Breaking the Implicit Contract: Using Pension Freezes to Study Lifetime Labor Supply *

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Abstract

This paper studies the recent and widespread elimination of traditional pensions and subsequent adoption of 401(k) plans by U.S. employers. Using thousands of firm-level natural experiments, it shows that unexpected losses in future compensation engendered by pension plan transitions induce a 1 percentage point increase in retirement on impact. Affected workers who do not retire immediately choose to lengthen their careers and exhibit a 2 percentage point reduction in retirement 10 years after the pension plan transition. Observed heterogeneity in retirement behavior is indicative of differences in wealth and in preferences for leisure. Using these credibly identified treatment effects as estimation targets, it fits a structural model of retirement and saving and uses the model to evaluate the effect of a counterfactual reform that eliminates Social Security payroll taxes for workers over age 60. Simulations from the estimated model show that the reform increases the average retirement age by one year and provides substantial welfare gains to older workers.

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1 Introduction

The aging of the baby boom generation poses stark challenges that affects not only the financial future of retirees but also the overall performance of the economy. As a large share of the population permanently withdraws from the labor force, economic growth will slow, more individuals will claim Social Security and Medicare benefits, and fewer workers will pay into these social insurance programs. To mitigate some of these adverse effects, researchers have proposed policies that incentivize delayed retirement by altering the tax code or by changing the structure of public and private pension benefits.

Predicting retirement responses to policy-induced changes in compensation structure is subject to two empirical challenges. The first challenge relates to defining the horizon that workers consider when making retirement decisions. Several studies including Krueger and Pischke (1992), Rogerson and Wallenius (2013), Brown (2013), and Manoli and Weber (2016) model retirement in the context of contemporaneous changes in compensation. In contrast, Stock and Wise (1990) emphasize that the retirement decision is determined not only by contemporaneous compensation but also by the entire path of expected future compensation.[1] The role of long horizons in determining retirement is important and has been validated empirically using both reduced-form and structural methods (see, e.g., Coile and Gruber (2007) and references therein). Nevertheless, a limitation of studies that do adopt a forward-looking view on retirement behavior is that they have been identified either using cross sectional variation or using panel fixed effect designs. These empirical approaches can be problematic because within- and between-person differences in future compensation are likely correlated with unobserved determinants of lifetime labor supply. Closely related to this concern, the second challenge stems from the fact that unanticipated changes in compensation generate both wealth and substitution effects, and the identification of the structural parameters governing these effects is difficult when relying on panel data alone (see, e.g., MaCurdy (1981)).

In this paper, I address both challenges. I use a novel source of variation to identify a model of retirement behavior in which workers' retirement decisions depend on both current and expected future compensation. My identification strategy relies on the large-scale restructuring of U.S. private sector defined benefit (DB) pension plans which began in the early 2000's. Since then, many employers have reneged on long-standing promises to their workers by eliminating generous DB pension accruals and replacing them with less lu-

[1] Implicit contracts that solve agency problems are a powerful force connecting current labor supply decisions to future compensation. See Lazear (1979), Lazear (1981) and Akerlof and Katz (1989) for important theoretical contributions.

crative defined contribution (DC) and cash balance (CB) pension plans.[2] These actions, known as pension freezes, allow workers to keep previously earned pension benefits but unexpectedly change the present value of future compensation that workers have been promised but are yet to be paid.[3] From a research perspective, pension freezes are useful because they generate unanticipated shifts in workers' age-compensation profiles which induce both wealth and substitution effects.[4] As I describe below, this source of variation credibly identifies preference parameters governing retirement behavior thereby providing a better way to predict how older workers will react to unexpected policy-induced changes in compensation structure.

To study why employers have increasingly restructured their DB plans and to examine how employees respond to these changes, I create a new dataset that matches information from Internal Revenue Service (IRS) administrative records on the universe of private sector pension plans with longitudinal employer-employee linked data from the Census Bureau. My research design pools together thousands of firm-level natural experiments and compares the labor supply behavior of workers whose employers freeze their DB plans with workers whose employers keep their DB plans intact.

On the firm side, I provide evidence that pension freezes are driven primarily by plan funding deficiencies and are unrelated to mass layoffs or employee age structure. On the worker side, I show that the retirement response to these shocks varies in two important dimensions. First, workers initially affected at different ages exhibit differing retirement responses because they experience compensation losses of varying magnitude. Second, holding age fixed, some workers respond to freezes by retiring early while others respond by retiring later. Early retirements reflect the dominance of substitution effects while delayed retirements reflect the dominance of wealth effects. Workers' dynamic response to pension freezes is therefore indicative of heterogeneity in wealth and/or preferences for leisure.

The administrative data that I use describe employment responses to pension freezes. These data do not include information on the dollar value of compensation changes induced by pension freezes . To estimate the pecuniary effects of pension freezes and to conduct counterfactual simulations, I develop and

[2] 401(k) plans are the most common type of DC plan. Unlike traditional DB pensions which guarantee workers an income stream in retirement, DC plans allow workers to accumulate retirement savings in tax-preferred accounts. Employers typically provide incentives for participation in these plans by matching worker contributions. CB plans are functionally similar to DC plans. More details are provided in Section 2.

[3] The abrupt nature of these changes are reflected in the sentiment of one disgruntled Verizon employee who, after hearing of the company's decision to freeze his DB pension, said "Oh, it's outrageous that they ... *change the rules in the middle of the game*." See "Verizon Unveils Major Changes to Retirement Benefits," National Public Radio, *All Things Considered*, December 6, 2005.

[4] Krueger and Pischke (1992), Brown (2013), and Gelber et al. (2016) also rely on unanticipated changes in pension compensation to study retirement behavior. These studies do not use variation in future compensation to identify a structural model or estimate the effect of counterfactual policies.

estimate a structural model of retirement timing and saving that relies on rich survey data from the Health and Retirement Study (HRS). The model incorporates heterogeneity in wealth and in preferences for leisure and allows work decisions to depend not only on current compensation but also on the option of higher earnings and increased pension benefits in the future as in Stock and Wise (1990). Unlike Stock and Wise (1990), however, the model allows for saving in multiple asset types, includes Social Security benefits, and features non-linear taxes.[5] I fit the model using the method of simulated moments (MSM) by matching quasi-experimental employment responses to pension freezes as observed in administrative data.

The model that I estimate highlights the importance of forward-looking behavior in governing the retirement decision and lends itself to evaluating the impact of counterfactual policies aimed at incentivizing delayed retirement through a permanent shift in future compensation trajectories. I examine one such proposal through the lens of the model. In particular, I consider eliminating the Social Security or Old Age and Survivors Insurance (OASI) component of the payroll tax for workers over the age of 60. This reform has been proposed as a way of lengthening lifetime labor supply by removing contribution requirements for workers who are fully vested in Social Security benefits (see, e.g., Burtless and Quinn (2002) and Goda et al. (2009)). Simulations from the estimated model predict that an unexpected elimination of the OASI payroll tax at age 60 causes employment rates to rise by an average of approximately 5 percentage points over a 20 year horizon which equates to a 1.1 year delay in the average retirement age. Equivalent variation from the reform averages $75,000 per worker.[6]

In this paper, I make three contributions to the literature. First, I provide the only available evidence of how older Americans have re-timed their retirement decisions in response to widespread DB pension freezes. These analyses, based on high-quality administrative data, shed new light on the ongoing transition from DB to DC pension provision. While prior studies examining the incentive effects of DB and DC pension plans have emphasized that DC plans encourage longer careers (see, e.g., Friedberg and Webb (2005)), the findings I present in this paper show that unexpected transitions from DB to DC plans generate a mixed response: some workers choose to shorten their careers whereas others choose to lengthen them. Second, I estimate a model of retirement and saving which is identified by plausibly exogenous variation in future compensation arising from pension freezes. This natural experiment-based identification strategy represents a departure from prior structural models of retirement that rely on cross sectional or panel data to isolate

[5]The model I use is a stochastic dynamic programming model of retirement and not an option value model as pioneered by Stock and Wise (1990). Lumsdaine et al. (1992) provide a comparison of the two approaches.

[6]Estimated in 2010 dollars with present values calculated at age 60.

variation in compensation (see, e.g., Stock and Wise (1990), Berkovic and Stern (1991), Rust and Phelan (1997), French (2005), and French and Jones (2011)). Finally, I provide evidence about the effectiveness of a counterfactual reform to payroll taxes designed to lengthen careers. In contrast to prior efforts evaluating the effect of payroll tax sunsets (Laitner and Silverman (2012) and Gustman and Steinmeier (2015)), the model and identification strategy employed in this paper explicitly account for the long-term option value channel of continued employment.

The remainder of this paper is structured as follows. Section 2 provides institutional details on the DB pension landscape in the United States and explains important recent changes influencing firms' decisions to freeze their plans. Section 3 outlines a model of retirement timing and saving and uses the model to evaluate how workers respond to pension freezes. Section 4 discusses three different sources of administrative data used in the analyses. Section 5 outlines the empirical framework and presents summary statistics. Section 6 provides empirical evidence on workers' labor supply responses to pension freezes. Section 7 explains the identification and estimation of the structural model and presents parameter estimates. Section 8 evaluates the counterfactual OASI payroll tax sunset. Section 9 concludes.

2 Why are employers freezing DB plans?

In 1980 DB plans covered 61 percent of pension eligible private sector workers. By 2015 the same statistic had fallen to 16 percent.[7] This overall decline occurred not only because of a surge in new 401(k) DC plans but also because of stagnation in the creation of new DB plans. For most of this period, DB plans continued to operate normally with only rare instances of distressed plan terminations triggered by firm bankruptcy.[8] Starting in the late 1990's, however, several prominent firms began converting their DB plans to CB plans. CB conversions switched pension accruals away from formulas that were based on years of service and earnings, to account based plans that provided participants employer contributions that were proportional to earnings and a market linked rate of return on previous contributions.[9] In the early 2000's this shift was

[7] See Table E7, Private Pension Plan Bulletin Historical Tables and Graphs, U.S. Department of Labor, 2018.

[8] The Omnibus Budget Reconciliation Act of 1987 reduced the ability of DB sponsoring employers to take tax deductions for pension contributions. This change led to a spike in non-distress terminations between 1987 and 1990 (see, e.g., Table A-9 in Pension Insurance Data Book 1996, PBGC Single Employer Program https://www.pbgc.gov/documents/1996databook.pdf).

[9] CB plans are functionally very similar to DC plans: they provide participants with individual accounts whose value is tied to earnings levels. There are, however, two differences. First, CB plans allow for larger maximum pre-tax deferrals than DC plans. Second, it is common in CB plans for employers to bear some interest rate risk by promising a minimum rate of return on the value of the account. For these reasons, CB plans are subject to the same funding obligations required of DB plans and are legally treated as DB plans.

amplified as many employers altogether ended traditional DB pension accruals in actions known as hard freezes.[10] The incidence of CB conversions and hard freezes between 1999 and 2015 is shown in Figure 1. By 2015, about half of all private sector single employer DB plans had either been converted to CB plans or hard frozen, affecting about 40 percent of active participants or 4.1 million workers.[11]

2.1 Costs of DB plan provision have become increasingly volatile

Firm's decisions to renege on DB promises through CB conversions and hard freezes occurred in a deteriorating financial environment that increased the volatility of DB pension costs. As shown in Figure 2, the wake of the dot-com bubble and ensuing recession lowered the asset value of pension funds substantially. In 2000, the private sector DB system had $1.44 in assets for each dollar of future liabilities. By 2004, the funding ratio had slipped to 0.85. As the funding position of DB plans worsened, statutory provisions required firms to increase annual contributions; consequently, aggregate payments into DB pension funds rose five-fold from $26 billion in 2000 to $124 billion in 2003. Low interest rates and stock market losses during the Great Recession weakened firms' funding positions drawing further increases in required pension contributions. These shocks disproportionately affected plans with marginal funding status as they were not buffered against large contributions requirements in the same way that overfunded plans were. The role of worsening plan finances as a key predictor of subsequent pension freezes is demonstrated greater detail in Appendix C, which relies on firm-level microdata.[12]

In the midst of major changes to the finances of DB pension funds, the Pension Protection Act (PPA) was signed into law in 2006. The PPA established more conservative standards on the interest rates that sponsors could use to discount future liabilities, reduced the period over which sponsors needed to amortize funding deficits from 15 years to 7 years, and required that plans with funding ratios of 80 percent or below make additional minimum contributions and pay higher insurance premiums to the Pension Benefit Guarantee

[10] Over the same period, employers also began closing their DB plans to new entrants in actions known as soft-freezes. I do not consider soft-freezes in this paper.

[11] Hard freezes are exceedingly rare in the public sector affecting less than 0.5 percent of eligible state and local government workers. The main reason for this difference owes to differing legal protections in the private and public sectors. The Employee Retirement Income Security Act of 1974 (ERISA), which governs private pensions, explicitly allows sponsors to modify future pension rules provided that earned pension benefits are not reduced. In the public sector, which is not subject to the provisions of ERISA, several state governments protect both earned and unearned future pension benefits. See, e.g., Monahan (2012).

[12] Munnell and Soto (2007), Bovbjerg et al. (2008), and Rauh et al. (2020) also find that cost savings and funding volatility are important determinants of firms' decisions to freeze their DB plans. A compliance check on frozen DB plans conducted by the IRS in 2012 and obtained through a Freedom of Information Act (FOIA) request for this research project further corroborates this conclusion finding that sponsors typically froze their plans due to funding deficiencies.

Corporation (PBGC).[13] These key provisions of the PPA, which were phased-in as of 2008, raised statutory minimum pension contributions and imposed greater cost pressure on DB sponsors with marginal funding status.

2.2 Legal constraints to freezing plans have been alleviated

Between 1998 and 2000, a handful of prominent employers had converted traditional DB plans to CB plans. Older employees, who stood to lose substantial future pension accruals as a result these transitions, brought class action lawsuits against their employers claiming that CB conversions violated the age discrimination provisions of the Employee Retirement Income Security Act of 1974 (ERISA) (see, e.g., Zelinksy (2000)). As these cases played out in the court system, the legality of CB conversions remained uncertain. The threat of litigation along with large potential settlement costs for class action lawsuits likely constrained other employers from converting traditional DB plans. In 2006, however, a Federal appeals court ruled that IBM's CB conversion was age-neutral, thereby ending uncertainty surrounding the legality of what was seen by many as an important test for restructuring traditional DB plans.[14] In the same year the new PPA law provided guidelines that CB conversions needed to meet in order to be considered age-neutral. Together, the appeals court ruling and the PPA's new provisions gave willing employers the legal cover they needed to restructure their DB plans.

3 Model of retirement and saving

This section develops a model of retirement timing and saving. Using the model, I show that pension freezes generate both substitution and wealth effects and therefore have an ambiguous impact on retirement behavior. I explain how heterogeneity in wealth and in preferences for leisure implies differential retirement responses for workers faced with freeze-induced losses in future compensation. I summarize these comparative statics into three empirically testable implications.

[13] Some of the PPA's requirements were relaxed during the Great Recession as pension sponsors sought relief from strict funding targets. For instance, The Preservation of Access to Care for Medicare Beneficiaries and Pension Relief Act of 2010 allowed firms to elect extended amortization periods for any two plan years between 2008 and 2011. The extensions were for 9 or 15 years rather than the 7 year requirement of the PPA.

[14] See, e.g., Mary Williams Walsh, "Issues Left Unresolved on Pensions," *New York Times*, Jan. 17, 2007.

3.1 Defined benefit pension incentives

Before characterizing the model, I illustrate key features of DB plans and their effect on total compensation using data from the HRS. The left panel of Figure 3 shows the age-compensation profile for the average, DB eligible, HRS respondent between the age of 50 and 70. The dashed line shows wage and salary compensation. The solid line adds DB and DC pension accruals to wage and salary compensation. Notably, about half of the respondents in the DB eligible sample have non-zero DC balances.[15] Two types of non-linearities typical to DB pensions are evident in the figure. First, DB accruals generate prominent spikes in compensation. At age 55, which is a common early retirement age (ERA) in many DB plans, workers can begin claiming benefits thereby generating a substantial jump in pension wealth. After the ERA, accruals grow at a slower rate as workers approach the normal retirement age (NRA) which is typically 65. After the NRA, it is common for DB accruals to no longer grow in a manner that is actuarially fair and, in fact, become negative in real terms. This downturn occurs because workers who postpone retirement do not obtain sufficiently large increases in pension benefits even though they will obtain those benefits for fewer (mortality adjusted) years.[16] In the figure, pension compensation is positive for workers over 65 only because DC accruals offset negative DB accruals.

The profiles shown in the left panel of Figure 3 illustrate how DB plans generate strong incentives for workers to remain employed through the ERA in order to collect generous retirement benefits. In contrast, after age 65, DB plans generate strong incentives for workers to retire. Underpinning these carefully designed incentives is an implicit contract between firms and workers: firms make long-term unenforceable commitments to workers in which continued employment through retirement age will be rewarded with lucrative pension benefits. Workers on the other hand exert effort over the course of their careers and avoid early termination that would result in the loss of promised pension benefits (see, e.g., Lazear (1981), Kotlikoff and Wise (1985), and Lazear and Moore (1988) for theory and evidence). By freezing DB pensions, firms are unilaterally reneging on this implicit contract.

The following section outlines a model of retirement in the presence of DB pension promises and uses the model to understand how worker behavior changes in response to pension freezes.

[15] Earnings and pension benefits are computed for each individual at each age, so the age-based variation in compensation reflects plan-specific formulas for accruals and not changes in sample composition due to retirement.

[16] This implicit tax on continued work is a common feature of DB pensions specifically designed to encourage retirement (see, e.g., Chapter 12 in Gustman et al. (2000)).

3.2 Setup

Individuals are heterogenous in age ($a \in \{50, 51, \ldots, 80\}$), non-pension wealth $A_a \in [0, \infty)$, DC pension wealth $W_a^{DC} \in [0, \infty)$, and the extent to which they dislike working, g. For individual ι currently aged a, the disutility of working is modeled as

$$g_{\iota a} = \underbrace{\gamma + \phi a}_{\text{deterministic component}} + \underbrace{f_{\iota a}}_{\text{random component}} \tag{1}$$

$$f_{\iota a} = \rho f_{\iota, a-1} + v_{\iota a}, \tag{2}$$

where $v_{\iota a} \sim \mathcal{N}(0, \sigma_v^2)$ is an iid disturbance term. The deterministic component of g captures changes in preferences for leisure that are common to workers of the same age, whereas the random component captures individual specific differences in health, disability status, and non-pay aspects of employer-employee match quality. I assume that utility from consumption exhibits constant relative risk aversion (CRRA) and that consumption and leisure are separable. Under these assumptions, flow utility for an individual ι aged a is given by

$$\frac{c_{\iota a}^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - g_{\iota a} \times \mathbf{1}\left\{\iota \text{ is working at age } a\right\}. \tag{3}$$

Earnings at age a are given by e_a which is taxable in the period that it is earned. Conditional on remaining employed, all workers share the same deterministic age-earnings profile with earnings at age a given by e_a. DC wealth evolves according to

$$W_{\iota a}^{DC} = W_{\iota, a-1}^{DC}(1 + r) + e_a(m_{\iota a}^w + m^e(m_{\iota a}^w)) \tag{4}$$

$$\bar{C} \geq e_a(m_{\iota a}^w + m^e(m_{\iota a}^w)), \tag{5}$$

where r is the interest rate and $m_{\iota a}^w$ is the fraction of earnings that a worker defers towards her DC account on a pre-tax basis. $m^e(m_{\iota a}^w)$ is the fraction of earnings that the worker's employer contributes to her DC account. m^e is expressed as a function of $m_{\iota a}^w$ reflecting commonly used employer incentives for participation in DC plans. IRS rules limit total contributions to be less than a threshold value $\bar{C}$.[17]

Workers earn DB pension wealth on the basis of a deterministic formula which is set by firms. The

[17] In 2010 the total contribution limit was \$49,000 with workers over age 50 being allowed to make an extra \$5,500 in catch-up contributions. These values are updated annually by the IRS based on cost of living adjustments. See https://www.irs.gov/pub/irs-tege/cola_table.pdf

formula takes earnings history, tenure, and age as its arguments and returns the value of DB pension wealth:

$$W_a^{DB} = \mathcal{B}(\text{earnings,tenure,age}). \tag{6}$$

If a worker chooses to retire at age a, she obtains the annuity value of her DB wealth, which is b_a^{DB}. Workers also accrue Social Security benefits based on their earnings history in the form of an annuity whose value at age a is given by b_a^{SS}. Like the DB annuity, Social Security can only be claimed in retirement. $b_a = b_a^{DB} + b_a^{SS}$ is the total annuity income for an individual who chooses to retire at age a.[18] I assume that individuals cannot hold debt or borrow against DC pension assets, so $A_{\iota a} \geq 0$ and $W_{\iota a}^{DC} \geq 0$.

