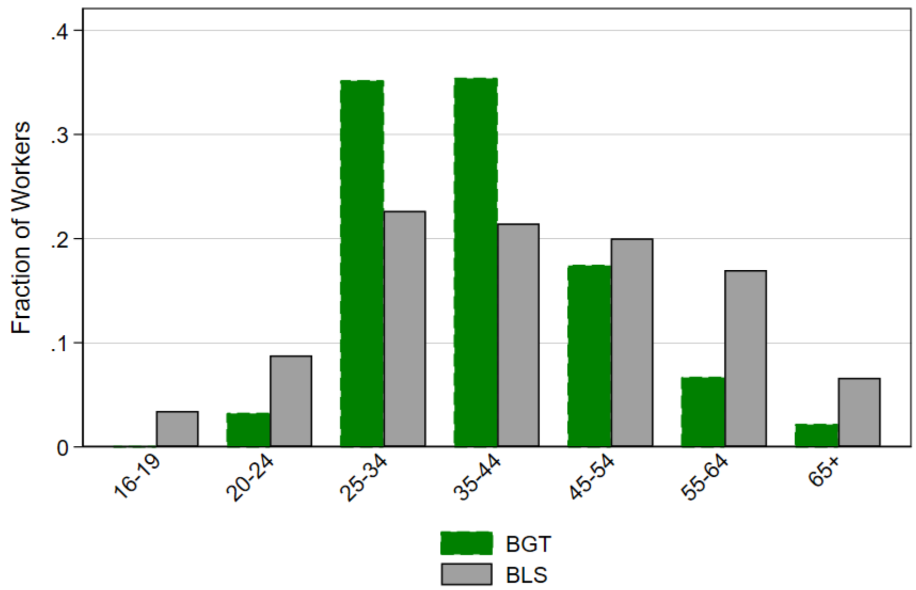
Figure A.3: Percentage of Labor Force Captured in Lightcast Resume Data



Notes: This figure shows the percentage of the workforce that is captured in the Lightcast resume data each year in our sample. The total workforce is from the Bureau of Labor Statistic's Occupation Employment Statistics. The Lightcast count includes all resumes.