Total compensation for worker ι currently aged a is

$$\chi_{\iota a} = \underbrace{e_a(1 - m_{\iota a}^w)(1-\tau)}_{\text{non-deferred compensation}} + \underbrace{\Delta W_{\iota a}^{DC}}_{\text{DC accrual}} + \underbrace{\Delta W_a^{DB}}_{\text{DB accrual}}, \tag{7}$$

where τ is tax rate applied to income after pre-tax deferrals have been made.[19] Equation (7) reflects the assumption that workers have passed the age where real earnings growth contributes to higher Social Security benefits. Consequently, there are no increments to Social Security wealth from additional years of employment.

3.3 Value of retirement

To conserve notation, denote age a variables by v and age $a+1$ variables by v'. The value of retirement at age a is V_a^R which is written recursively as

$$V_a^R(b, A, W^{DC}) = \max_{A', W^{DC'}} \left\{ u(c) + \beta(1 - p_a) V_{a+1}^R(b, A', W^{DC'}) \right\} \tag{8}$$

$$\text{s.t. } c \leq \left(b + W^{DC} - \frac{W^{DC'}}{1+r} \right)(1-\tau) + A - \frac{A'}{1+r}. \tag{9}$$

In equation (8), $u(c)$ is utility from consumption, β is the annual discount factor, and p_a is the subjective probability of death within one year for an individual currently aged a. Annuitized pension income (b) is

[18] 62 is the earliest age at which workers can claim Social Security benefits. When estimating the model, I assume that workers who choose to retire before age 62 start claiming Social Security benefits at age 62.

[19] Income tax can be reduced by elective deferrals to DC accounts but payroll taxes apply to all earned income up to the relevant earnings caps.

fixed at the age of retirement which is why b rather than b' appears in the continuation value. Given the state variables and the budget constraint, the retirees consumption choice is recast as the choice of how to decumulate pension and non-pension wealth at each age. Pension income, which is the sum of annuitized income and liquidated DC pension wealth, is taxable while liquidated non-pension wealth is not taxable.

Notably, the value function treats retirement as a self absorbing state which excludes the possibility of short-term bridge employment. The assumption of self-absorbing retirement is important in the context of this paper because it makes future compensation contingent on current labor supply in a very stark way: if a worker enters the retirement state, her future labor market options are entirely foreclosed. I provide empirical evidence in Section 6.1 that workers affected by pension freezes tend to follow a once-and-for-all retirement pattern which is consistent with the modeling assumption I make here.

3.4 Value of working

Denote the age a vector of state variables for a working individual by $X = (e, g, b, W^{DC}, A)$. The value of working at age a is V_a^W which is written recursively as

$$V_a^W(X) = \max_{A', m^w} \left\{ u(c) - g + \beta(1 - p_a) E_{g'} \left[\max \left\{ V_{a+1}^R(b', A', W^{DC'}), V_{a+1}^W(X') \right\} \right] \right\} \tag{10}$$

$$\text{s.t. } c \leq e(1 - m^w)(1 - \tau) + A - \frac{A'}{1 + r}. \tag{11}$$

In equation (10), flow utility from consumption is offset by the disutility of working g. The expectation operator for the continuation value term integrates over the random variable g'. By remaining employed at age a, workers preserve the possibility of obtaining higher earnings and higher pension accruals in the future which is reflected in the continuation value. Given the state variables, the budget constraint (11), and the DC accumulation constraints (4) and (5), workers choose how much non-pension wealth to accumulate and what fraction of their earnings to defer towards DC pensions. I assume that DC pension wealth is illiquid until retirement.[20]

[20] IRS rules allow penalty free distributions from DC accounts after age $59\frac{1}{2}$. Distributions taken prior to $59\frac{1}{2}$ are subject to a 10 percent tax. Distributions must start at age $70\frac{1}{2}$. I do not incorporate these institutional features into the model.

3.5 Optimal retirement decision

A worker retires when $V_a^R \geq V_a^W$. This condition defines a cutoff value $\bar{g}_a$ so that any draw of $g_a \geq \bar{g}_a$ will lead to retirement. Solving for $\bar{g}_a$ yields

$$\bar{g}_a = u(c_a^W) - u(c_a^R) + \beta(1-p_a)\times \tag{12}$$
$$\Bigg[\overbrace{E_{g'}\left[\max\left\{V_{a+1}^R(b', A', W^{DC'}), V_{a+1}^W(X')\right\}\right]}^{\text{1: Continuation value of working}} - \overbrace{V_{a+1}^R(b, A', W^{DC'})}^{\text{2: Continuation value of retiring}}\Bigg]$$
$$\text{Option value of working one more period}$$

where c_a^W and c_a^R are the optimal consumption choices in the work and retirement states at age a. Consider terms 1 and 2 on the right side of equation (12). Higher future earnings and the potential for higher pension accruals raise term 1 and increase the incentive for continued work. On the other hand, higher levels of retirement wealth raise term 2, thereby generating an incentive to retire. These two offsetting incentives are key determinants of the optimal retirement decision, which is summarized by the cutoff value $\bar{g}_a$.

In this framework, the decision about whether to continue working or to retire is determined by the option value channel which embodies the implicit contract of continued employment with the firm: By remaining employed in the current period, the worker obtains earnings growth and increased pension benefits in the future. Furthermore, because DB pension wealth is backloaded and cannot be ported between employers, the option value of working has a particularly strong firm-specific component. Following Stock and Wise (1990), work decisions in this model vary not only due to period-by-period changes in compensation, but also due to changes in the option value of continued employment which is embedded in term 1.

3.6 The effect of a pension freeze is theoretically ambiguous

When employers renege on long-term promises by freezing DB pensions, workers experience changes to the total value of compensation that they had previously expected to earn by retirement. The effect of these shocks is illustrated in the right-hand panel of Figure 3. The solid blue line shows the path of total compensation in a world where DB plans are kept intact (i.e. no pension freezes occur). When a DB plan is frozen, workers keep all previously earned benefits but no longer earn any new DB accruals. Instead, workers who do not already participate in DC plans are offered the chance to do so after the freeze.[21] These

[21] In the HRS sample the underlies the figure, about half of all DB eligible respondents have no DC wealth.

changes are shown using dashed red lines which simulate the effect of a DB pension freeze for workers aged 52 and 65. The post-freeze simulations shown in the figure assume that respondents without DC wealth begin actively participating in a hypothetical new DC plan after the freeze.

The figure highlights that pension freezes shift the age-compensation profile in different ways based on the age at which workers experience them. The average 52 year-old experiences large initial losses in compensation followed by gains after age 63. In contrast, the average 65 year-old experiences much smaller losses, followed by immediate gains. In fact, workers over age 65 experience unambiguous gains. The main reason that pension freezes have positive effects on compensation over the long-term is because workers with DC plans can continue to accumulate pension wealth even at ages where traditional DB plans would penalize continued work.[22]

Now consider terms 1 and 2 on the right side of equation (12) for a worker who is under age 65 when her plan is frozen. Holding all else fixed, the loss in DB accruals generates two opposing effects. First, reductions to b^{DB} lower the return to working (term 1) thereby decreasing the option value of working and generating a substitution effect on labor supply. Second, reductions to b^{DB} make workers poorer in retirement (term 2) thereby increasing the option value of working and generating a wealth effect on labor supply. The same mechanisms work with opposite signs on a worker who is over age 65 when her plan is frozen: freezes reduce the penalty for continued work thereby increasing labor supply through the substitution effect. At the same time, greater pension wealth accumulation raises the continuation value of retirement thereby lowering labor supply through the wealth effect. Since substitution and wealth effects work against each other, the impact of freezes on retirement behavior cannot be signed.

Despite the overall theoretical ambiguity, two sources of heterogeneity allow me to characterize the following testable predictions about how pension freezes affect labor supply.

1. Between-age heterogeneity

   (a) *The relative strength of wealth and substitution effects varies by age:* Workers under 55 when their plans are frozen have large accruals still outstanding and experience substantial losses in compensation. Workers over 55 have less left to earn from their DB pensions when their plans are frozen and therefore experience smaller losses in compensation. As such, wealth effects are

[22] In the post-65 age range, there is a second reason that freezes generate positive effects on total compensation. DB formulas typically link benefits to pay earned over the last few years of a worker's career. Because pay falls after age 60, a worker in a non-frozen plan will see her benefit shrink as her pay declines while a worker whose plan is frozen will see her benefit stay fixed.

more important for workers under 55. Conversely, substitution effects are more important for workers over 55.

(b) *The effect of freezes on employment is reversed after age 65:* Because workers over the age of 65 experience increases rather than decreases in deferred compensation, their initial labor supply response should be reversed in sign relative to workers under the age of 65.

2. Within-age heterogeneity

(a) *Short-term responses are dominated by the substitution effect:* Short ex-ante work horizons reduce the role for wealth effects since workers are about to retire anyway. Thus, the response of workers near the margin of retirement at the time of the freeze (i.e. those with high values of $g_{\iota a}$, $A_{\iota a}$, and $W_{\iota a}^{DC}$) is dominated by the substitution effect. These workers will choose leisure over work when faced with a freeze.

4 Data

In this section I describe three distinct data sources that I use to estimate the effect of freezes on worker behavior. Pension plan data come from IRS Form 5500, employer characteristics come from the Census Longitudinal Business Database (LBD), and matched employer-employee data come from the Longitudinal Employer Household Dynamics (LEHD) dataset. I am able to link 92 percent of plans from Form 5500 to employers in the LBD and 89 percent of those LDB employers to the LEHD dataset.[23] Detailed descriptions of the datasets and the linking procedures that I use are provided in Appendix A.

4.1 Pension characteristics: Form 5500

Form 5500 (F5500) is an annual plan-specific filing that is collected jointly by the IRS, Department of Labor (DoL), and the PBGC to ensure compliance with ERISA. These publicly available data contain rich information on the universe of privately sponsored pension plans. When DB plans are converted to CB plans or hard frozen, this information is reported on F5500, thereby allowing me to identify plans whose participants are affected by freezes.[24] F5500 data also include important pension plan characteristics such

[23] These datasets have previously been used in conjunction to study the role of fringe benefits on employee mobility in Decressin et al. (2009).

[24] Plans are considered frozen in F5500 if they meet the following condition: "[a]s of the last day of the plan year, the plan provides that no participant will get any new benefit accrual (whether because of service or compensation)."

as the number of plan participants, the present value of pension wealth for plan participants, the value of pension accruals earned by participants in the filing year, and the typical age at which participants claim benefits from the plan.

F5500 filings are identified by a combination of a Federal Employer Identification Number (EIN) and a employer designated Plan Number (PN) that remain consistent over time. While these identifiers are sufficient to match pension plans to single-unit (i.e. operating only one establishment) firms, they are not sufficient for matching to multi-unit (i.e. operating multiple establishments) firms. This is because payroll tax filings for establishments that are part of a multi-unit firm may be recorded under different EINs than the one used in F5500. Attempting to match the F5500 to establishment level data on EIN alone would therefore generate many false non-matches. To overcome this issue, I turn to the Census Business Register (BR).

4.2 Firm characteristics: Census Business Register and Longitudinal Business Database

The Census Business Register (BR) is a database of the universe of establishments in the United States.[25] It includes information on business location, organization, industry, and information on revenue, payroll, and employment that is collected from administrative tax records as well as survey data. The relationship between establishments belonging to multi-unit firms are determined using responses to the company organization survey, the economic census, and the annual survey of manufactures. Establishments that are part of the same multi-unit firm share the same Census assigned firm identification number even if they have different EINs.

I rely on the presence of EINs in both the F5500 and the BR to create an initial link between the two files. Secondary to this link, I use the Census firm identifier to identify *all* the establishments associated with a multi-unit pension plan sponsor.[26] Having matched F5500 records to the BR, I use the Census firm identifier to further match those records to the LBD. The LBD is a cleaned and research ready version of the BR that is restricted to active employers in the private sector.[27]

[25] Information about the BR is confidential and protected by Title 13 and Title 26, U.S. Code. Information in the following paragraph is drawn from https://www.census.gov/econ/overview/mu0600.html

[26] In the absence of the Census firm identifier, I would only be able to identify those multi-unit establishments that shared the same EIN as the one reported on F5500, thereby generating a false non-match problem alluded to earlier.

[27] See Jarmin and Miranda (2002) for details.

4.3 Worker characteristics: Longitudinal Employer Household Dynamics

To study outcomes at the individual level, I turn to the LEHD which is a quarterly matched employer-employee dataset constructed from state-level unemployment insurance (UI) records.[28] These data cover almost all wage and salary workers in the United States but exclude individuals who are self-employed. In the LEHD, employers are identified using a state UI account number known as the SEIN. I rely on the crosswalk between the SEIN and the Census firm identifier developed in Haltiwanger et al. (2014) to link pension plans in the matched F5500-LBD data to employers in the LEHD.[29]

An important feature of the LEHD is that states become part of the dataset at different points in time. For example, Maryland enters in 1985:Q2 whereas Mississippi enters only in 2003:Q3. Because of staggered entry, the scope of the data grows continuously over time.[30] As a consequence, when I link an employer from the LBD to the LEHD in a given year, I only capture those individuals who work in a state that has already entered the dataset as of that year.

4.4 Sample restrictions and data structure

Appendix Table A1 describes the results of four data linking and sample restriction procedures. The first row shows the match rate between the universe of DB plans extracted from F5500 database between 1996 and 2014 and the BR. The massive scope of the BR allows for a 92 percent match rate at the plan-year level and a 95 percent match rate at the participant-year level.[31]

The set of plan-years represented in the F5500-BR merge contains a mix of firms that sponsor just one DB plan and firms that sponsor multiple DB plans.[32] I limit my sample to firms that have a single plan within the 1996-2014 window for which I have F5500 data. When firms have multiple plans, I retain only those employers who choose either to never freeze their plans, or freeze them all at the same time. The principle driver of this restriction is that I cannot observe individual pension plan coverage. Consequently, when firms sponsor multiple plans, there is no way of knowing — using the F5500, LBD, or LEHD data — which plan a worker may be covered by. By imposing this restriction, however, I can ascertain whether

[28] See Abowd et al. (2009) for details.

[29] I rely on the 2014 snapshot of the LEHD, which incorporates UI data from 49 states and the District of Columbia through the first quarter of 2015. Alabama is not included in the version of the data that I use.

[30] A number of populous states enter the data relatively early. Illinois enters in 1990, California and Pennsylvania in 1991, Florida in 1992, and New York and Texas enter in 1995.

[31] F5500 reports the count of active participants — i.e. covered workers — in each plan.

[32] Firms that sponsor multiple DB plans typically do so to cover different types of workers. For example, a firm may sponsor different DB plans for salaried and hourly workers or unionized and non-unionized workers.

workers at a given firm have been affected by a freeze in a given year. This sample restriction allows me to retain 94 percent of firm-years but only about 40 percent of worker-years. The discordance between these two rates reflects the fact that only the very largest employers sponsor multiple DB plans.

Having matched F5500 records to the BR and the LBD, I structure the data as follows. I treat each year from 2001-2014 as an experiment year, which is indexed by l.[33] This terminology reflects the research design wherein each experiment year yields a fresh sample of firm-level pension freezes. Workers employed at freezing firms five years prior to a given experiment year constitute the treated group while workers employed at non-freezing firms five years prior to a given experiment year constitute the comparison group. I impose the restriction that firms file F5500 for 5 calendar years prior to the experiment year, which I refer to as the pre-period. I then match the firm-experiment year data to the LEHD, the results of which are shown in the third row of Table A1. I recover 89 percent of firm-experiment years and 93 percent of employee-experiment years. Finally, as shown in the fourth row of Table A1, I restrict the sample to firm-experiment years for which important pension plan data is not missing.[34]

When considering the implications of pension freezes on worker decisions, it is worth reiterating that I do not observe individual information on pension plan coverage. To study worker responses in a way that limits the potential for misclassification error, I restrict the sample to firms where DB eligibility is near universal. I impose this restriction by retaining firms where the DB coverage rate is 80 percent or greater in the pre-period.[35] Within the high-coverage rate firms, I select all workers employed at $l-5$, who have at least two years of tenure as of $l-5$, and who will be between the age of 50 and 70 in year l.[36]

Having discussed the key sources of data and explained how I link and organize these data for analysis, I turn next to the regression framework and associated identification assumptions that I use to estimate causal effects.

[33] I start with 2001 because it is the first year in which pension freezes are reported in F5500. Only a handful of firms engaged in CB conversions prior to 2001.

[34] Important pension plan information includes plan assets and liabilities, accruals earned during the plan year, and the typical benefit claim age for the plan.

[35] The firm-wide DB coverage rate is the ratio of active participants in the plan as reported in F5500 to the count of total employees in the LBD. The 80 percent average coverage rate requirement is based on years $[l-5, l-2]$, i.e. between 5 and 2 years prior to the experiment year. Restricting the sample this way likely eliminates soft freezes in which the firm's plan is closed to new workers. A firm that imposes a soft freeze is likely to see its DB coverage rate decline as workers quit or retire but are not replaced with new, DB eligible, workers.

[36] The two year tenure restriction ensures that workers are fully vested in their pensions as of the cohort year when they may become subject to a freeze. This calculation is based on the 7 year maximum full vesting period allowed for DB plans by ERISA. Note that tenure measurements are right censored in the LEHD when a worker's employment spell begins prior to the year in which the state that they work in enters the data.

5 Empirical framework for estimating treatment effects

This section describes the regression framework I adopt to analyze the impact of pension freezes on a variety of labor market outcomes. The identifying assumption is that pension freezes are independent of unobserved determinants of labor supply, conditional on a set of worker characteristics, firm characteristics, and fixed effects. Summary statistics lend credibility to the identifying assumptions.

5.1 Regression specification

Let i index firms, let j index cells that bin together workers in the same firm-state-gender-age-tenure-experiment year, and let t index calendar years. Let $k = t - l$ index years relative to the experiment year. Within each cell, the firm represents a worker's employer as of $k = -5$, and tenure represents the duration of employment at firm i as of $k = -5$. Consider the following regression framework for a given experiment year, l,

$$y^l_{j(i)t} = \alpha_i + \gamma^l_t + \boldsymbol{x}^{l'}{}_{j(i)t}\boldsymbol{\beta}^l + \sum_{k=-5}^{m(l)} \delta^l_k T^l_{ik} + \varepsilon^l_{j(i)t} \tag{13}$$

where $y^l_{j(i)t}$ measures a labor supply outcome of interest, α_i is a firm fixed effect, γ^l_t is a calendar year fixed effect, and $\boldsymbol{x}^l_{j(i)t}$ is a vector of controls for age, gender, state, race, education, tenure, and prior earnings.[37] T^l_{ik} is an indicator variable that equals 1 if the firm freezes its plan and the current period is k. $\varepsilon^l_{j(i)t}$ is the error term which represents unobserved determinants of labor supply.[38] The parameters of interest are the δ^l_k coefficients which capture the dynamic treatment effect of pension freezes on worker outcomes.

To maximize the precision of the estimates, I stack data from each of the experiment years together and estimate a version of equation (13) where

$$y^l_{j(i)t} = \alpha_i + \gamma_{lt} + \boldsymbol{x}^{l'}{}_{j(i)t}\boldsymbol{\beta} + \sum_{k=-5}^{13} \delta_k T^l_{ik} + \varepsilon^l_{j(i)t}. \tag{14}$$

In equation (14), calendar year fixed effects are replaced by experiment year-by-calendar year fixed effects which allow economy-wide shocks to differentially affect workers in each experiment year. In contrast, the

[37] State is defined based on the location of the workplace in $k = -5$. I control for prior earnings using two variables: the log of average annual earnings prior to $k = -5$ and the growth rate of earnings prior to $k = -5$.

[38] The upper limit of the sum, $m(l)$, represents the number of available post-period years for experiment year l. The maximum available post-period duration is 13 years (this happens when $l = 2001$ as the data runs out in 2014).

effect of the $\boldsymbol{x}^l_{j(i)t}$ and T^l_{ik} variables are assumed to be constant across experiment years. This estimation strategy allows workers in the comparison group in a given experiment year to enter the treated group in a subsequent experiment year if their employer freezes pensions in the future. In this implementation, the δ_k coefficients are identified by within-experiment year between-firm variation in worker outcomes as well as within-firm between-experiment year variation in worker outcomes. Standard errors are clustered at the firm level.

5.2 Identification

The δ_k parameters in equation (14) represent causal effects of pension freezes on worker outcomes under the assumption that $E[\varepsilon^l_{j(i)t}|\alpha_i, \gamma_{lt}, \boldsymbol{x}^l_{j(i)t}, T^l_{it}] = 0$. Put differently, unobserved determinants of worker labor supply are assumed to have zero mean conditional on firm fixed effects, experiment year-by-calendar year fixed effects, worker level controls, and the freeze indicators. This assumption might be violated by two important sources of bias. First, firm-specific economic distress in the pre-period may result in a subsequent freeze as well as a reduction in firm-specific labor demand through downsizing.[39] Second, it is possible that freezing and non-freezing firms systematically differ in terms of pension generosity and benefit claiming provisions in the pre-period which can influence post-period differences in labor supply behavior.

To account for time-varying pre-period confounders, I rely on propensity score re-weighting. The main idea behind the use of propensity scores is to make the treatment and comparison group units more comparable in terms of observed pre-period characteristics thereby mitigating concerns that post-period differences in behavior are subject to bias. In this setting, the propensity score is the cell-level probability of experiencing a freeze expressed as a function of pre-period variables which influence both firms' decision to freeze and workers' labor supply responses. To mitigate concerns related to pre-freeze firm distress as an omitted variable, the propensity score model includes the pre-period trend in firm size and in worker compensation. To mitigate concerns that differences in plan- and firm-level characteristics between treatment and comparison groups are responsible for post-period labor supply decisions, the propensity score model also includes pre-period trends in pension wealth, pension accruals, benefit claim ages, the age structure of employment at the firm, retirement rates, employment rates, and employer-to-employer transition (E-E) rates. Appendix D provides more details on the conditioning set and explains how the propensity scores are transformed into

[39] Along with a broader set of statistics on firm dynamics around the freeze, I show in Appendix C that freezing and non-freezing firms do not differ in terms of their pre-period probability of experiencing distress.

weights when estimating equation (14).

Beyond these key threats to the identification strategy, two other confounding effects are potentially at play. First, it is possible that funding deficiencies that lead firm's to freeze their DB plans also resulted in cut backs to health insurance benefits. These unobserved changes could generate their own income and substitution effects on labor supply choices.[40] While these changes are not directly verifiable in the data that I use, indirect evidence from surveys suggests that firms have not altered health benefits as a consequence of freezes.[41] Second, it is possible that observed changes in labor supply are influenced by network effects within the firm. This breakdown of the so called stable unit treatment value assumption (SUTVA) could occur if freeze-affected workers' retirement decisions are influenced not only by changes in compensation but also changes by the retirement decisions of their peers. I ignore peer retirements as a first order concern when interpreting the results because available evidence on the magnitude of peer effects of this variety indicate that they are extremely small.[42]

5.3 Summary Statistics

Before showing the impact of freezes on worker outcomes, I present a summary of raw data on pre-period characteristics of workers and their employers. These statistics are based on workers employed at the sample of firms where the pre-period coverage rate is in excess of 80 percent. A table showing firm characteristics for the full sample of DB sponsoring employers is provided in Appendix C.

In Table 1 I show pre-period summary statistics for workers split into three different groups based on age as of the experiment year.[43] Workers in the sample are employed with DB sponsoring firms as of $l-5$, and the statistics are computed by averaging over five pre-period years. The top panel shows worker characteristics while the lower panel shows pension plan and firm characteristics. Because the statistics are computed from a worker-level dataset, pension and firm characteristics are worker weighted. For each age-

[40] Employer sponsored health insurance is reported on F5500 filings. However, the reporting requirement only exists for employers who cover more than 100 workers. More importantly, changes in health insurance plan characteristics cannot be ascertained from F5500.

[41] There are no reports of changes to employer provided health insurance benefits in a sample of 17 large publicly traded firms that froze their plans between 2004 and 2008 as compiled by the Boston College Retirement Research Center (see http://crr.bc.edu/uncategorized/fact-sheets/). Similarly, a Government Accountability Office (GAO) survey of freezing employers indicates no reported changes to health benefits (see Bovbjerg et al. (2008)).

[42] Hamman et al. (2016), who use large-scale linked employer-employee data from Germany to investigate these spillovers on retirement behavior, find that one additional peer retirement (at the establishment level) increases the probability of retirement for men by 0.01 percentage points and produces no detectable effect on women.

[43] Using 55 and 65 as the modal ERA and NRA in DB plans, 50-55 year-old workers are below the ERA at the time of the freeze, 56-64 year-old workers are between the ERA and the NRA at the time of the freeze, and 65-70 year-old workers are over the NRA at the time of freeze.

specific panel, the first column shows the propensity score re-weighted comparison group mean, the second column shows the difference between the treatment and the comparison group, and the third column shows the p-value for the null hypothesis that there is no difference between the two groups. Across the three sub-samples, workers are well educated with relatively high earnings and the gender split is close to 50-50. Demographic characteristics, pre-period labor market outcomes, pension plan generosity, and firm-level characteristics are very similar in the treated and control groups.[44]

Secondary to the differences between treatment and comparison groups within each age bin, there are also several notable differences between the three age bins. Workers in the younger two age bins are less likely to be white and male, more likely to have a college degree, and have higher earnings. Tenure, measured five years prior to the experiment year, is approximately equal across the three age groups.[45] Finally, the oldest workers are employed at substantially smaller firms with a higher proportion of workers over age 60 and a lower proportion of workers under age 45. Differences in firm-wide age structure across the three age groups could reflect differences in DB pension formulas or other unobserved workplace characteristics. Some of these differences are reflected in higher average pension wealth and delayed retirement claim ages at firms that employ the oldest workers in the sample. Appendix Table G1 shows the same statistics without propensity score re-weighting provides additional evidence of broad similarity between workers in the treated and control groups.

6 How pension freezes affect labor supply and employer attachment

In this section, I use the regression framework and identification strategy developed earlier to investigate the causal impact of pension freezes on the labor supply and employer attachment. I show how freezes have heterogeneous labor supply effects based on the age at which workers experience them. In addition, I show that freezes have heterogenous effects holding age fixed. The treatment effects I present here are consistent with the testable implications developed in the theoretical model.

[44] It is important to note that the measures of pension wealth are based on plan-wide totals and should not be seen as representative of the workers in each age bin

[45] The absence of variation in tenure between workers of different ages is an artifact of the way that states enter the LEHD dataset. If a state enters the dataset after a given employer-employee relationship is established, then the employer-employee history is left censored and tenure is understated.

6.1 Employment, retirement, and earnings

Figure 4 plots the δ_k coefficients from specification (14) using the cell-level employment rate as the outcome variable. To investigate age-specific heterogeneity in labor supply responses, I split the data by age as of the experiment year using the same age groups as in Table 1. I then estimate the regression model on each age group separately and show the coefficients in the respective panels of the figure.

Looking first at the far left panel shows that treated workers in the 50-55 year-old age group exhibit a small reduction in employment rates in the first six years of the post-freeze period. Reductions in employment reflect substitution effects (i.e. reduced lifetime labor supply), although the economically small magnitude of the coefficients and their statistical insignificance suggests that offsetting wealth effects (i.e. increased lifetime labor supply) are equally important for workers in this age group. After about 8 years post-freeze, wealth effects start to dominate the labor supply response and workers in the treated group experience a 1.5 - 3.3 percentage point increase in employment relative to the comparison group. Another way of stating this finding is that the employment rates of both treated and comparison groups are declining in this age range, but the decline is markedly slower for treated workers. The muted substitution effect and substantial wealth effect that characterizes labor supply responses for 50-55 year-old workers aligns with the fact that large DB accruals are earned before age 55. As such, workers at or under 55 when first faced with a freeze experience large net losses in compensation thereby eliciting strong wealth effects in favor of continued employment.

Moving next to the central panel of the figure shows that substitution effects play an important role on impact for treated workers in the 56-64 year-old age group. In the first six years of the post-freeze period, employment rates for treated workers fall by 1.0 - 1.7 percentage points relative to the comparison group. Starting about 8 years post-freeze, treated workers' labor supply diverges in the opposite direction from the comparison group as the employment rate differential rises by 1.2 - 2.1 percentage points. As with 50-55 year-old workers, the tendency of freeze affected workers to lengthen their working lives relative to the comparison group is indicative of dominant wealth effects. Appendix Figure G1 shows that freeze-affected women are more likely to exhibit substitution effect dominant responses whereas freeze-affected men are more likely to exhibit wealth effect dominant responses.

Most DB plans incentivize retirement by making the real value of DB accruals negative after age 65. When DB plans are frozen and replaced with DC plans, this implicit tax on continued employment is reduced

as workers can obtain offsetting DC accruals at ages where they would otherwise have been penalized. The right most panel of Figure 4 shows labor supply behavior that is consistent with higher returns to work for the treatment group relative to the comparison group. Treated workers over age 65 increase their employment rates by 1.2 - 4.5 percentage points which reflects dominant substitution effects. While these effects are not as precisely estimated, they are economically meaningful and align with theoretical predictions and the institutional design of DB plans.

Empirical evidence shown in Figure 4 lines up with the three theoretical predictions outlined in Section 3. Substitution effects are larger for 56-64 year-old workers relative to 50-55 year-old workers which is a consequence of the former group losing less total compensation than the latter group (prediction 1(a)). Substitution effects are positive because of increased labor market returns for workers over 65, but negative for workers under 65 because of reduced labor market returns (prediction 1(b)). Finally, looking within the first two age groups, substitution effects play a dominant role in the short-term response of the most marginally attached workers who lower their employment rates (prediction 2(a)).

Figure 5 shows the impact of freezes on retirement, which is defined as a permanent departure from paid employment in the LEHD.[46] Freeze induced changes in retirement rates are virtually mirror images of the employment effects shown in Figure 4, indicating that non-employment and retirement are essentially equivalent for workers affected by freezes. This finding indicates that bridge jobs appear not to be an important transition phase for freeze-affected workers who cut their careers short. It also substantiates the model's assumption of self-absorbing retirement. On the whole, the treatment effects for retirement reinforce employment-based findings.

Figure 6 shows the effect of freezes on the log of annual earnings. All the estimates shown here are conditioned on the sample of individuals with positive earnings in a given year. The far left panel shows that there are no evident changes in earnings for 50-55 year-old workers in the first 6-7 years of the post-freeze period. After 7 years, workers in the treated group exhibit slower age-related earnings declines which manifest as a positive earnings differential. In the final few years of the sample window, treated group workers' earnings exceed those of control group workers by about 15 log points. This difference likely arises from continued full-time work for the treated group relative to transitions into part-time or part-year work for the comparison group. It is consistent with wealth effects of the freeze inducing longer careers in

[46] See Appendix B for details on how retirement status is measured in the LEHD and how it compares with retirement status for a comparable sample of respondents in the HRS.

full-time status.

For 56-64 year-old workers, who are shown in the central panel, the pattern is somewhat different. Treated workers experience a statistically significant earnings dip of 1.5 - 4 log points in the first five post-freeze years. This dip could arise for two reasons. First, treated workers who shorten their careers — i.e. exhibit dominant substitution effects in the short-term — may work less than full-time or less than full-year right after the freeze. These reductions in labor supply would appear as earnings losses. Second, it is possible that these workers experience wage declines in the short-term brought on by firm-specific factors.[47] The fact that 50-55 year-old workers do not experience earnings losses suggests that wage reductions are unlikely to be the only cause for the observed earnings dip that 56-64 year-old workers experience. In contrast, the long-term pattern shows a 20-30 log point increase in earnings relative to the comparison group, provides evidence of dominant wealth effects wherein freeze-affected workers delay retirement and continue in full-time or full-year employment while comparison group workers transition to part-time or part-year employment. As was the case for the 50-55 year-old age group, it is important to reiterate that the positive long-term earnings differential reflects a slower decline rather than an increase earnings levels.

Earnings differences for 65-70 year-old workers, shown in the far right panel, are not precisely estimated over the sample window. However, the post-freeze coefficients indicate a fairly sustained drop in earnings of about 15 log points relative to the comparison group. Thus, while freezes induce workers over 65 to delay retirement, the pattern of earnings changes suggest that continued employment for these workers likely comes in the form of more part-time employment. That the oldest workers in the labor market are willing extend their careers at less than full-time rates complements recent survey-based evidence on the importance of flexible hours in supporting longer working lives (Ameriks et al. (2018)).

6.2 Employer attachment

While the treatment effects shown thus far relate to the decision about whether to work and how much to work, they do not address the decision about where to work. E-E transitions are a potentially important margin of adjustment particularly given that pension freezes induce employer-specific rather than worker-specific or market-wide changes in compensation. In this subsection, I exploit the matched employer-employee structure of the LEHD to study differences in worker mobility between the treatment and com-

[47] Analyses of firm-level payroll data shown in Appendix C indicate that freezes lower firm-wide average earnings by approximately 2.5 log points. These earnings changes could stem from the changing post-freeze age composition of the firm's workforce or from reductions in offered wages.

parison groups.

Figure 7 shows the percentage point change in the probability of leaving one's DB sponsoring employer.[48] In the data, a worker is coded as having experienced an employer change if the EIN associated with their UI record in the LEHD changes. It is worth noting that not all EIN changes reflect employee mobility as some firms change their EINs in the course of a merger or acquisition. The large spike in transitions for treated workers that occurs four years prior to the freeze year in the left panel and the center panel is likely an artifact of firm-level EIN recoding.

One period after the freeze, treated workers in the 50-55 and 56-64 year-old age group appear to respond with small but statistically significant increases in employer transitions. For 50-55 year-old workers the transition rate increases by 1.4 percentage points off a baseline rate of 2.9 percent. For 56-64 year-old workers, the transition rate increases by 0.8 percentage points off a baseline rate of 2.8 percent. The magnitude of these effects indicates that relatively younger workers faced with compensation losses from a pension freeze have better outside options to exercise than workers closer to retirement age. After the first year, there is a statistically significant pattern of reduced E-E transitions among workers in the treated group. Transition rates fall by 1.2 percentage points for 50-55 year-old workers and about 0.6 to 0.9 percentage points for 56-64 year old workers. When considered alongside the earnings results, reduced E-E mobility is consistent with continued employment in career jobs for treated group workers as opposed to the counterfactual transition to part-time or bridge jobs for comparison group workers. E-E mobility for workers over 65 is largely unaffected by freezes.[49]

Reduced E-E transition rates for workers in the younger two age groups lines up with the time window where dominant wealth effects lead to increased employment and higher propensity for full-time work. Ironically, the ability of workers to extend their careers in order to make up for lost compensation comes from extended attachment to the very employers responsible for the pension freeze. Reduced E-E mobility, even in the face of substantial employer-specific compensation shock, indicates that full-time work opportunities are limited outside of workers' long-term employers. As such, robust demand for the labor services of older workers within their long-term employers is a key requirement to accommodate policies aimed at supporting longer working lives.

The results I have presented thus far characterize treatment effects of pension freezes on labor supply

[48] I.e. the employer that worker's are attached to in period $l - 5$.

[49] Coefficient estimates are suppressed due to small sample sizes for latter part of the estimation window.

outcomes. These estimates provide insights about heterogeneity in workers' preference for long careers and illustrate the importance of the right type of labor demand in sustaining those longer careers. Nevertheless, because I do not observe detailed pension benefit provisions I cannot estimate the post-freeze value of lost DB accruals or the change in DC accruals. The absence of data on pecuniary costs of pension freezes prevents direct estimation of labor supply elasticities. To estimate elasticities indirectly, I rely on estimating and simulating data from the structural model which I turn to next.

7 Solving and estimating the structural model

In this section, I explain how I solve and estimate the structural model numerically using MSM (McFadden (1989), Duffie and Singleton (1993)). I identify the model's parameters by matching model-based simulations of employment responses to pension freezes to those observed in real-world administrative data.

7.1 Estimation

I estimate the model in two steps. In the first step, I calibrate several parameters (e.g., earnings, pension accruals, DC match rates, Social Security benefits, tax rules, mortality rates, discount factors, and interest rates) using HRS survey data and other external data sources. Appendix E.1 provides a detailed description of the calibrations. In the second step, I estimate the model's preference parameters $\boldsymbol{\theta} = (\sigma, \gamma, \phi, \rho, \sigma_v)$ using MSM. The procedure is as follows:

1. For a given value of $\boldsymbol{\theta}$, I numerically solve the model using value function iteration under two different scenarios. In the first scenario, DB accruals progress normally. In the second scenario, I freeze DB accruals for each age between 56 and 64 and compute an alternative set of decision rules.

2. I simulate initial assets and work disutility draws for 5000 individuals who are initially aged 51 to 59 using information from the HRS. I apply decision rules from the no-freeze scenario to obtain work histories and asset accumulation paths from the initial age up to age 80 (the terminal age) to create a simulated control group.