Figure A.4: Lightcast Resume Representativeness

(a) Age in Lightcast versus BLS



(b) Education in Lightcast versus BLS

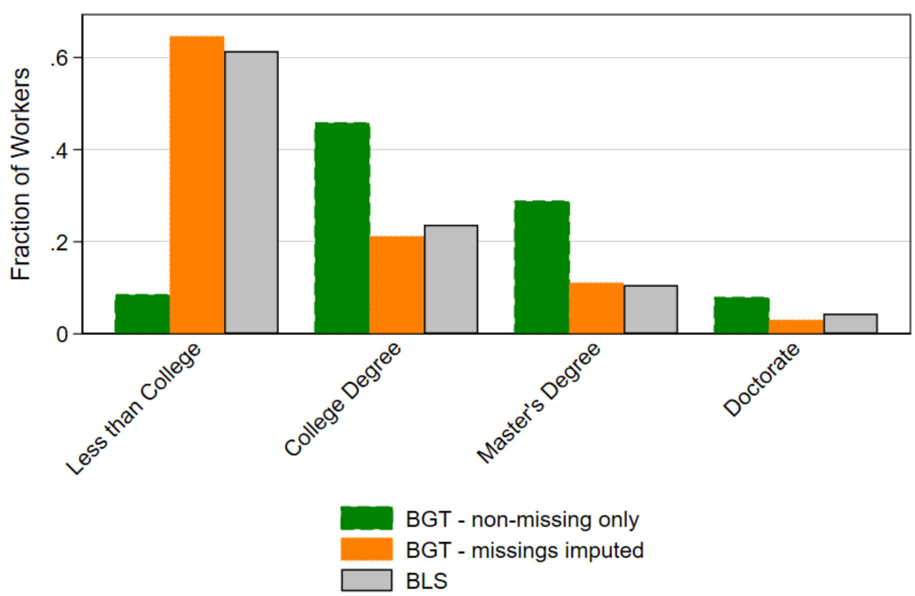
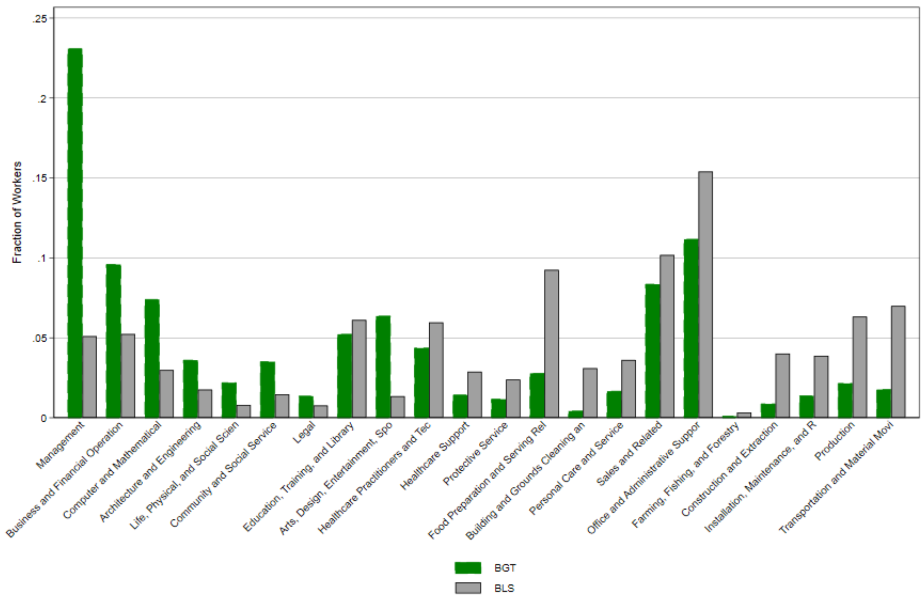
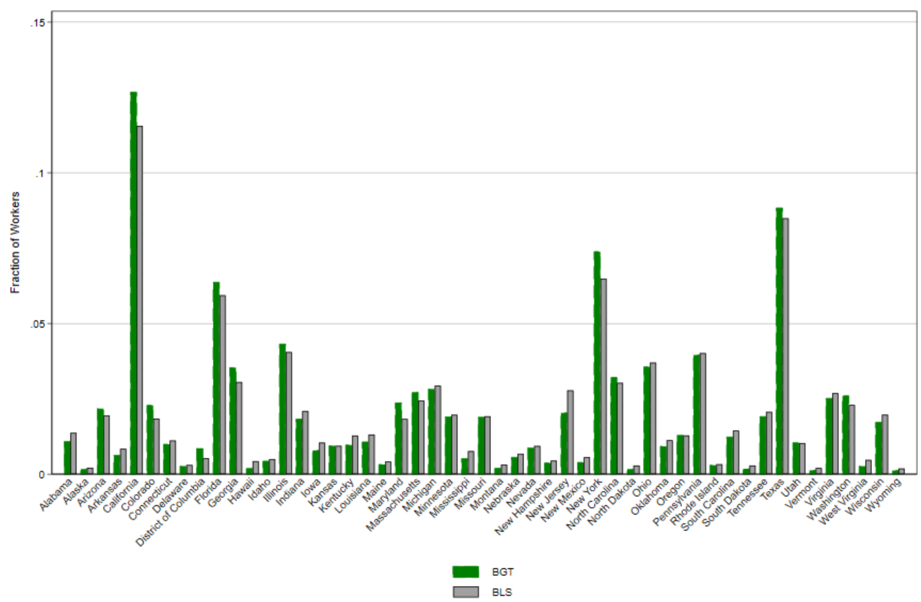