3. Next, I apply the freeze decision rules for the same population of individuals — i.e. individuals with the same initial assets and work disutility draws —starting five years after the initial age. Individuals in this exercise have the same work and asset accumulation choices as the simulated control group for

the first five years, but have different work histories and asset accumulation choices once faced with a DB freeze. I call this sample the simulated treated group.

4. I compute two sets of moments using the simulated control and treated groups. The first set of moments is the difference in average employment rates between the two groups (the simulated treatment effect). I compute these differences for 12 periods, starting from the period of the freeze (12 moments). The second set of moments is the employment rate time trend for the simulated control group. I compute the trend moments starting four periods prior to the freeze and lasting five periods after the freeze (10 moments). I then compare the 22 simulated moments with same moments estimated from LEHD data (real-world moments).

5. I iteratively repeat this procedure for different values of $\boldsymbol{\theta}$ and choose the estimate that minimizes the distance between the simulated moments and the real-world moments.

Further details on the solution algorithm and the estimation procedure are provided in Appendix E.2.

7.2 Identification

Identification of the model's parameters derives from two key sources of variation in real-world data. The first set of moments, which capture the age-based decline in employment rates in the comparison group, identify the constant (γ) and slope (ϕ) terms of the deterministic component of g.

The second set of moments — i.e. the dynamic treatment effect — is informative about within-age variation in individual preferences for continued work. Equation (12) helps to explain the identification argument for (σ, ρ, σ_v). Notice that $\bar{g}$ is composed of two separate terms: the first term is the change in utility from consumption at retirement, and the second term is the option value of working. Freezes affect both terms. Changes in $\bar{g}$ driven by post-freeze re-optimization of consumption choices provide information about individuals preference for smooth consumption profiles over the life-cycle. This source of variation in $\bar{g}$ aids in the identification of the intertemporal elasticity of substitution (IES), σ.[50]

The treatment effect estimates reveal that freeze-induced changes in the option value of work induce early retirement for some workers and delayed retirement for others. These differences are informative about the persistence (ρ) and variance (σ_v) of the idiosyncratic component of g. In particular, ρ and σ_v need

[50]Note that consumption data are not directly used to identify σ; rather, variation in $\bar{g}$ induced by freezes indirectly aids in identification.

to be large enough so that workers of the same age exhibit different retirement behavior when affected by a compensation shock of the same magnitude. For workers of a given age, those with high values of g have stronger preferences for leisure and retire early. On the other hand, those with low values of g have weaker preferences for leisure and choose to delay retirement.

7.3 Model fit and parameter estimates

Figure 8 shows how simulated moments compare with observed moments. The left panel shows the employment rate trend for 56-64 year old workers who are not subject to freezes. The light colored area shows the region where simulated moments are specifically targeted to match real-world moments, whereas the shaded region shows out-of-sample fit. The model fits the data reasonably well both in and out-of-sample. The right panel compares simulated treatment effects to real-world treatment effects, all of which are used as estimation targets. This panel shows that the model captures the magnitude and the timing of employment rate fluctuations induced by pension freezes.

Table 2 shows the estimated parameters. The IES estimate is close to 1, which is equivalent to log utility. Because the 5 preference parameters in $\boldsymbol{\theta}$ are identified using 22 moments, I am able to conduct a χ^2 overidentification test. The model is formally rejected on the basis of this test, which I report in the last row of the table. The main reason that the test statistic is large is that the estimation procedure does not account for variance associated with first-step parameters obtained from the HRS (e.g, earnings profiles, DB pension wealth accruals, DC match functions, etc.) Consequently, the variance of second-step simulated moments is understated and the weight attached to each moment (which is inversely related to variance) is large.[51]

7.4 Employment elasticities

In the model, labor supply responses to changes in compensation are governed by the fraction of individuals who are marginal with respect to the decision to work or retire which, in turn, is a function of the preference parameter $\boldsymbol{\theta}$. I compute elasticities non-parametrically by plugging averages from simulated data into the following expression

$$\hat{\eta}_a = \frac{\hat{E}\left[\Delta \text{emp}_{\iota a}\right] / \hat{E}\left[\text{emp}^C_{\iota a}\right]}{\hat{E}\left[\Delta \chi_{\iota a}\right] / \hat{E}\left[\chi^C_{\iota a}\right]}. \tag{15}$$

[51] Standard errors are understated for the same reason.

In equation (15), $\hat{\eta}_a$ is the elasticity of employment with respect to a one period shock in current compensation for workers aged a.[52] I estimate $\hat{\eta}_a$ by simulating a 5 percent increase in pre-tax wage compensation and reading off the model implied change in employment rates for different ages. $\Delta\text{emp}_{\iota a}$ is the difference in a worker's employment status with and without the age a shock to compensation. $\text{emp}^C_{\iota a}$ is a worker's employment status without the compensation shock. Analogous definitions apply to the post-tax current compensation measures $\Delta\chi_{\iota a}$ and $\chi^C_{\iota a}$. $\hat{\eta}_a$ is defined for the sample of workers who are employed at $a-1$.

$\hat{\eta}_a$ is the extensive margin labor supply elasticity governing employment responses to short-lived tax changes . This definition of the labor supply response to compensation changes does not account for the option value of continued work as in Stock and Wise (1990). To account for this forward-looking dimension of retirement behavior, I define $\hat{\eta}^{PV}_a$ as the elasticity of employment with respect to the present value of future compensation:

$$\hat{\eta}^{PV}_a = \frac{\hat{E}\left[\Delta\text{emp}_{\iota a}\right]/\hat{E}\left[\text{emp}^C_{\iota a}\right]}{\hat{E}\left[\Delta\omega_{\iota a,R^*}\right]/\hat{E}\left[\omega^C_{\iota a,R^*}\right]}, \tag{16}$$

where

$$\omega_{\iota a,R^*} = \underbrace{\sum_{t=a}^{R^*}(1-p_a)(1+r)^{t-a}\chi_{\iota t}}_{\text{PV from } k \text{ to retirement}}. \tag{17}$$

Conditional on being employed at age $a-1$, $\omega_{\iota a,R^*}$ is the present value of future compensation, R^* is the period in which the worker retires, $(1-p_a)$ is the likelihood of being alive at age a, and r is the real interest rate. Because R^* is the ex-ante or pre-shock expected retirement age, $\Delta\omega_{\iota a,R^*}$ in equation (16) represents the change to the present value of compensation that the worker was expecting to receive before retirement. $\hat{\eta}^{PV}_a$ re-casts a one period shock to compensation at age a and expresses it in terms of a change in the present value of compensation that the worker was expecting to earn before retirement. This parameter is consistent with the notion that retirement decisions involve a comparison of the value of working and retiring at all future ages. I estimate $\hat{\eta}^{PV}_a$ using the same simulated 5 percent shock to wage compensation at age a but I

[52] Because retirement is self-absorbing in the model, $\hat{\eta}_a$ calculated using model based simulations are not directly comparable to elasticity estimates based on model simulations or real-world data where workers can leave and re-enter the labor market (see, e.g., French (2005), Brown (2013), and Gelber et al. (2017)). With self-absorbing retirement, the value of retirement (V^R) does not nest future re-entry into the labor market. Thus, larger compensation cuts — or reductions in option value — are needed to induce retirement relative to a model where V^R nests future re-entry into the labor market. Consequently, the elasticity estimates that I present are lower bounds relative to a model where retirement is not self absorbing.

calculate the present value impact of that shock using equation (17).

Table 3 shows the two types of elasticities for workers who experience compensation shocks at age 58, 60, and 62.[53] The estimates in the table show that while workers appear to be only weakly responsive to a single period change in compensation, re-casting the change in terms of its effect on the long-term compensation yields a substantially larger elasticity. At age 60 for instance, the estimated employment elasticity with respect to a one period change in after-tax compensation is 0.15 while the option value-based elasticity is 0.9. This difference in elasticities illustrates how measuring the retirement response to one-period-ahead changes in the reward to working understates the importance of forward-looking behavior in explaining retirement decisions.

In the next section, I exploit the full structure of the estimated model to emphasize this difference by examining how a permanent elimination of OASI payroll taxes for older workers affects their retirement behavior.

8 Evaluating the effectiveness of a counterfactual payroll tax reform

In this section, I study the effect of eliminating the OASI component of the payroll tax for older workers. I focus on transition cohorts for whom the policy change is unexpected. The main idea behind this reform proposal is to remove disincentives for longer careers that exist under current law. While payroll taxes are applicable to all years of work, the Social Security benefit formula is based on the 35 years of highest paid work. For the typical older worker over the age of 55 or 60 who no longer experiences real earnings growth, an additional year of work generates no substantial increase in Social Security benefits. Nevertheless, because all workers contribute OASI payroll taxes regardless of age, workers who remain employed beyond the 35 year vesting age experience tax burdens with no offsetting benefit increases. By relieving these fully "paid up" workers from additional payroll tax contributions, the reform has the potential of lengthening careers. Understanding the costs and benefits of the reform requires quantifying behavioral responses which I do here using the estimated model.

The flavor of reform that I consider involves an unexpected elimination of the OASI payroll tax for workers who are over age 60. To simplify the analysis, I assume that workers currently bear the full burden of the

[53] In the estimates presented in the table, I estimate $\hat{E}\left[\Delta \text{emp}_{\iota a}\right]$, $\hat{E}\left[\Delta \chi_{\iota a}\right]$, and $\hat{E}\left[\Delta \omega_{\iota a, R^*}\right]$ using within-person variation thereby holding age and work disutility (g) fixed. When computing elasticities, I assume that R^* is known to the worker with perfect certainty. This assumption ignores the effect of randomness in g.

tax which implies that the counterfactual reform raises income by 10.6 percent (under current law workers and firms each pay 5.3 percent). I assume that the disability insurance (DI) and hospital insurance/Medicare (HI) components of the payroll tax are unaffected as is the Social Security benefit formula.[54] To more accurately portray incentives affecting the majority of employees in the current and future workforce, I remove DB pensions from the model.

Figure 9 shows model simulations of employment rate trends for workers between the age of 56 and 75 under current law and under the reform.[55] The two trends diverge starting at age 60, with employment rate differences peaking at 15.3 percentage points at age 66. Averaging over the entire post-60 age window, the reform increases employment rates by 5.2 percentage points.

Table 4 provides additional statistics comparing the two different regimes. The left panel shows moments from the distribution of a variety of outcomes under current law, while the right panel shows the same moments under the reform. The third panel shows the mean difference in outcomes. Reflecting the overall increase in employment rates, the average retirement age under the reform rises by 1.1 years. Longer careers allow workers to accumulate almost $8,000 more in their DC retirement accounts and provide about $23,000 more in federal income taxes. These gains accrue against a loss in payroll tax revenue of approximately $28,000. Finally, as shown in the lower panel of the table, I find that equivalent variation from the reform averages almost $75,000 per worker implying a substantial welfare gain. This estimate is an order of magnitude larger than the one reported by Laitner and Silverman (2012) which is attributable primarily to the fact that I do not attempt to make the reform revenue neutral in this basic analysis.[56]

Taken together, the counterfactual analysis presented here shows that the relatively elastic labor supply of older workers can be harnessed to extend their careers with an OASI payroll tax sunset at age 60. I find that older workers would obtain non-trivial welfare gains from the reform and have more income in retirement although net revenues collected from workers after age 60 decline by about 4 percent.

[54] DI and HI payroll tax components collectively amount to 4.7 percent.

[55] Because the reform is unexpected there is no difference in employment rates prior to age 60. Simulated workers are included in the sample if they are employed at age 55.

[56] The way that Laitner and Silverman (2012) build revenue neutrality into their analysis is to require a small increment to payroll tax contributions in the pre-vesting period. This increase in pre-vesting age taxes results in lower consumption over the entire life-cycle and smaller equivalent variations.

9 Conclusion

In this paper, I exploit widespread and understudied shifts in employer-sponsored pension benefit programs to better understand how retirement behavior responds to changes in compensation. Over the last 20 years many employers have reneged on long-standing promises to continue supporting traditional retirement benefits in the face of rising costs of provision. Although these changes are substantial, there is no evidence on how they have affected workers' labor market outcomes. Creating a new dataset that brings together detailed administrative information on pension plan characteristics with matched employer-employee data, I study the impact of these unexpected shocks on employment, retirement, earnings, and employer attachment for workers between the age of 50 and 70.

I find evidence of substantial heterogeneity among workers, even among those of the same age. When faced with freeze-induced compensation changes, some workers choose to retire early while others choose to delay retirement, thereby illustrating that differences in wealth and preferences for leisure are important in explaining retirement decisions. Using these quasi-experimental treatment effects as targets, I estimate a structural model of retirement and saving that allows for heterogeneity in wealth and leisure preferences. I use the model to simulate the effect of a counterfactual policy that eliminates OASI payroll taxes for workers who are fully vested in their Social Security benefits. Simulations from the estimated model show that eliminating the tax at age 60 induces a 1.1 year delay in the average retirement age and produces large welfare gains.

The empirical setting and the model adopted in this paper highlight the importance of forward-looking behavior in determining labor supply decisions, particularly retirement decisions. It is likely that unobserved determinants of the relationship between employers and employees, such as implicit contracts with a rich set of contingencies, drive the association between current labor supply and expected future compensation (see, e.g., Lazear (1981) and Akerlof and Katz (1989)). These contingencies create tight bonds between employers and employees that many standard models of labor supply do not incorporate. Notably, the durability of these relationships and the impact they have on forward-looking labor supply behavior are not unique to DB-style incentives, which are no longer common in the U.S. private sector. For instance, median tenure for workers between the age of 55 and 64 has remained unchanged for two decades despite major economic transitions including the demise of DB pensions.[57] This fact suggests that a better understanding

[57] Median tenure, as reported by the Bureau of Labor Statistics, for workers in the 55-64 age range in 1998 and in 2018 was 10.1 years.

of the mechanisms driving long-term employer-employee relationships is critical in explaining lifetime labor supply behavior.

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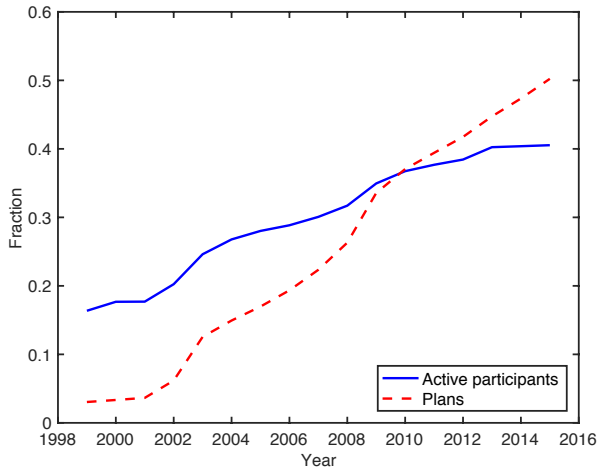
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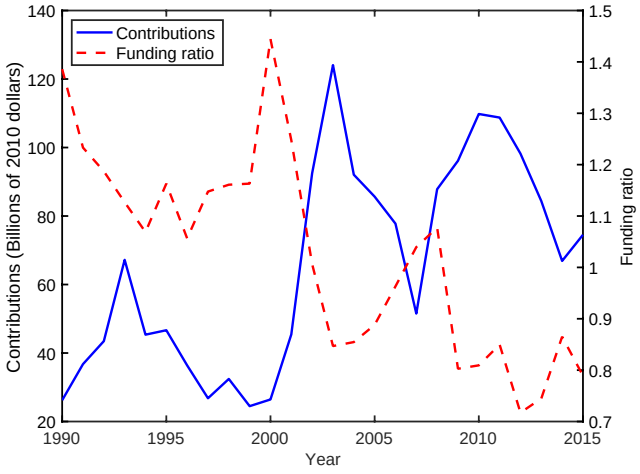
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Figure 1: DB plans hard frozen or converted to cash balance



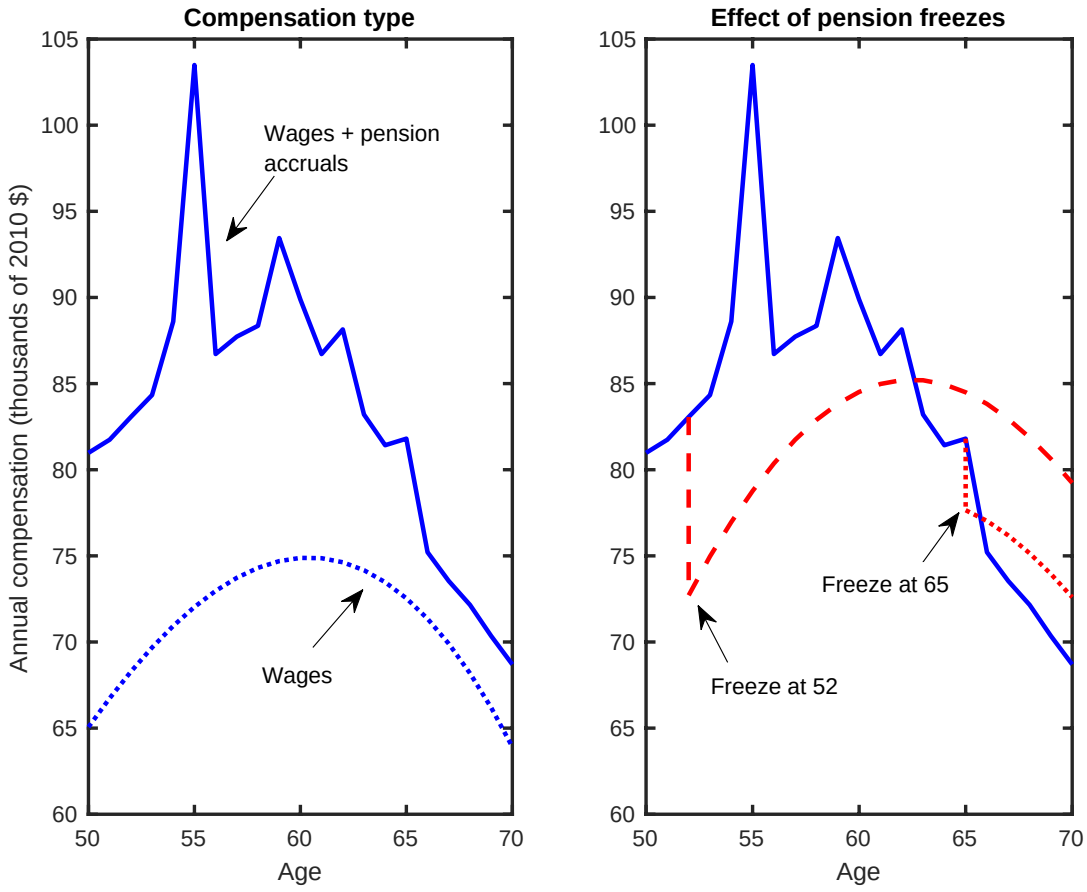
Notes: The dashed red line shows the share of private sector, single employer, DB pension plans that have been hard frozen or converted to cash balance plans. The solid blue line shows the share of active participants in DB plans that have been hard frozen or converted to cash balance plans. Time series are based on 1999-2015 F5500 microdata.

Figure 2: Pension costs and funding ratios



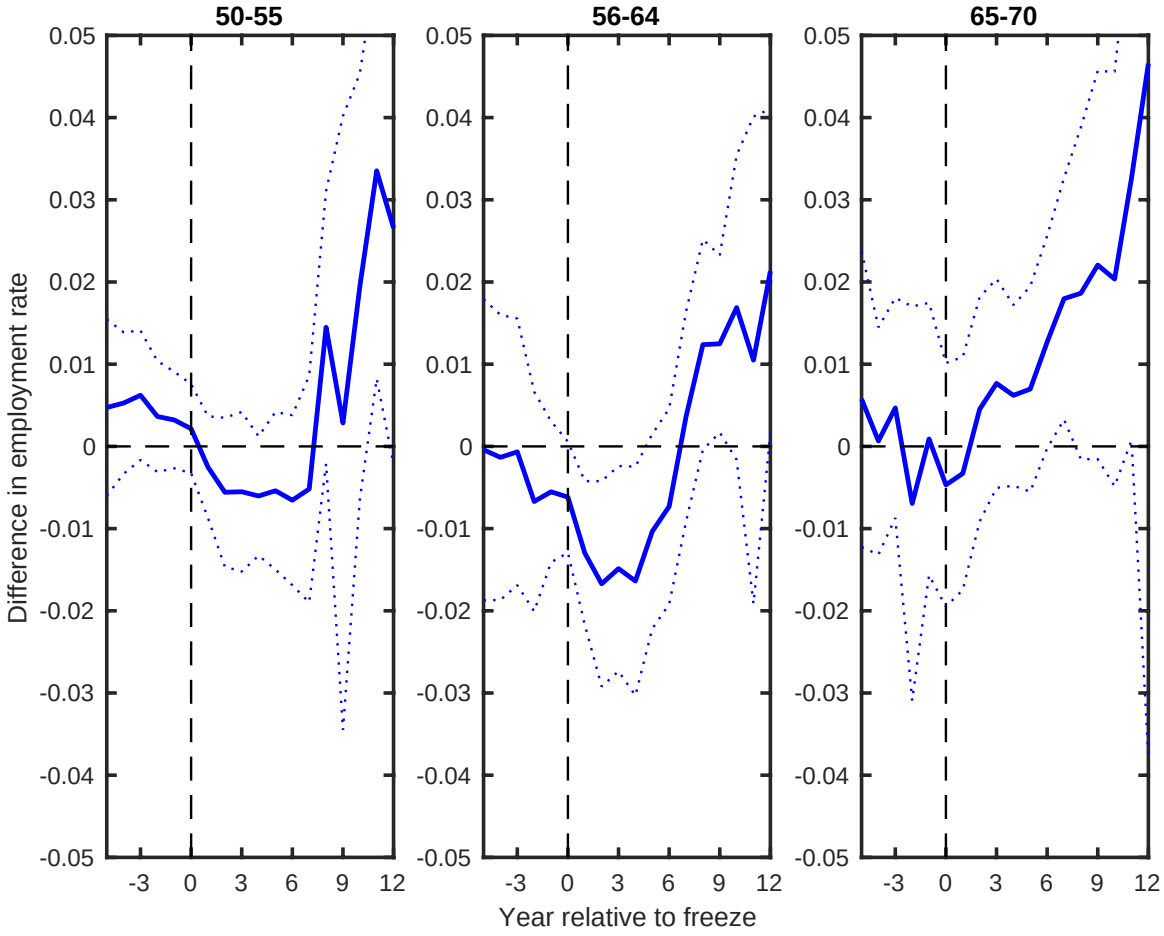
Notes: This figure shows total contributions and aggregate funding ratios for private sector, single employer, DB sponsors. Total contributions (solid blue line) are measured on the left axis. Funding ratios (dashed red line) are measured on the right axis. The funding ratio is the ratio of the market value of assets to the present value of future pension liabilities. Contributions data are drawn from the Department of Labor's Private Pension Plan Bulletin Historical Tables and Graphs 1975-2015. Funding ratios are drawn from the PBGC Pension Insurance Data Book, 2016.

Figure 3: Simulated effect of pension freezes on total compensation



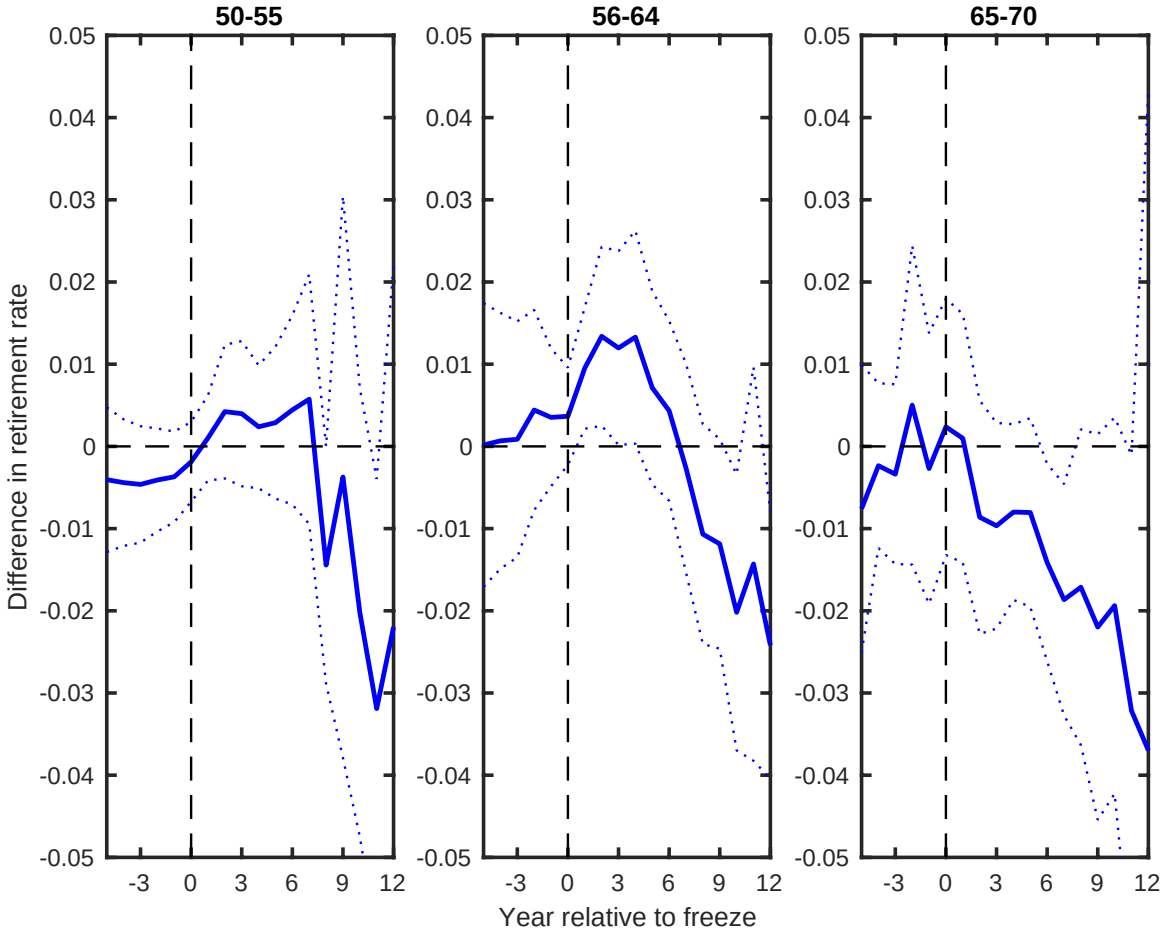
Notes: This figure is based on data from DB eligible HRS respondents in the 2010 wave who are employed in the private sector. For simulated freeze compensation paths, post-freeze DB accruals are set to zero. Respondents with DC plans are assumed to continue participating in them at the same rate; post-freeze contribution rates for respondents without DC plans are imputed using the sample average rate for actively contributing respondents. See Appendix F for details on the sample and simulation of post-freeze compensation.

Figure 4: Impact of freezes on employment



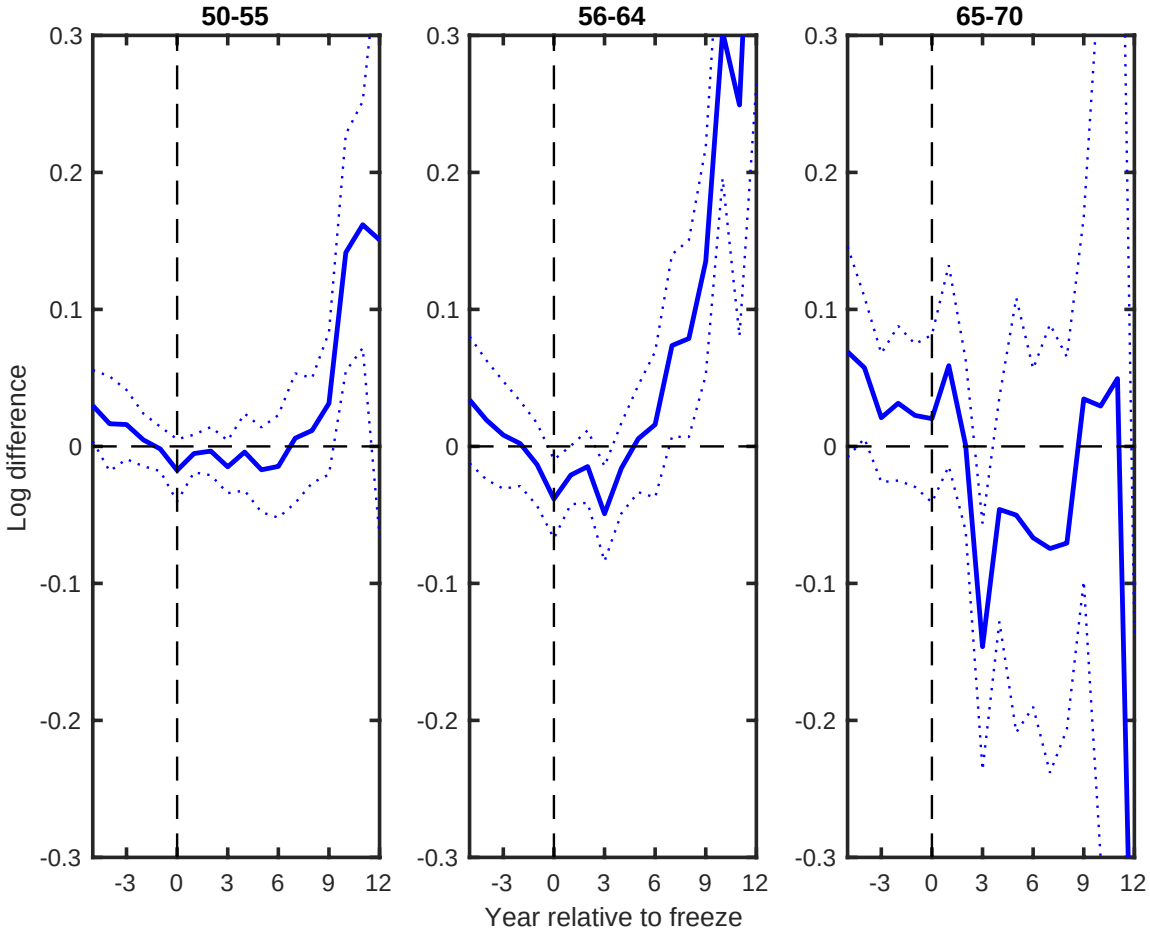
Notes: This figure shows the time path of the treatment effect of the freeze on employment rates for workers in the three different groups based on age at the time of the freeze. The p-values for F-tests that the coefficients for periods -5 to -1 are jointly zero are .41, .38, and .35 for each of the three age groups respectively. Dotted lines show 95 percent confidence intervals which are based on standard errors clustered at the firm-level.

Figure 5: Impact of freezes on retirement



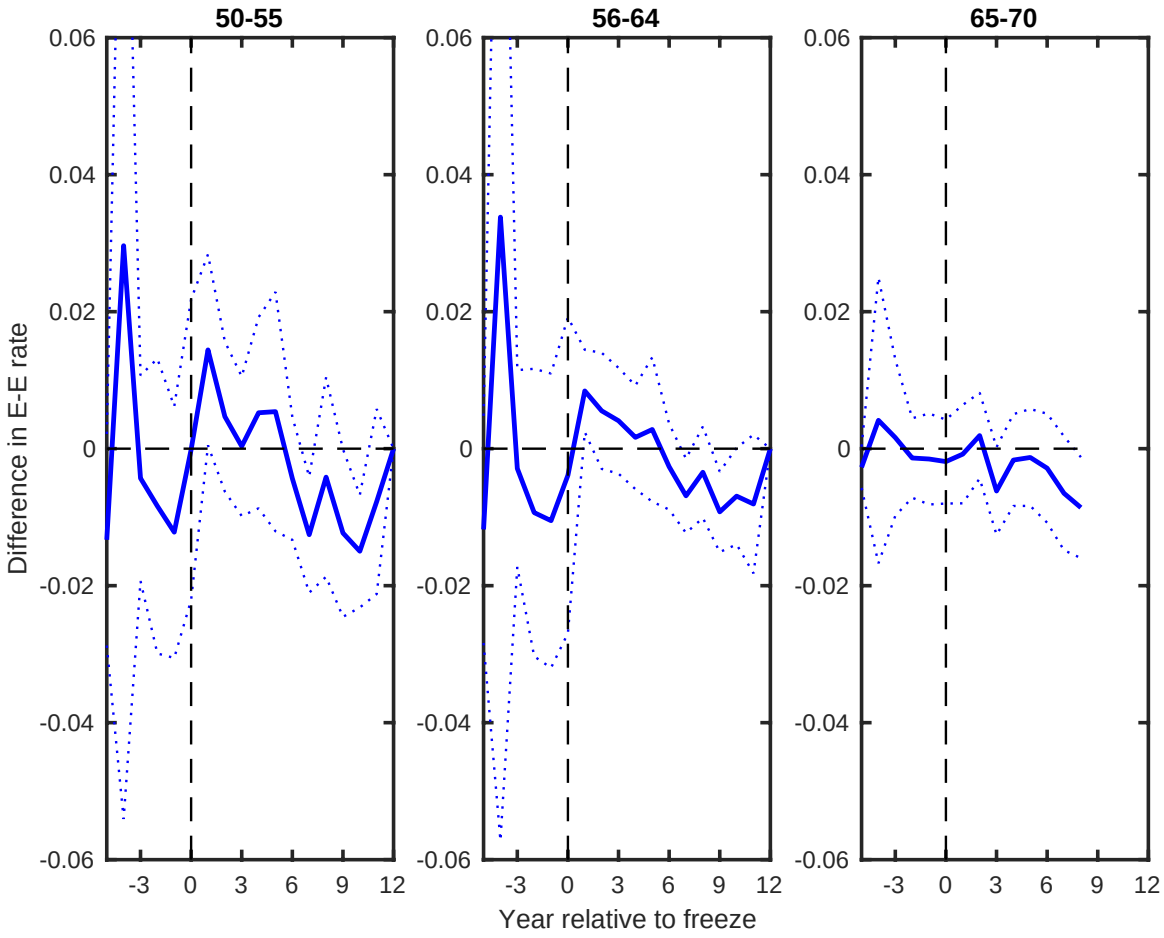
Notes: This figure shows the time path of the treatment effect of the freeze on retirement rates for workers in the three different groups based on age at the time of the freeze. The p-values for F-tests that the coefficients for periods -5 to -1 are jointly zero are .64, .77, and .35 for each of the three age groups respectively. Dotted lines show 95 percent confidence intervals which are based on standard errors clustered at the firm-level.

Figure 6: Impact of freezes on log annual earnings



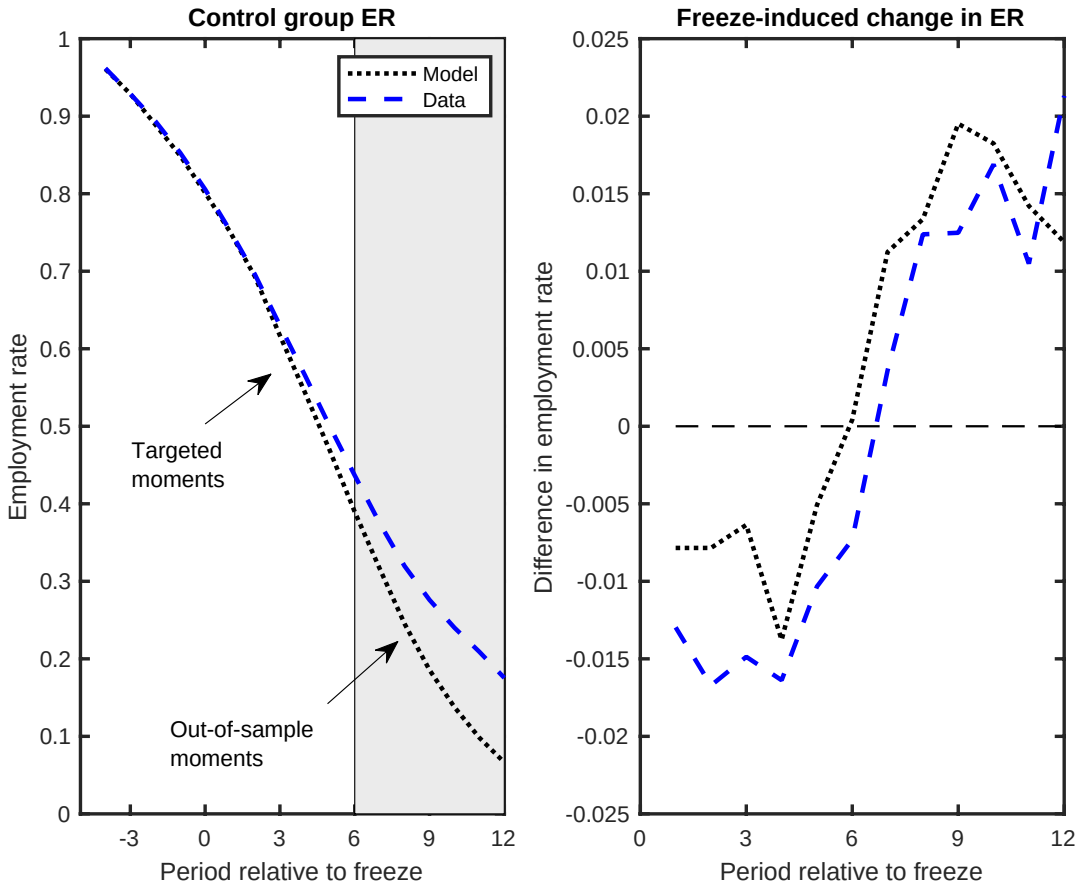
Notes: This figure shows the time path of the treatment effect of the freeze on log annual earnings for workers in the three different groups based on age at the time of the freeze. The p-values for F-tests that the coefficients for periods -5 to -1 are jointly zero are .17, .30, and .31 for each of the three age groups respectively. Dotted lines show 95 percent confidence intervals which are based on standard errors clustered at the firm-level.