Figure A.4: Lightcast Resume Representativeness (continued)

(c) Occupation in Lightcast versus BLS



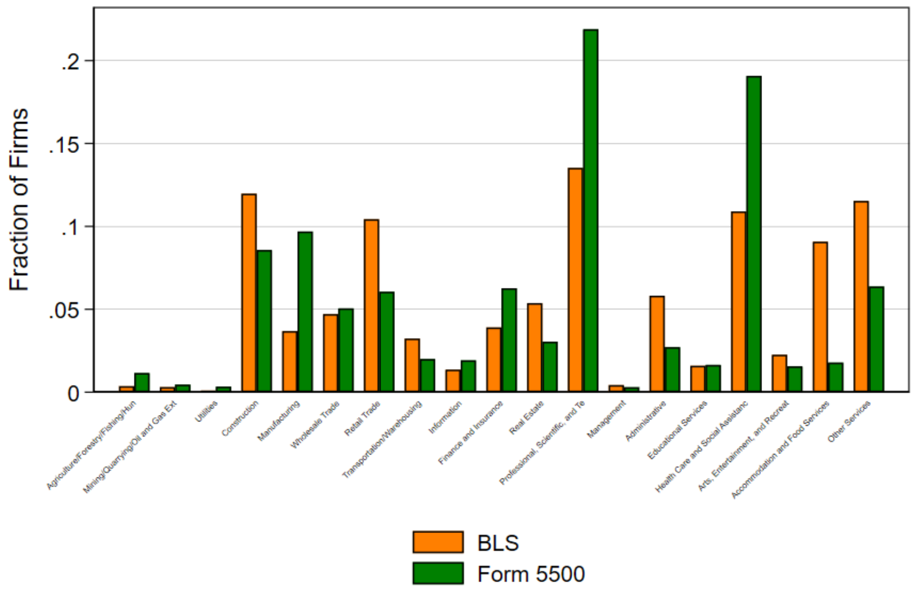
(d) State in Lightcast versus BLS



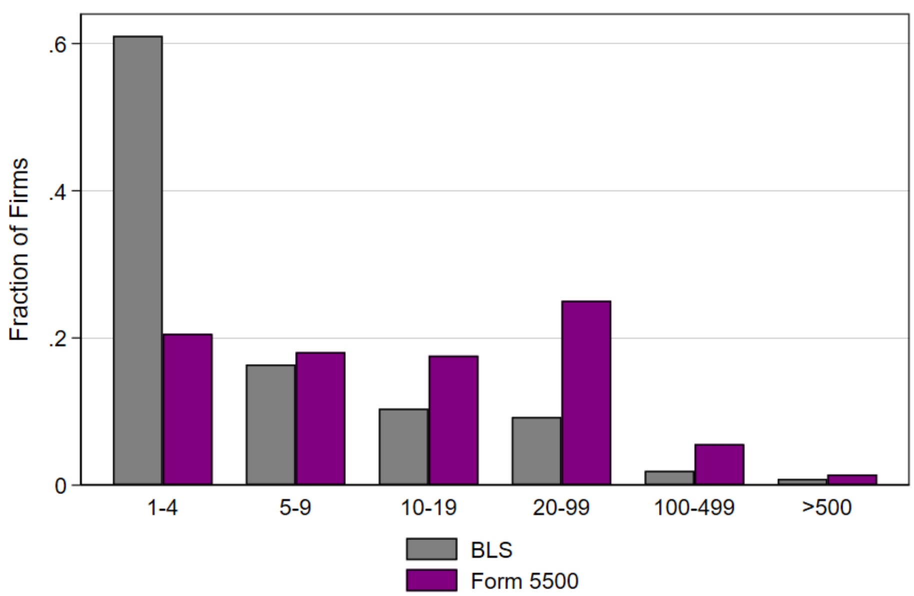
Notes: These figures shows the distribution of demographic characteristics in Lightcast (formerly Burning Glass Technologies, labeled BGT) versus the Bureau of Labor Statistic's Occupation Employment Statistics. Resumes from Lightcast include only those with non-missing current job-info.