Figure 7: Impact of freezes on employer attachment



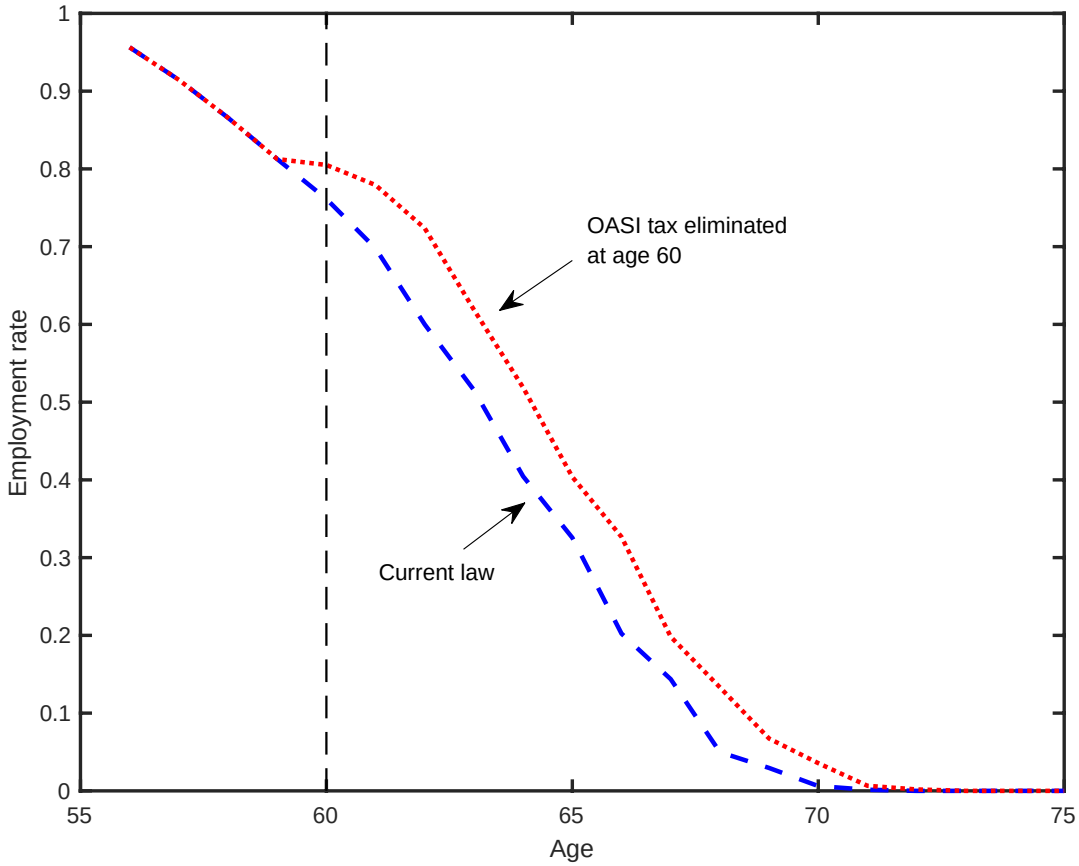
Notes: This figure shows the time path of the treatment effect of the freeze on log annual earnings for workers in the three different groups based on age at the time of the freeze. The p-values for F-tests that the coefficients for periods -5 to -1 are jointly zero are .01, .06, and .58 for each of the three age groups respectively. Dotted lines show 95 percent confidence intervals which are based on standard errors clustered at the firm-level.

Figure 8: Data moments compared to model simulated moments



Notes: The left panel shows the employment rate trend for 56-64 year-old workers, all of whom are employed 5 periods prior to the freeze. The right panel shows the difference between the treated and control group employment rates. Dotted lines show moments from simulated data. Dashed lines show moments from observed data. The shaded region includes moments that are not targeted in the estimation.

Figure 9: Effect of OASI tax sunset at age 60 on employment rates



Notes: This figure shows the evolution of the employment rate under two scenarios. The dashed blue line shows the employment rate trend under current law. The dotted red line shows the counterfactual employment rate trend under a regime where the OASI payroll tax is unexpectedly eliminated at age 60. The trends are based on model simulations for a sample of workers who are employed at age 55.

Table 1: Pre-period summary statistics split by age group

Variable	50-55			56-64			65-70		
	Comp. mean	Diff.	p-value	Comp. mean	Diff.	p-value	Comp. mean	Diff.	p-value
Worker characteristics									
Age	52.5	0.001	0.93	59.6	-0.031	0.32	67.0	0.016	0.56
Male	0.475	0.025	0.46	0.487	0.023	0.55	0.494	0.014	0.76
High school	0.232	-0.001	0.93	0.232	-0.001	0.93	0.294	0.001	0.98
Some college	0.324	-0.006	0.55	0.312	-0.007	0.42	0.290	-0.005	0.58
College or more	0.386	0.008	0.81	0.392	0.010	0.77	0.311	0.008	0.76
White	0.791	0.022	0.20	0.826	0.020	0.25	0.838	0.027	0.25
Black	0.096	-0.011	0.15	0.079	-0.010	0.12	0.069	-0.010	0.21
Hispanic	0.068	-0.003	0.81	0.053	0.000	0.97	0.049	-0.005	0.61
Other race	0.045	-0.008	0.27	0.043	-0.009	0.23	0.044	-0.013	0.31
Earnings ($)	65,140	-1,477	0.75	65,280	-2,337	0.58	47,770	-3,562	0.13
Tenure at $l-5$	7.8	-0.943	0.15	8.2	-0.977	0.11	8.0	-0.623	0.17
Retired	0.022	0.000	0.99	0.056	0.002	0.57	0.189	0.006	0.59
In labor force	0.964	-0.001	0.83	0.927	-0.003	0.47	0.779	-0.006	0.66
Switched $l-5$ employer	0.047	0.012	0.22	0.042	0.012	0.24	0.030	0.003	0.45
Pension and firm characteristics									
Log DB pension wealth/active participant	10.07	0.072	0.86	10.15	0.039	0.92	10.43	0.043	0.82
Log DB pension accrual/active participant	7.43	0.094	0.80	7.49	0.054	0.88	7.60	0.052	0.77
Pension plan claim age	62.8	-0.1	0.70	62.9	-0.1	0.72	64.4	0.0	0.88
Log firm size	8.55	-0.017	0.98	8.40	0.007	0.99	7.31	-0.162	0.74
Fraction workforce ≤ 45	0.580	0.010	0.44	0.568	0.007	0.61	0.542	-0.003	0.80
Fraction workforce [46,50]	0.146	-0.002	0.62	0.141	0.000	0.91	0.135	0.001	0.79
Fraction workforce [51,55]	0.124	-0.002	0.61	0.127	-0.001	0.78	0.124	0.001	0.89
Fraction workforce [56,60]	0.087	-0.002	0.63	0.095	-0.002	0.67	0.098	0.001	0.74
Fraction workforce [61,65]	0.044	-0.002	0.40	0.047	-0.002	0.52	0.066	0.000	0.99
Fraction workforce [66,70]	0.012	-0.001	0.38	0.013	-0.001	0.54	0.022	0.000	0.87
Fraction workforce ≥ 71	0.007	-0.001	0.33	0.008	-0.001	0.56	0.013	0.001	0.70
Comparison group workers	383000			373000			77000		
Treated group workers	60000			66500			11000		
Comparison group firms	7700			8600			4600		
Treated group firms	1500			1700			900		

Notes: Unless otherwise noted, statistics reported in the table average over the five year period preceeding any freeze activity. Pension wealth per active participant is computed as the present value of the liability owed to active participants divided by the number of active participants. Tenure is understated because the LEHD does not capture the complete history of an employer-employee relationship when states enter the dataset after a given employee-employer relationship is established. P-values for the difference between treatment and control groups are obtained by regressing the statistic of interest on a indicator variable for treatment status and clustering standard errors at the firm-level.

Table 2: Structural model parameter estimates

Parameter		Estimate	Standard error
IES	σ	0.958	0.004
Labor disutility persistence	ρ	0.869	0.003
Labor disutility standard deviation	σ_v	0.108	0.0005
Labor disutility age slope	ϕ	0.046	0.0001
Labor disutility constant	γ	-2.59	0.006
χ^2 statistic, 17 d.f.		236.8	

Notes: This table shows preference parameter estimates and standard errors for the structural model. See Appendix E for details.

Table 3: Employment elasticity estimates

		Age		
		58	60	62
Intertemporal elasticity	$\hat{\eta}$	0.180	0.154	0.302
		(0.044)	(0.040)	(0.057)
Option value elasticity	$\hat{\eta}^{PV}$	1.17	0.92	1.77
		(0.279)	(0.238)	(0.322)

Notes: This table shows two different definitions of the employment elasticity for older workers. Standard errors are computed using the delta method. See Section 7.4 for definitions.

Table 4: Counterfactual effects of OASI tax sunset at age 60

	Current law				Reform				Difference
Variable	p25	p50	p75	Mean	p25	p50	p75	Mean	Mean
Retirement age	62	64	66	64.6	64	65	67	65.7	1.1
DC wealth at retirement ($)	130,040	184,790	277,880	225,575	133,870	189,060	286,970	233,518	7,943
PV federal income tax remitted after 60 ($)	62,230	81,329	94,662	79,380	83,153	103,343	121,465	102,540	23,160
PV payroll tax remitted after 60 ($)	22,569	43,692	63,251	48,290	14,844	18,236	24,605	19,992	-28,298
					p25	p50	p75	Mean	
Equivalent variation ($, PV at age 60)					50,620	67,941	92,874	75,134	

Notes: Estimates are derived from model simulations under current law and under the reform. Simulated workers in the sample are all employed at age 55. Estimates are conditioned on not having retired before age 60. Monetary estimates are reported in 2010 dollars and present values are computed as of age 60. See text for details.

A Data Appendix

Form 5500

F5500 is an annual plan specific filing collected jointly by the IRS, DoL, and the PBGC to ensure compliance with ERISA.[58] Each plan in the F5500 database is identified by a combination of an EIN and plan number (PN). The PN is assigned by the plan's sponsor and stays fixed over the life of the plan. For form years 2000-2015, the DoL has prepared an edited research sample of the data in which logical and arithmetic errors are corrected and multiple filings for the same plan are de-duplicated. From 2000-2009, the research data include all pension plans with more than 100 participants and a 5 percent sample of plans with less than 100 participants. I use records from the research data where possible and add back small plans (i.e. those with less than 100 participants) from the raw data if they are excluded from the research sample. I de-duplicate multiple filings for the same plan in the raw data files by retaining the most recent filing in a given year. I obtained pre-1999 data through a FOIA request to the DoL. The sample that I use covers plan years ending 1996-2014.

I focus primarily on DB plans, but also obtain data on DC plans offered by employers who sponsor DB plans. Plan characteristics are coded using a set of numbers and letters. In post-1999 F5500 data, DB plans have prefix 1, DC plans have prefix 2 and 3, and welfare benefit plans — such as employer provided health insurance — have prefix 4.[59] Hard frozen DB plans are recorded using code 1I. Cash balance plans are recorded using code 1F. I eliminate supplemental plans which I identify by searching for any case versions of the string "supplemental" in the plan name field. I restrict my sample to single employer plans, thereby eliminating multi-employer DB plans.[60]

In addition to the main form, I include data taken from the actuarial information attachment. Prior to 2007 this attachment was labeled Schedule B. After 2009 it was labeled Schedule SB for single employer plans. For 2008, I impute actuarial data by interpolating between the 2007 and 2009 values because actuarial

[58] F5500 data for form years after 1999 are available at https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/public-disclosure/foia/form-5500-datasets.

[59] The codes are different prior to 1999. Welfare benefit plans only need to be reported with a F5500 filing when such plans cover more than 100 active participants.

[60] Multi-employer plans are arrangements between a group of firms and/or unions to provide pension benefits to eligible employees within the group.

information is unavailable in electronic format. The actuarial attachment contains important plan level data including detailed breakouts of plan assets and liabilities, accruals earned during the plan year, the average retirement age/benefit claim age, mortality and separation rate assumptions, etc.

Linking to the Census Business Register and Census Longitudinal Business Database

The BR is a database of the universe of establishments in the United States.[61] It includes information on business location, organization, industry, and information on revenue, payroll, and employment that is collected from administrative tax records as well as survey information. The relationship between establishments belonging to multi-unit firms are determined using responses to the company organization survey, the economic census, and the annual survey of manufactures. Establishments that are part of the same multi-unit firm share the same Census assigned firm identification number even if they have unique EINs.

To link the F5500 files to the BR, I match EIN-plan-end-years in F5500 to EIN-years in the BR. Because the massive scope of the BR, I am able to match approximately 92 percent of DB plan-years in the F5500 files to specific establishments in the BR (see row 1 of Table A1). Non-matches occur when a plan EIN does not map to any establishment with positive payroll in the BR which could happen, for example, when a plan is sponsored by a union or an employer-association.

The set of plan-years represented in the F5500-BR merge contains a mix of firms that sponsor just one DB plan and firms that sponsor multiple DB plans.[62] I limit my sample to firms that have a single plan within the 1996-2014 window for which I have F5500 data. When firms have multiple plans, I retain only those employers who choose either to never freeze their plans, or freeze them all at the same time. The principle driver of this restriction is that I cannot observe individual pension plan coverage. Consequently, when firms sponsor multiple plans, there is no way of knowing — using the F5500, LBD, or LEHD data — which plan a worker may be covered by. By imposing this restriction, however, I can ascertain whether workers at a given firm have been affected by a freeze in a given year. This sample restriction allows me to retain 94 percent of firm-years but only about 40 percent of worker-years (see row 2 of Table A1). The discordance between these two rates reflects the fact that only the very largest employers sponsor multiple DB plans.[63] Using Census firm identifiers, I match these data with the LBD which is a cleaned and research

[61] Information about the BR is confidential and protected by Title 13 and Title 26, US Code. The following information is drawn from https://www.census.gov/econ/overview/mu0600.html.

[62] Firms that sponsor multiple DB plans typically do so to cover different types of workers. For example, a firm may sponsor different DB plans for salaried and hourly workers or unionized and non-unionized workers.

[63] When firms sponsor multiple plans and pass the sample screen, I sum plan-level variables such as assets, liabilities, and

ready version of the BR. The LBD covers private sector establishments with non-zero payroll but excludes some industrial sectors (see p.4 of Jarmin and Miranda (2002) for details).

Having matched F5500 records to the BR and the LBD, I structure the data as follows. I treat each year from 2001-2014 as an experimental year, which is indexed by l.[64] This terminology reflects the research design wherein each year yields a fresh sample of firm-level pension freezes. For a given experiment year, the panel dataset of workers employed at freezing firms constitutes the treated group while the panel dataset of workers employed firms that do not freeze their plans constitutes the comparison group. I impose the restriction that firms file F5500 for their DB plans 5 calendar years prior to the experiment year, which I refer to as the pre-period. By requiring plan stability in the lead up to the experiment year, I implicitly follow a specific set of workers covered by a DB plan regardless of whether their employer merges, grows from single-unit to multi-unit, or vice versa. I match information on DC plans offered by the set of DB sponsoring employers to these data using the same EIN-based linking procedure described above. The key DC-related variable is the number of workers covered by DC plan(s). When a firm offers multiple DC plans, I pick the maximum number of active participants across plans and use that count to estimate the DC coverage rate at the firm.[65]

Linking to the Longitudinal Employer Household Dynamics

The LEHD is a quarterly matched employer-employee dataset constructed from state-level unemployment insurance (UI) records. The UI system covers 96 percent of wage and salary employment nationally, although the data exclude independent contractors, the unincorporated self-employed, railroad workers covered by railroad unemployment insurance, and some other minor categories of workers who are not covered by state-level UI laws. State and local government employees are included in the data but elected officials, members of the judiciary, and some emergency employees are excluded. Federal government workers and workers employed in Alabama are excluded from the version of the data that I use in this paper.

An important feature of the LEHD is that states enter the dataset at different points in time. For example, Maryland enters in 1985:Q2 whereas Mississippi enters only in 2003:Q3. Because of staggered entry, the

participant counts across all plans sponsored by the firm. I compute the weighted average of the retirement age reported on F5500 using the number of participants in each plan as weights.

[64] I start with 2001 because it is the first year in which pension freezes are reported in F5500. Cash balance conversions are reported in earlier years but the number of firms making CB conversions before 2001 is small.

[65] I use the maximum across plans rather than the sum across plans because workers can participate in multiple DC plans. The DC coverage rate is the ratio of the maximum number of DC participants from F5500 to the count of employees from the LBD.

scope of the data grows continuously over time.[66] I use the 2014 snapshot version of the LEHD, which provides matched employer-employee histories from each state's entry quarter up through 2015:Q1. I eliminate the single quarter of 2015 from these data as it represents partial year information on earnings and is not representative of the annual data structure that I employ.

In the LEHD, employers are identified using a state UI account number known as the SEIN while workers are identified using a variable known as a protected identification key (PIK). I begin by matching firm-level data from the F5500-LBD linked sample to the T26 Employer Characteristics File (ECFT26) in the LEHD. The ECFT26 is a SEIN-quarter-year level file that contains the Census firm identifier associated with each SEIN. Using this common unique identifier, I can match national plan- and employer- level characteristics from the F5500-LBD linked sample to state level employers in the LEHD. I recover 89 percent of firm-experiment years which corresponds to 93 percent of employee-experiment years from the F5500-LBD linked sample (see row 3 of Table A1). From this sample, I drop a small percentage of observations where certain pension plan variables are missing (see row 4 of Table A1).[67]

Worker sample

When considering the implications of pension freezes on worker decisions, it is important to reiterate that I do not observe individual information on pension plan coverage. To study worker responses in a way that limits the potential for misclassification error, I restrict the sample to firms where DB eligibility is near universal. I impose this restriction by retaining firms where the DB coverage rate is 80 percent or greater in the pre-period.[68] Within the sample of high-coverage rate firms, I use the LEHD Employment History File (EHF) to obtain matched employer-employee data. The EHF is a SEIN-PIK-year level file that provides the earnings history associated with each employer-employee combination. To these data, I add information on date of birth, race and ethnicity, and education from the Individual Characteristics File (ICF). I then select all workers employed at a DB sponsoring firm in $l-5$, who have at least two years of tenure as of $l-5$, and

[66] A number of populous states enter the data relatively early. Illinois enters in 1990, California and Pennsylvania in 1991, Florida in 1992, and New York and Texas enter in 1995.

[67] Critical pension plan information includes plan assets and liabilities, accruals earned in the filing year, the average benefit claim age for the plan.

[68] The firm-wide DB coverage rate is the ratio of active participants in the plan as reported in F5500 to the count of total employees in the LBD. The 80 percent average coverage rate requirement is based on years $[l-5, l-2]$ — i.e. between 5 and 2 years prior to the experiment year. Restricting the sample this way likely eliminates soft freezes in which the firm's plan is closed to new workers. A firm that imposes a soft freeze is likely to see its DB coverage rate decline as workers quit or retire but are not replaced with new eligible workers.

who will be between the age of 50 and 70 in the experiment year .[69]

Table A1: Data linkage and sample restrictions

Match/restriction type	N	Match rate	Person weighted rate
F5500-BR (plan-years)	852000	0.922	0.947
Multi-plan restriction (firm-years)	699000	0.942	0.378
LBD-LEHD (firm-experiment years)	1419000	0.885	0.933
No missing pension data (firm-experiment years)	1256000	0.930	0.972

Notes: F5500 data are based on years ending 1996-2014. Pension data is treated as missing if plan liabilities, assets, accrual amounts, and claim ages are either missing or unreadable in electronic format and cannot be interpolated.

[69]The two year tenure restriction ensures that workers are fully vested in their pensions as of the experiment year when they may become subject to a freeze. This calculation is based on the 7 year maximum full vesting period allowed for DB plans by ERISA.

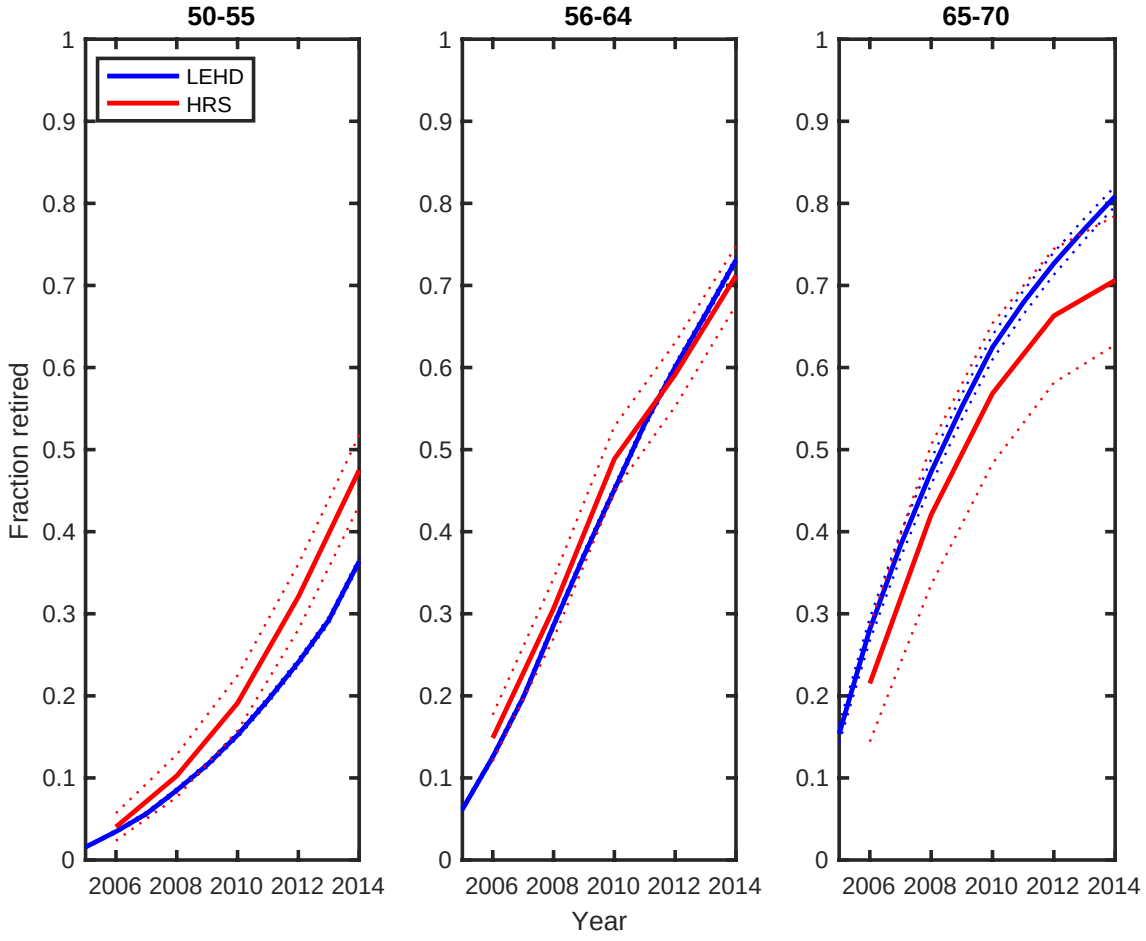
B Imputing retirement in the LEHD

In the LEHD, a worker is employed if they have positive earnings in a given year. The definition of retirement is somewhat more involved. I classify an individual as having retired in year t if the last year in which she received non-zero earnings was $t-1$. In this definition, retirement only occurs when an individual completely withdraws from paid employment. Recall, however, that both definitions exclude work in the form of self-employment because the LEHD data are based on UI covered earnings. To examine the potential for misclassification of retirement in administrative data, I compare the retirement rate of employed, DB eligible, respondents from the 2004 wave of the HRS with a comparable sample of individuals in the LEHD drawn from the 2004 experiment year whose pensions have not been frozen.[70]

These comparisons between HRS and LEHD data are shown in the three panels of Figure B1, which split the samples into three age categories as of 2004. The retirement rates align very well for the 56-64 year-old age group but diverge somewhat for the 50-55 and 65-70 year-old age groups. For 65-70 year old individuals, the HRS-based rates are lower than the LEHD-based rates which potentially reflects the fact that self-employment is not covered in the LEHD. For the 50-55 year old age group, the HRS-based rates are higher than the LEHD-based rates. This discordance exists even when HRS retirement rates are constructed from a question asking respondents if they have zero earnings.

[70] Retirement in the HRS is inferred from a respondent's labor force status report. To align with the LEHD-based definition of permanent departure from paid employment, I consider an HRS respondent as retired only if they continually report their labor force status as retired. In this definition, a respondent who reports being retired in 2006 but re-enters the labor force in 2010 will not be counted as a retiree in the dataset. The labor-force-status-based retirement statistics are very similar to those constructed from a question asking respondents if they have zero earnings from employment.

Figure B1: HRS versus LEHD retirements



Notes: HRS data are based on respondents who are working as of 2004 and are eligible for employer sponsored DB pension plans. LEHD data are based on the sample of individuals employed at DB sponsoring firms as of 2004 where the firm-wide coverage rate is $\geq$ 80 percent. Sample splits are based on age as of 2004.

C Firm and plan characteristics around the freeze

This appendix describes how firm and plan characteristics evolve around the freeze. I establish three facts. First, I show that worsening plan finances rather than worsening firm performance is the main predictor of DB pension freezes. Second, I show that the aftermath of a freeze leads to small but persistent reductions in firm size and average pay. Third, I show that DB freezes generate an immediate transition towards DC plan participation.

C.1 Pre-freeze environment

To describe the environment prevailing prior to the firms freeze decision, I show several characteristics of firms and their pension plans averaged over a five year pre-period in Table C1. Comparing the left and right panels of the table shows the freezing firms are very similar in terms of size, average pay, employee age structure, and DB pension plan characteristics. DB and DC coverage rates within the two sets of firms are both approximately 70 and 35 percent respectively. The lack of any meaningful difference in employee age structure, pension liability, pension accrual rates, and claim ages indicates that the freezing firms are not disproportionately staffed by older workers at the threshold of retirement. Put differently, firms that freeze their plans are not on the brink of a large liability cliff. The likelihood of experiencing a mass layoff, which is recorded as a 30 percent reduction in employment and labeled firm distress, is about 5.5 percent in both groups. Economic distress driven by a large negative shock in the output market is therefore not a leading reason for freeze decision either.

They key distinction between freezing and non-freezing firms lies in the financial health of their DB plans. For every dollar in future liabilities, non-freezing firms have $1.10 in assets. The same ratio — referred to as the funding ratio — is 1.05 for firms that ultimately freeze their plans. The PPA designates plans with funding ratios under 80 percent as being "at-risk" or distressed. Using the PPA's threshold, 20 percent of freezing firms are have distressed plans whereas the same rate is 15 percent for non-freezing firms. Funding deficiencies are particularly important from a cost management perspective because gaps must be closed to meet statutory requirements. Furthermore, once underfunded, plans are no longer buffered against financial market shocks the way overfunded plans are. Required contributions towards underfunded plans therefore become larger and more volatile in the face of market risk.

Table C2 shows coefficients from a linear prediction model using freeze in the experiment year as the

outcome and a variety of pre-event characteristics as predictors. The regressions are estimated on data pooling over a five year pre-period, thereby allowing for the inclusion of firm fixed effects. Columns 1 and 2 do not include firm fixed effects, while columns 3 and 4 do. The regressions show that a 1 percent improvement in the funding ratio lowers the likelihood of a future freeze by 2.5 percentage points. This partial effect is stable and statistically significant across all four specifications. Firm size is negatively correlated with future freezes, but the magnitude of the effect is small: a 1 percent increase in firm size lowers the likelihood of a future freeze by 0.2 to 0.5 percentage points. In specifications with firm fixed effects, employee age structure has no statistically significant impact on freezes and the magnitudes of the partial effects are negligible when expressed in proportional terms. DB plans that are collectively bargained are about 2.5 percentage points less likely to experience a freeze which implies that unions offer approximately the same protective effect as a one percent improvement in plan funding. Industry fixed effects, which are included in columns 2 an 4 have no appreciable impact on the estimated coefficients indicating that industry-specific factors are not important, conditional on the other predictors in the model.

C.2 Post-freeze changes

Figure C1 compares the evolution of four variables between freezing and non-freezing firms before and after the freeze. Each panel plots coefficients from an event study regression using the specification described in equation (14) with firm-cohort-year level data. Note that the estimated coefficients are net of firm fixed effects and therefore remove time invariant unobserved heterogeneity between firms. In each panel, the horizontal axis represents the calendar year relative to the experiment year.

The upper row of Figure C1 shows the difference in log of total employment and log of average pay between freezing and non-freezing firms. The estimated coefficients show that freezes lead to a persistent 2.5 percent reduction for both outcome variables — a gap which closes only after about 10 years. Post-freeze differences in size and pay between the two types of firms represent some combination of changes to the age or seniority composition of the firm's workforce after a freeze either through labor supply responses or changes in labor demand, although it is not clear from firm-level data alone what the role for each channel is.[71] The lower left panel of Figure C1 shows that the fraction of DC covered workers starts to rise about 2 years prior to the DB freeze reflecting expanded DC plan eligibility, more generous DC match rates,

[71] The person-level analyses presented in Section 6 isolate labor supply factors by using propensity score methods to condition on the pre-freeze path of firm size which serves as a proxy for latent changes in output demand for the firm.

or transitions to opt-out rather than opt-in DC enrollment.[72] In the period right around a DB freeze, DC coverage rates increase by about 5 percentage points off a baseline coverage rate of about 35 percent. In subsequent years, non-freezing firms gradually increase their DC coverage and catch up to the DC coverage rate prevailing at freezing firms. Whether the catch up occurs through soft-freezes that close existing DB plans to younger workers, or through more generous incentives for DC participation, the results shown here provide evidence that DB freezes accelerate the inevitable transition towards DC pension coverage within firms. Evidence for increased DC participation is important in explaining the extended labor force participation of some freeze-affected workers as it allows them to offset DB losses.

The lower right panel of Figure C1 shows the change in the likelihood of a freezing firm to experience economic distress, which is defined as a reduction in employment of 30 percent or greater. The coefficient estimates from an unweighted regression (in blue) show that the immediate aftermath of a freeze induces a 1.5 percentage point increase in the probability of distress which lasts for two years. When the same regression is weighted by firm size (in red), thereby representing the change in the probability of freeze affected workers experiencing large employment contractions, the point estimates are economically and statistically insignificant. As such, it appears that distress is concentrated among smaller firms.

[72] DC coverage is measured as the ratio of the maximum number of participants across a firm's DC plans to total employment.

Table C1: Pre-period firm and plan characteristics

	Non-freezing firms		Freezing firms	
Variable	Mean	Std. error	Mean	Std. error
Size	273.7	3.3	254.6	19.5
Average earnings ($)	69300	252	68010	520
Firm age	20.9	0.0	21.2	0.1
Multi-unit	0.273	0.001	0.250	0.003
Fraction workforce ≤ 45	0.579	<0.001	0.578	0.001
Fraction workforce [46,50]	0.117	<0.001	0.115	0.001
Fraction workforce [51,55]	0.110	<0.001	0.109	0.001
Fraction workforce [56,60]	0.092	<0.001	0.095	0.001
Fraction workforce [61,65]	0.057	<0.001	0.060	0.001
Fraction workforce [66,70]	0.024	<0.001	0.023	<0.001
Fraction workforce ≥ 71	0.022	<0.001	0.020	<0.001
Distressed firm	0.056	<0.001	0.057	0.001
DC plan offered	0.502	0.001	0.521	0.003
DC plan coverage rate	0.348	0.001	0.362	0.002
DB plan coverage rate	0.723	0.000	0.708	0.001
DB pension wealth/ptcp ($)	98910	372	101600	1612
DB pension accrual/ptcp ($)	14200	41	14690	145
Average benefit claim age	63.2	0.0	63.3	0.0
Collectively bargained plan	0.040	<0.001	0.030	0.001
Funding ratio	1.11	0.00	1.05	0.00
Distressed plan	0.159	0.001	0.193	0.002
Firm-experiment years	428000		28500	
Firms	22500		6500	

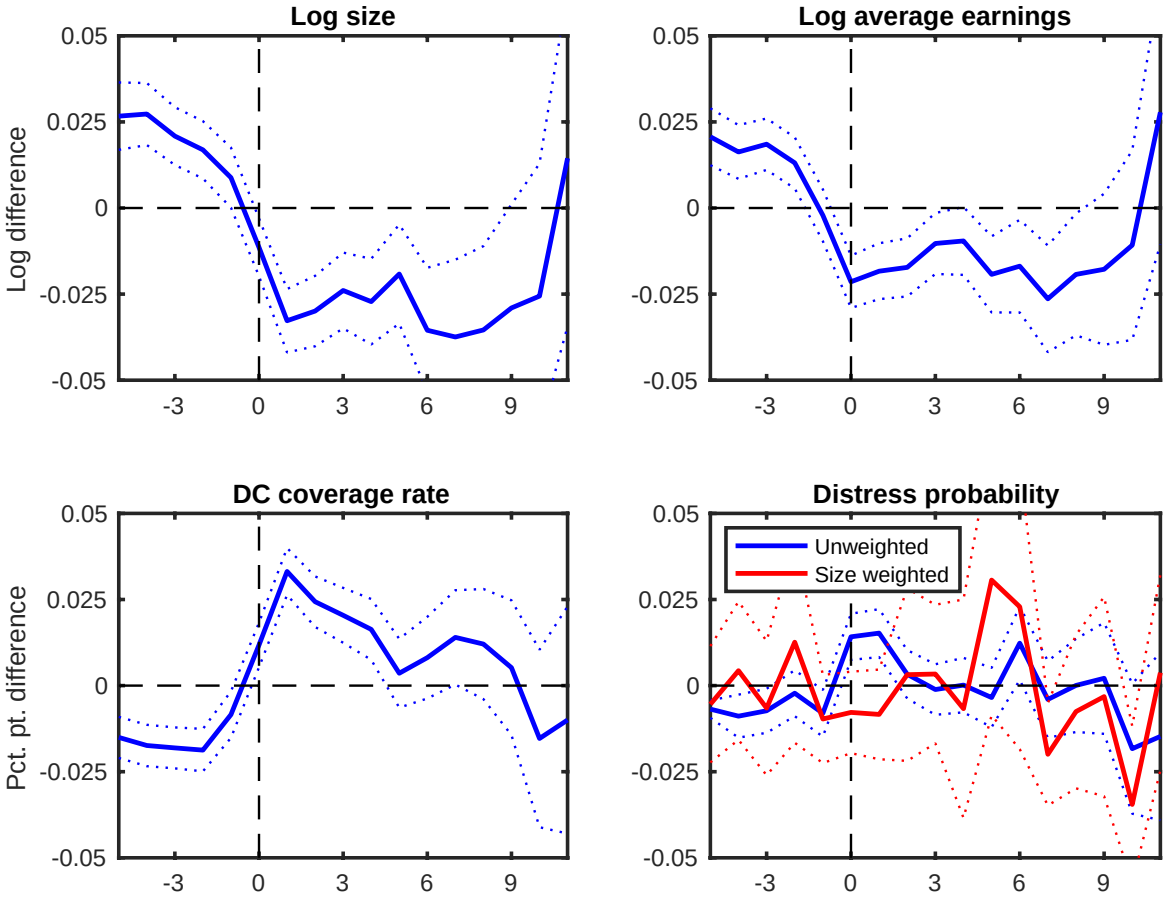
Notes: Statistics reported in the table average over the five year period preceeding any freeze activity. All dollar values are expressed in 2010 terms. Pension wealth per participant is computed as the present value of the liability owed to active participants divided by the number of active participants. Plan-years are coded as distressed if their ratio of assets to liabilities is under 80 percent — the threshold below which DB plans are considered "at risk" in the Pension Protection Act of 2006. Firm-years are coded as distressed if firm-wide year-on-year employment shrank by 30 percent or more.

Table C2: Predictors of future freezes

Variables	(1)	(2)	(3)	(4)
Log funding ratio	-0.0264***	-0.02545***	-0.0258***	-0.0258***
	(0.0020)	(0.0020)	(0.0022)	(0.0022)
DB coverage rate	-0.0075**	-0.0029	0.0008	0.0009
	(0.003)	(0.0030)	(0.0036)	(0.0036)
Firm age	-0.00009	0.00001	0.00027	0.00034
	(1.04e-04)	(1.07e-04)	(5.49e-04)	(5.40e-04)
Log size	0.0026***	0.0021***	-0.0055**	-0.0056**
	(6.32e-04)	(6.51e-04)	(0.0024)	(0.0024)
Log average pay	0.00004	-0.00063	-0.00591***	-0.00598***
	(0.00114)	(0.00117)	(0.00182)	(0.00181)
Fraction workforce ≤ 45	0.0168*	0.0178*	-0.0141	-0.0143
	(0.0098)	(0.0099)	(0.0124)	(0.0124)
Fraction workforce [46,50]	0.0097	0.0119	-0.0115	-0.0117
	(0.01083)	(0.0109)	(0.013)	(0.013)
Fraction workforce [51,55]	0.0085	0.0114	-0.0217*	-0.022*
	(0.01068)	(0.0107)	(0.0131)	(0.0131)
Fraction workforce [56,60]	0.0223**	0.0251**	-0.0106	-0.0108
	(0.01087)	(0.0109)	(0.0129)	(0.0129)
Fraction workforce [61,65]	0.0253**	0.0272**	0.0037	0.0036
	(0.0116)	(0.0116)	(0.0131)	(0.0131)
Fraction workforce [66,70]	0.0024	0.0036	0.0069	0.0069
	(0.0124)	(0.0124)	(0.0123)	(0.0123)
DB plan collectively bargained	-0.0215***	-0.0257***		
	(0.0035)	(0.0036)		
Firm offers DC plan	0.0016	0.0030*		
	(0.0016)	(0.0016)		
Multi-unit firm	-0.0119***	-0.0069***		
	(0.0023)	(0.0024)		
Observations	456000	456000	456000	456000
Adjusted R-squared	0.015	0.016	0.362	0.362
Firm FE	No	No	Yes	Yes
Experiment year-calendar year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
Number of firm clusters	23500	23500	23500	23500

Notes: Robust standard errors, clustered at the firm level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions are estimated on a panel dataset that pools the five year period preceeding any freeze activity .

Figure C1: Firm characteristics around freezes



Notes: Dotted lines show 95 percent confidence intervals which are based on standard errors clustered at the firm level. Horizontal axes show years relative to the experiment year. Firm-years are coded as distressed if firm-wide year-on-year employment shrank by 30 percent or more.

D Propensity score re-weighting

For workers in cell $j(i)$, denote the probability of experiencing a freeze, or the propensity score, by $\hat{p}(\boldsymbol{z}_{j(i)})$. $\boldsymbol{z}_{j(i)}$ is a vector including all pre-period observations on log firm size, firm-level averages of log total pension wealth and log pension accruals per working participant, average benefit claim age from the pension plan, the age structure of the firm's workforce, cell-level annual earnings, retirement rates, labor force participation rates, and employer-to-employer transition rates. I also condition on state, gender, tenure, and earnings averaged over the workers LEHD history prior to $l-5$. $\hat{p}(\boldsymbol{z}_{j(i)})$ is estimated using logistic regression.