Figure A.5: Form 5500 Firms versus BLS

(a) Industry by Number of Firms



(b) Firm Size by Number of Firms



Notes: These figures shows the distribution of firms and employment by industry and by firm size. The Form 5500 sample is all firms that filed Form 5500 in 2019. The BLS sample is from the Bureau of Labor Statistics database.

Figure A.6: Example Survey Questions

(a) 401(k) with 3% match versus no 401(k)

Scenario 1

	Job 1	Job 2
Annual Earnings when working full time:	$51,500	$50,500
Retirement benefits:	None	Company sponsored 401(k) with matching of 100% up to 3% (for a total possible match of $1,515 per year)
Healthcare benefits:	No	No
Vacation:	20 days of paid vacation	20 days of paid vacation
Work flexibility:	No remote work option	No remote work option

Note that with Job 2, your pre-tax take home pay will be $1000 lower annually, or approximately $83 lower per month.

Select which you would be more likely to accept.

Job 1

Job 2

(b) 401(k) with 5% match versus no 401(k)

Scenario 4

	Job 1	Job 2
Annual Earnings when working full time:	$51,000	$52,500
Retirement benefits:	Company sponsored 401(k) with matching of 100% up to 5% (for a total possible match of $2,550 per year)	None
Healthcare benefits:	No	No
Vacation:	20 days of paid vacation	20 days of paid vacation
Work flexibility:	No remote work option	No remote work option

Note that with Job 1, your pre-tax take home pay will be $1,500 lower annually, or approximately $125 lower per month.

Select which you would be more likely to accept.

Job 1

Job 2

Figure A.6: Example Survey Questions (continued)

(c) 2 Days of Remote Work per Week versus No Remote Work

Scenario 2

	Job 1	Job 2
Annual Earnings when working full time:	$50,000	$51,500
Retirement benefits	Company sponsored 401(k)	Company sponsored 401(k)
Healthcare benefits:	Yes	Yes
Vacation:	20 days of paid vacation	20 days of paid vacation
Work flexibility:	2 days of remote work per week	No remote work option

Note that with Job 1, your pre-tax take home pay will be $1,500 lower annually, or approximately $125 lower per month.

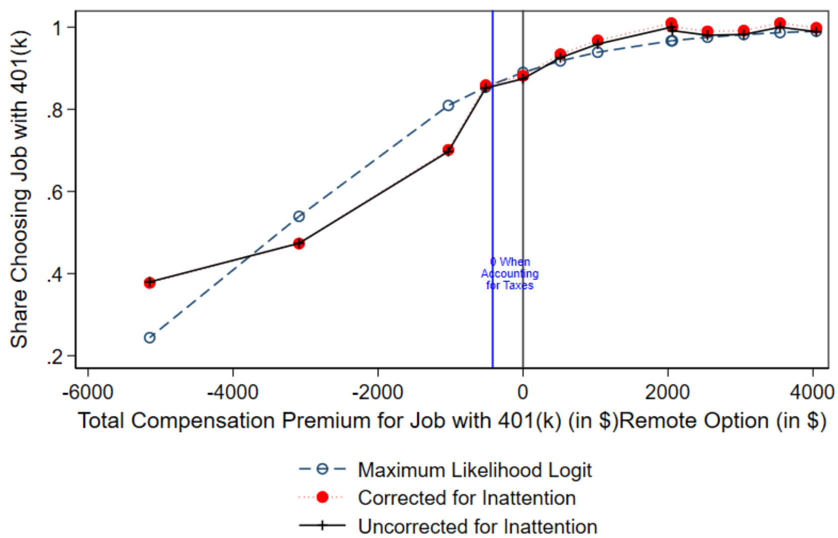
Select which you would be more likely to accept.

Job 1

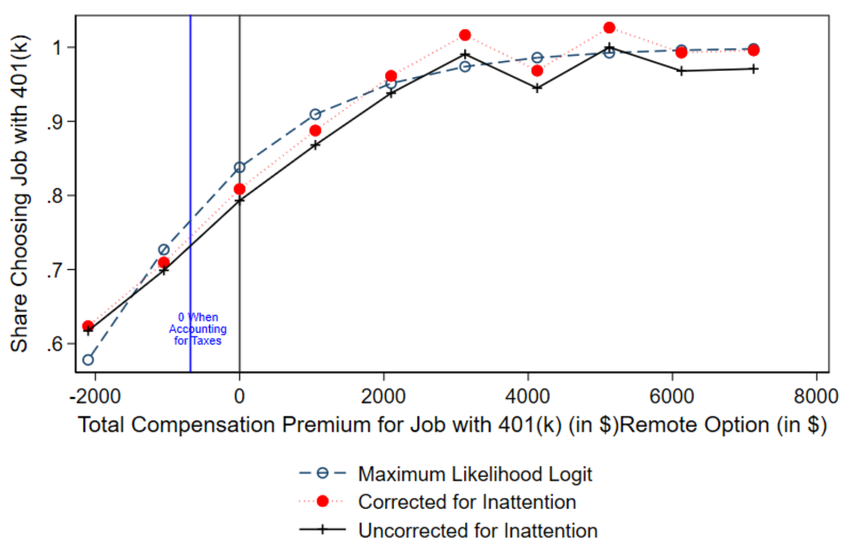
Job 2

Figure A.7: Willingness to Pay for Retirement Benefits and Remote Work Option

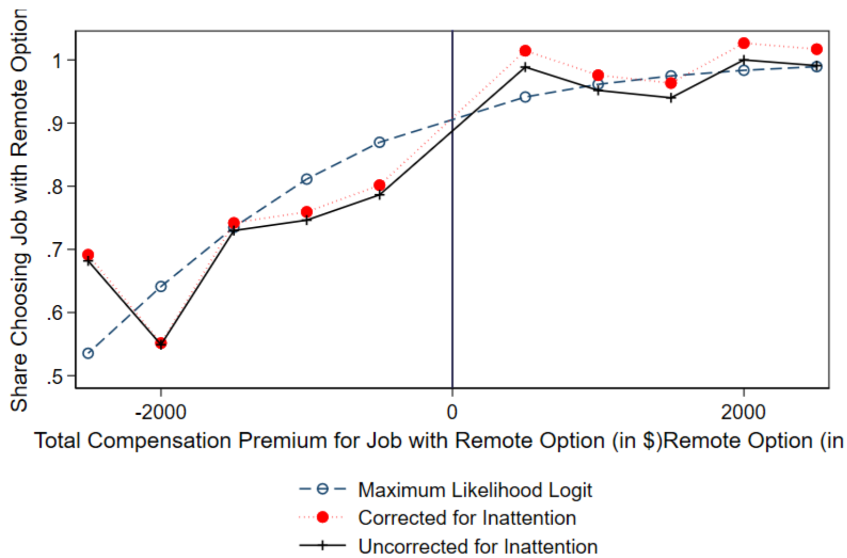
(a) 401(k) offers 3% match versus no 401(k)



(b) 401(k) offers 5% match versus no 401(k)



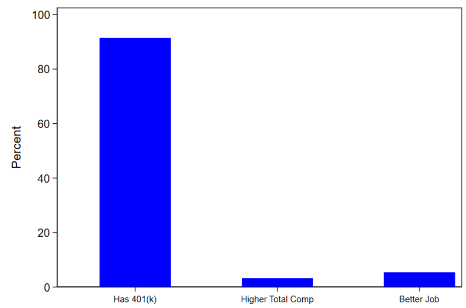
(c) 2 Days of Remote Work per Week versus no Remote Work



Notes: These plots show the fraction of participants who chose the job with the better benefits plotted against the difference in total compensation. The total compensation gap is the total compensation for the job with the better benefit minus the total compensation for the job with the worse benefit. Based on a survey of 1,600 participants.

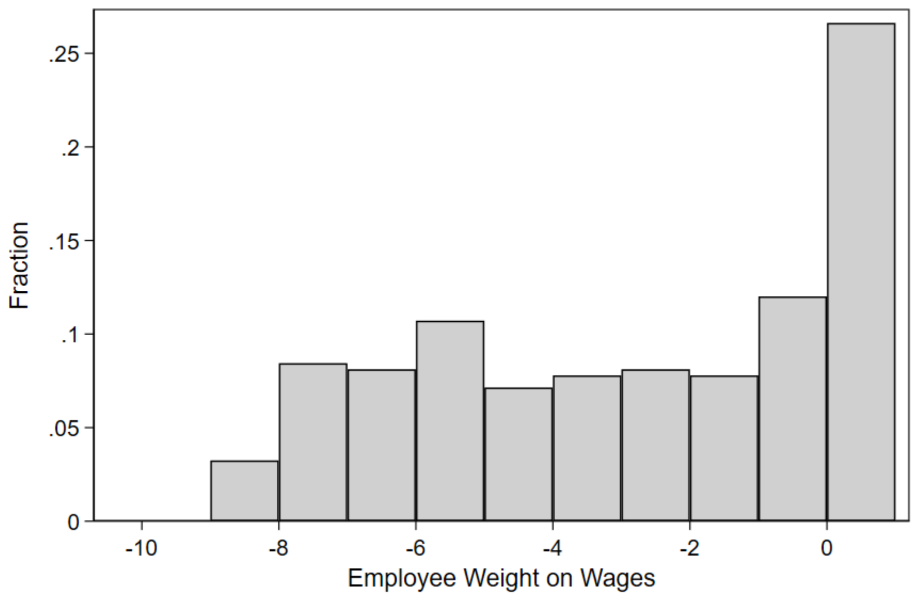
Figure A.7: Reasons for Choosing Selected Job - Extensive Margin of Retirement Benefits

(a) Chose job with 401(k) versus job with no 401(k) when the 401(k) job pays less



Notes: These plots show the distribution of reasons for choosing a given job, conditional on that job paying less than the alternative. Based on a subsample of 300 participants.

Figure A.8: Histogram of Wage Weights



Notes: This figure shows a histogram of the values of γ_l, the weight on wages, estimated in the on-the-job random search model.

Table A.1: Example non-discrimination tests

Passing Firm				
Employee	Salary	Employee Deferral	Employer Contribution (100% of the first 3%)	Actual Contribution Percentage
Person 1	$150,000	$15,000	$4,500	3%
Person 2	$30,000	$0	$0	0%
Person 3	$30,000	$1,500	$900	3%
Person 4	$30,000	$1,200	900	3%
Mean ACP of HCEs				3%
Mean ACP of NHCEs				2%
Failing Firm				
Employee	Salary	Employee Deferral	Employer Contribution (100% of the first 3%)	Actual Contribution Percentage
Person 1	$150,000	$15,000	$4,500	3%
Person 2	$30,000	$0	$0	0%
Person 3	$30,000	$400	$400	1.3%
Person 4	$30,000	$200	200	.67%
Mean ACP of HCEs				3%
Mean ACP of NHCEs				.67%

Table A.2: OES Average Wage by CBSA and 5-digit SOC

	Log OES Salary			Log OES Hourly Wage		
	(1) Median	(2) Mean	(3) Quantile within occupation	(4) Median	(5) Mean	(6) Quantile within occupation
Log Lightcast Salary	1.034***	1.110***	0.912***			
	(0.00600)	(0.00573)	(0.00435)			
Log Lightcast Hourly Wage				1.034***	1.110***	0.912***
				(0.00598)	(0.00572)	(0.00435)
Observations	85840	85949	85949	85696	85805	85805
Adjusted R^2	0.812	0.868	0.789	0.812	0.868	0.789

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Means and medians are calculated within CBSAs and 5-digit SOC codes. Quantiles are within 5-digit SOC codes across CBSAs. Regressions are weighted by employment share in the OES. Lightcast data is from all postings from 2010-2019 with wage and/or salary data available. When a range is given, we use the midpoint of the range.

Table A.3: Summary Statistics of Lightcast Postings Data with Wages

	(1)
Average Annual Salary	50247.39
	(29205.36)
Average Hourly Wage	24.17
	(14.16)
# of Positings per Firm	645.90
	(2985.64)
# of Firms	1,246,673
# of 5-digit SOC codes	437
# of CBSAs	929
# of Unique Jobs	8,014,427

Notes: This table shows summary statistics of the Lightcast postings data with available wage information from 2010-2019. Standard deviations, where applicable, are in parentheses. Shows only jobs with non-missing, wage, industry, occupation, and location information.

Table A.4: Resume Summary Statistics

	Mean	P10	P25	P50	P75	P90
Job Length (excluding current job, in months)	46	5	12	26	57	115
Job Length (including current job, in months)	36	4	11	23	47	82
# of Jobs per Resume	2.57	1	1	1	4	6
# of Years on Resume	15	4	8	14	21	30
# of Transitions per Resume	1.57	0	0	0	3	5
# of Resumes with Non-Missing Current Job	83,811,149					
# of Transitions:						
All	106,028,627					
Not within-firm	65,583,761					
Within Occupation, Industry and CBSA	860,230					

Notes: This table shows summary statistics from the Lightcast Resume Data. Only resumes with non-missing current job info that had been updated after 2019 are included.

Table A.5: Summary Statistics of DC Plans in Form 5500, 2010-2019

	Mean	Median	Standard Deviation
Total # of Active Plan Participants	120.39	6.00	2741.93
Total Current Employees	88.50	12.00	1882.92
Total Plan Assets (Millions of $s)	8.45	0.56	213.31
Ratio of Employer Contribution to Total Contributions	0.31	0.30	0.33
Employer Contributions per Participant ($)	3122.69	1399.86	7775.97
Implied NDT Failure (ever in sample)	0.06	0.00	0.23
Corrective Distributions per Person ($, Conditional on Paying Some)	111.34	28.67	1556.83
Has a Health Plan (%)	14.68	0.00	35.39
Health Spend ($) per Person (Conditional on Having a Health Plan, Large Plans Only)	4805.75	4286.99	22334.05
# of Unique Years per Firm	6.95	8.00	2.97
# of Unique Firms	1174495		
% of Firms that are Small Plans	80		

Notes: This table show summary statistics for all defined contribution plans in Form-5500 from 2010-2019. Small plans are those with less than 100 participants.

Table A.6: Willingness to Pay for Retirement Benefits: Survey Evidence, Other Conditions

	401(k) with a 3% match versus no 401(k)	401(k) with a 5% match versus no 401(k)	2 days of remote work per week versus no remote work option)
Fraction that chose job with benefit	0.851	0.885	0.842
	(1628)	(1004)	(1004)
Conditional on:			
Job with benefit having a lower wage	0.767	0.796	0.740
	(1003)	(499)	(535)
Job with benefit having a higher wage	0.986	0.974	0.957
	(625)	(505)	(469)
Job with benefit having lower total comp	0.635	0.659	0.7405
	(513)	(182)	(535)
Job with benefit having higher total comp	0.965	0.960	0.957
	(918)	(703)	(469)
Job with benefit having lower total comp, net of taxes	0.635	0.659	0.740
	(513)	(182)	(535)
Conditional on choosing job with lower total compensation and with better benefit:			
WTP	3245	3950	1400
	(326)	(120)	(396))
WTP as a percent of wages	6.3	7.5	2.7
	(326)	(120)	(396))
WTP in total comp	1797	1522	1400
	(326)	(120)	(396)
WTP as a percent of total comp	3.5	3.9	2.7
	(326)	(120)	(396)
Tax saving	713	869	308
	(326)	(120)	(396)
WTP in total comp, net of taxes	1083	653	1092
	(326)	(120)	(396)
Cost of retirement plan to employer (excluding fixed/set-up costs)	1447	2427	0
	(326)	(120)	(396)

Notes: This table shows summary statistics for the survey conditions that test willingness to pay simultaneously for the intensive and extensive margin of retirement benefits and for remote work capability. Numbers in parentheses show the number of participants who answered for the relevant condition. Based on a survey of 1,600 participants.

Table A.7: Maximum Likelihood Estimates of Willingness to Pay in Survey, Other Conditions

Treatment	Mean	SD	P25	P50	P75
Willingness to Pay for the Intensive and Extensive Margin of Employer Contributions					
401(k) with 3% match versus no 401(k)	3589.41	3130.58	1692.29	3589.41	5486.52
	(246.83)	(192.70)	(169.17)	(246.83)	(347.14)
401(k) with 5% match versus no 401(k)	2492.70	2598.19	918.211	2492.70	4067.20
	(283.70)	(282.87)	(197.19)	(283.70)	(425.28)
Willingness to Pay for Remote Work Capability					
2 Days of Remote Work per Week versus no Remote Work Option	2935.24	2022.59	1709.56	2935.24	4160.92
	(208.16)	(199.08)	(137.10)	(208.16)	(311.41)

Notes: This table shows the distribution of the willingness to pay estimates from the survey. Estimates are from an inattention-corrected maximum likelihood logit model using data from the experiment. Bootstrapped standard errors based on 1000 samples are in parentheses.

Table A.8: Evidence for Heuristics in Experimental Choices

	Fraction
All experiments:	
Always chooses job with benefit	0.468
Always chooses job without benefit	0.071
Always chooses job with higher salary	0.203
Always chooses job with higher total comp	0.257
Retirement experiments only:	
Always chooses job with benefit	0.523
Always chooses job without benefit	0.075
Always chooses job with higher salary	0.241
Always chooses job with higher total comp	0.326
Observations	1629

Notes: This table shows the fraction of participants that followed the listed heuristic when completing the survey. The top panel includes the condition which tested for willingness to pay for remote work. The bottom panel shows only the conditions that tested for retirement benefits.

Table A.9: Transitions in Resume Waterfall

All	106,028,627
Non-missing industry, occupation, location info	88,162,464
Not within firm	65,583,761
Within Occupation	12,720,065
Within Industry	3.024,264
Within CBSA	860,230

Notes: This table shows the number of transitions in the Lightcast resume data that correspond to each criteria. These numbers are prior to matching with the other data sources.

Table A.10: Effect of Changing Wages or Recruiting Success - Equivalent Effects to a 1pp Increase in Employer Contribution Rate

	p50	p25	p75
Equivalent Effect on Increase in Hiring			
% Increase in Wage Required	2.7		
% Change in number of new hires	0.41	0.19	0.81
Net cost per one new hire	1480.99	1054.32	2128.59
Net cost per employee	0.17	0.00	2.69
Equivalent Cost per New Hire			
% Increase in Wage Required	14		
% Change in number of new hires	1.98	0.88	3.76
Net cost per one new hire	8131.94	5789.15	11687.86
Net cost per employee	0.92	0.00	14.71

Notes: This table shows the effect of changing wages to get a) the same effect on recruiting success a 1 percentage point increase in employer contribution rate b) the same cost as a 1 percentage point increase in employer contribution rate.