In the setting being considered in this paper, the parameter of interest is the average treatment effect on the treated (ATET) — i.e. the impact of pension freeze shocks on the labor supply of workers affected by those shocks. To estimate the ATET, each comparison group unit is re-weighted by $\frac{\hat{p}(\boldsymbol{z}_{j(i)})}{1-\hat{p}(\boldsymbol{z}_{j(i)})}$. Following Busso et al. (2014), the weights are first normalized to sum to 1 so that the number of weighted units in the comparison group is unaffected by the re-weighting procedure.

Constructing good counterfactuals for treated group units requires that comparison group units with the same $\hat{p}(\boldsymbol{z}_{j(i)})$ — i.e. the same ex-ante probability of experiencing the treatment — can be found in the sample. This requirement is referred to as the "common support condition" or the "overlap condition." Formally, the common support condition for the ATET parameter requires that $\hat{p}(\boldsymbol{z}_{j(i)}) < 1$ for all $j(i)$. In practice, the treatment and comparison groups in the data I use share a large region of common support and the maximum $\hat{p}(\boldsymbol{z}_{j(i)})$ is lower than 1.

E Solution and estimation of the structural model

E.1 Calibrated parameters

Most of the calibrated first-step parameters are drawn from pension eligible respondents in the HRS. The HRS provides high quality information on DB pension wealth which is computed using summary plan descriptions (SPDs) obtained either directly from respondent's employers or from attachments to F5500 administrative records. Information from these documents is coded along with relevant data on respondent's past and future earnings projections and job tenure to calculate pension wealth at prospective retirement ages. These calculations are done using a software system known as the Pension Estimation Program (PEP).[73]

Linked pension data are available for the 1992, 1998, 2004, and 2010 survey wave years of the HRS. While the 2004 and 2010 samples are most relevant because they coincide with the time period that I analyze, I rely exclusively on the 2010 linked pension sample for two reasons. First, unlike prior waves, the 2010 wave explicitly separates public and private sector plans. By focusing on respondents working in the private sector, I am able to align the survey data to reflect private sector pension provisions which constitute the relevant subset for the analysis. Second, the 2010 sample explicitly flags a small number of CB plans as being different than conventional DB plans. This distinction allows me to isolate the sub-sample where the evolution of pension accruals occurs under the status-quo — i.e. where participants do not experience a freeze. Frozen DB plans are not common in the HRS; only 6 respondents report having experienced one in the 2010 survey wave.

In what follows, I describe a variety of parameters that are calibrated using data on pension eligible respondents in the 2010 survey wave of the HRS.

DB pension wealth accruals

DB pension wealth in the PEP is calculated using the following formula

$$W_q^{DB} = \sum_{t=q}^{119} p_t \left(\frac{1+COLA}{1+i} \right)^{t-T_0} B_{t|q}, \tag{18}$$

where W_q^{DB} is the present value of pension wealth at potential retirement date q, p_t is the probability of survival in period t conditional on being alive in period q, $COLA$ (cost of living adjustment) is the plan

[73] See Fang et al. (2016) for more details.

specific annual growth rate of payments (for most DB plans in the HRS $COLA = 0$), i is the nominal interest rate, and $B_{t|q}$ is the annual pension benefit in period t conditional on retiring in period q.[74] DB pension wealth is based on the maximum of wealth at the plan's normal retirement age, early retirement age, and vested deferred value of benefits. When respondents have wealth in multiple plans, I sum pension wealth over each plan. Nominal values of W_q^{DB} are then converted to 2010 dollars.

I average across respondents in the sample to compute real DB wealth at each prospective quit age. I use the mortality and real interest rate assumptions from the PEP to convert these values into their the annuity equivalents at each quit age which are denoted by $\{b_a^{DB}\}_{a=51}^{80}$.

Earnings

In the PEP, earnings from the 2010 survey wave are projected forward and backward for different quit dates using the following formula

$$\log(e_q) = \log(e_{2010}) + \alpha_m(q - 2010) + \beta_1 \text{age}_q + \beta_2 \text{age}_q^2, \tag{19}$$

α_m is nominal wage growth and β_1 and β_2 adjust for age-based changes in earnings. I estimate β_1 and β_2 separately for men and women using the within-job earnings histories for DB eligible workers in the HRS. α_m is set at 5 percent. I convert these values to 2010 dollars and then average the earnings projections across respondents by quit age to compute an age-dependent earnings function $\{e_a\}_{a=51}^{80}$.

Social Security benefits

For respondents who have yet to claim benefits, Social Security wealth in the HRS is computed by passing the respondent's administrative earnings record along with projected future earnings into the Social Security benefit formula. The benefit levels obtained from the formula are used to compute the present value of Social Security benefits at age 62, 65, and 70 (see Fang et al. (2016)). These values are reported in 2010 dollars. Because individuals cannot claim Social Security prior to age 62, I set Social Security wealth prior to that age as 0. I linearly interpolate Social Security wealth for ages between 62, 65, and 70. I use the mortality and real interest rate assumptions from the PEP to convert these values into their the annuity equivalents at

[74] p_t are based on the 2010 version of gender-specific cohort mortality tables published by the Social Security Administration (SSA). The 2010 pension wealth calculations assume a nominal interest rate of 5.7 percent and an inflation rate of 2.8 percent according to economic assumptions detailed in the 2010 Annual Report of the Board of Trustees of the Old Age, Survivors, and Disability Insurance (OASDI) trust funds of the SSA.

age which are denoted by $\{b_a^{SS}\}_{a=51}^{80}$. Because Social Security benefits do not increase after age 70, I set $\{b_a^{SS}\}_{a=71}^{80} = b_{70}^{SS}$.

DC match function

The employer's DC match function, $m^e(m^w)$, is based on respondent reports of their own and employer contributions expressed as a percentage of earnings in the 2010 survey wave. Recall that m^e is the fraction of earnings that employers contribute to DC accounts and is a function of the employees' own contribution rate m^w. To obtain the match function, I first bin worker contribution rates into 0.01 sized intervals and then compute the median employer contribution rate within each interval which is denoted by $\tilde{m}^e$. I then regress binned worker contribution rates on median employer contribution rates for $m^w \in [.01, .065]$. Fitted values from the regression ($E[\tilde{m}^e|m^w]$) represent the estimated match function. Approximating the data for $m^w > .065$, I assume that $E[\tilde{m}^e|m^w > .065] = E[\tilde{m}^e|m^w = .065]$ which implies that employer matching contributions stop once workers contribute 6.5 percent of earnings. The estimated match function is

$$\hat{m^e}(m^w) = \begin{cases} .011 + .39m^w & \text{if } m^w \leq .065 \\ .0364 & \text{if } m^w > .065 \end{cases} \tag{20}$$

Initial DC wealth and non-pension wealth

I assume that initial DC balances (W^{DC}) and non-pension assets (A) are distributed log-normally. For each initial age (i.e. between 51 and 59), I simulate assets using log-normal parameters estimated from the distribution of A and W^{DC} for pension eligible respondents in the 2010 HRS. In these calculations, A is defined as household non-pension assets inclusive of spousal DC wealth, whereas W^{DC} is the respondent's DC wealth. log-normal parameters are estimated on the sample or respondents where A and W^{DC} are non-negative. I then use these parameter estimates to simulate W^{DC} and A for workers initially aged 51-59.

Additional parameters

The discount factor (β) and real interest rate (r) are based on values consistent with the PEP assumptions.[75] The maximum DC contribution limit, $\bar{C}$, is calibrated using 2010 IRS rules. Age specific mortality rates

[75]The real interest rate is 2.9 percent which is based on the 2010 SSA OASDI trust fund report assumption. I assume that the annual discount factor is 0.97 to be consistent with a real interest rate of approximately 3 percent.

expressed as the probability of dying within one year, $\{p_a\}_{a=51}^{80}$, are based on the 2010 actuarial life table published by the Social Security Administration (SSA). I average the gender-specific rates into a combined rate for each age and then divide by p_{81} to impose a maximum age of 80 for all simulated individuals. Finally, I use the NBER TAXSIM calculator to compute income and payroll tax liabilities when solving the model.

Table E1 provides a summary of all the calibrated parameters of the model and their sources.

E.2 Solution algorithm

The model does not have an analytical solution, so I solve it numerically by backward recursion. The state variables in the model are (a, e, g, A, b, W^{DC}) of which g, A, and W^{DC} are continuous and exhibit both within- and between-age heterogeneity. I discretize the continuous state variables over finite dimensional grids of size 6 for g, 20 for A, and 20 for W^{DC}. Grid points for A and W^{DC} are narrowly spaced for low values and widely spaced for high values. Iterating backward from the final age for a given value of $\boldsymbol{\theta} = (\sigma, \gamma, \phi, \rho, \sigma_v)$:

1. I compute the probability distribution over next period's work disutility which arises from randomness in the AR(1) component f. I employ the Rouwenhorst (1995) approximation for the AR(1) term to obtain $P(f' = f_{l'}|f = f_l)$ for $l, l' = 1, \ldots, 6$. I then use these probabilities to estimate

$$E_{f'}\left[\max\left\{V_{a+1}^{R}(a+1, b', A', W^{DC'}), V_{a+1}^{W}(X')\right\}\right] \tag{21}$$

   At age 80, $V^W = V^R = 0$ as no workers live beyond that age and there are no bequests.

2. For each value of the state variables (within the current age iteration), I compute V^W and V^R and the associated decision rules as follows:

   (a) To obtain V^W, I compute the income and payroll tax rate faced by a worker for each potential $W^{DC'}$ choice given the earnings level for the current age. I then search over the $W^{DC'}$ and A' grid points to find the highest value of V^W . I impose the maximum contribution constraint $(\bar{C})$ and preclude decumulation of DC balances while working by setting the associated values of V^W to negative infinity. This grid search defines the decision rules for DC accumulation and non-pension saving (or dissaving) while working.

(b) To obtain V^R, I compute the income tax rate faced by a retiree for each potential $W^{DC'}$ choice given the annuity income obtained by retiring at the current age. I then search over the $W^{DC'}$ and A' grid points to find the highest value of V^R. I preclude accumulation of DC balances in retirement by setting the associated values of V^R to negative infinity. This grid search defines the decision rules for DC decumulation and non-pension saving (or dissaving) while retired.

(c) I compute the retirement decision for each value of the state variables by comparing V^W to V^R. If $V^W \leq V^R$, then the work decision is retirement. Else if $V^W > V^R$, then the work decision is to stay employed.

3. The solution algorithm terminates when value functions and decision rules have been obtained for each age.

I compute a separate set of value functions and decision rules by imposing pension freezes at ages 56-64. A worker who experiences a pension freeze at age a has $b^{DB}_{a+k} = b^{DB}_a$ for all $k > 0$. I apply earnings reductions as estimated from LEHD data for workers who are affected by freezes between the age of 56 and 64.[76] To the extent that career lengths change due to the freeze, I assume that they do not affect the value of Social Security wealth. This assumption reflects the fact that most workers over 55 already have long work histories and do not accrue substantial increases in Social Security benefits through continued work. Other than the change to b^{DB} and the earnings path, all other parameters remain the same.

E.3 Estimation

Having solved the model for a given value of $\boldsymbol{\theta}$ by obtaining decision rules for each age, I simulate data as follows

1. I simulate initial assets and work disutility draws for 5000 individuals who are initially aged 51 to 59.[77] I apply decision rules from the no-freeze scenario to obtain work histories and asset accumulation paths to create a simulated control group. I use linear interpolation to infer the optimal decision rules for simulated values of A, W^{DC}, and g that lie between the grid points.

2. Next, I apply the freeze decision rules for the same population of individuals — i.e. individuals with

[76] Earnings losses occur in the year of the freeze and in the next four years. The estimates are -3.8 percent, -2.1 percent, -1.5 percent, -4.9 percent, and -1.6 percent. See the middle panel of Figure 6.

[77] The share of individuals of each initial age is equal to the share of DB eligible working respondents in 2010 HRS.

the same initial assets and work disutility draws —starting five years after the initial age. Individuals in this exercise have the same work and asset accumulation choices as the simulation control group for the first five years, but have different work histories and asset accumulation choices once faced with a DB freeze. I call this sample the simulated treated group.

3. I compute two sets of moments using the simulated control and treated groups. The first set of moments is the average employment rate by age for the simulated control group. I compute the control group levels starting four periods prior to the freeze and lasting 6 periods after the freeze. The second set of moments is the difference in average employment rates between the two groups (the simulated treatment effect). I compute these differences for 12 periods starting from the period of the freeze.

Denote the vector of simulated moments by $\hat{\boldsymbol{h}}^S(\boldsymbol{\theta})$. Denote the analogous vector of observed moments from real-world (LEHD) data by $\hat{\boldsymbol{h}}^D$. The distance between the simulated and real-world moments is

$$\boldsymbol{m}(\boldsymbol{\theta}) = \hat{\boldsymbol{h}}^S(\boldsymbol{\theta}) - \hat{\boldsymbol{h}}^D. \tag{22}$$

The MSM estimate of $\boldsymbol{\theta}$ is given by

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}\in\Theta}{\operatorname{argmin}}\, \boldsymbol{m}'(\boldsymbol{\theta})\boldsymbol{W}\boldsymbol{m}(\boldsymbol{\theta}) \tag{23}$$

where $\boldsymbol{W}$ is a weighting matrix.

I estimate $\hat{\boldsymbol{\theta}}$ using a two step procedure. In the first step, I set $\boldsymbol{W} = \zeta\boldsymbol{I}$ where $\boldsymbol{I}$ is the identity matrix and ζ is a scaling vector. The scaling vector re-weights treatment effect moments by a factor of 10 to give them approximately the same numerical importance as the employment trend moments. I make this adjustment because the treatment effect moments are economically very informative but are numerically an order of magnitude smaller than the employment trend moments. Denote by $\hat{\boldsymbol{\theta}}_1$ the parameter vector obtained using the first step weighting matrix which I estimate using the Nelder-Meade algorithm.[78] In the second step, I re-estimate the simulated moments 500 times holding $\hat{\boldsymbol{\theta}}_1$ fixed but re-drawing random components of the simulation that introduce sampling variability (i.e. g and the initial values of A and W^{DC}). Using this parametric bootstrap procedure, I compute the variance-covariance matrix of the simulated moments which is denoted by $\hat{\boldsymbol{S}}(\hat{\boldsymbol{\theta}}_1)$. I then estimate $\hat{\boldsymbol{\theta}}_2$, the final parameter estimate, by setting $\boldsymbol{W} = \hat{\boldsymbol{S}}^{-1}(\hat{\boldsymbol{\theta}}_1)$.

[78] I use a variety of starting values to avoid the possibility of the parameter search procedure converging to a local minimum.

To obtain standard errors, I compute $\hat{\boldsymbol{D}} = \frac{\partial \boldsymbol{h}^S(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}'} \mid_{\hat{\boldsymbol{\theta}}_2}$ numerically by using 10 small random deviations around $\hat{\boldsymbol{\theta}}_2$ and re-calculating $\boldsymbol{h}(\boldsymbol{\theta})$ at each perturbed value. I then average $\frac{\partial \boldsymbol{h}^S(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}'}$ across the perturbations to compute

$$\boldsymbol{Q} = (1 + N_S^{-1}) \left[\hat{\boldsymbol{D}}' \hat{\boldsymbol{S}}^{-1}(\hat{\boldsymbol{\theta}}_1) \hat{\boldsymbol{D}} \right]^{-1} \tag{24}$$

where $N_S = 1$ is the number of simulations associated with the estimate of $\hat{\boldsymbol{\theta}}_2$. The square root of the diagonal of $\boldsymbol{Q}$ is the vector of standard errors for $\hat{\boldsymbol{\theta}}_2$ (Duffie and Singleton (1993)).

Table E1: Calibrated parameters

Parameter	Value	Description	Source
r	0.029	Real interest rate	HRS PEP/SSA
β	0.97	Annual discount factor	$r \approx .03$
$\bar{C}$	\$54,500	Maximum combined contribution limit to DC plans (2010 level)	IRS
$\{\mu_a^A, \sigma_a^A\}_{a=51}^{59}$		Scale and shape parameters for non-pension wealth distribution for initial ages 51-59	HRS
$\{\mu_a^{W^{DC}}, \sigma_a^{W^{DC}}\}_{a=51}^{59}$		Scale and shape parameters for DC wealth distribution for initial ages 51-59	HRS
$E[\tilde{m}^e \vert m^w]$		Employer DC contribution rate expressed as a function of the worker's contribution rate	HRS
$\{b_a^{DB}\}_{a=51}^{80}$		Age-specific DB pension annuity	HRS
$\{b_a^{SS}\}_{a=51}^{80}$		Age-specific Social Security annuity	HRS
$\{p_a\}_{a=51}^{80}$		Age-specific mortality rate adjusted so that $p_{81} = 1$	SSA
$\{e_a\}_{a=51}^{80}$		Age-specific annual earnings	HRS
$\tau(\cdot)$		Federal income and payroll tax liabilities (2010 laws)	NBER TAXSIM

Notes: See Appendix E.1 for details.

F Simulated pension freezes in the HRS

This Appendix describes how I construct the simulation underlying Figure 3. The simulations are based on the sample of DB eligible HRS respondents from the 2010 survey wave who are employed in the private sector and are not in hybrid or CB plans as of the survey date.[79] Using these data, I consider three age-specific components of compensation: DB wealth, earnings, and DC wealth.

For survey respondents, the PEP provides estimates of DB wealth at each potential quit date on the basis of equation (18). In addition, the PEP provides earnings projections at each potential quit date for each respondent on the basis of equation (19). DC wealth is reported by respondents as of the survey year (i.e. 2010). I use these measures along with self-reported own and employer contribution rates (m^w and m^e) to construct estimates of past and projected future values of DC wealth using the law of motion described in equation (4).[80] Notably, DC wealth in 2010 is 0 for approximately half of the sample. I then combine these estimates of DB wealth accruals, earnings, and DC wealth accruals to compute total compensation at each potential quit age using equation (7).[81] Finally, I average the data across respondents and quit dates to obtain the "no-freeze" path of compensation.

To simulate a hypothetical DB pension freeze for workers aged a^F, I make two changes. First, I assume that the annuity value of nominal DB wealth is frozen as of a^F. This is equivalent to receiving no new accruals either due to tenure increases or due to earnings growth.[82] Second, I assume that respondents with no DC wealth as of a^F — i.e. about half the sample — begins contributing to a hypothetical new DC plan starting at age a^F. I assume that contribution rates for these workers are equal to the sample averages of m^w and m^e for respondents with non-zero DC wealth. Respondents who have non-zero DC wealth are assumed to continue contributing at the same rate as they did prior to age a^F. Having defined post-freeze DB and DC wealth evolution, I combine the estimates of post-freeze DB wealth accruals earnings, and DC wealth accruals to compute total compensation at each potential quit age using equation (7). I then average these data across respondents and quit dates to obtain the "Freeze at a^F" path of compensation. I conduct these

[79] Frozen DB plans are not common in the HRS; only 6 respondents report having experienced one in the 2010 survey wave. I assume that all non-hybrid and non-CB plans in the 2010 sample are not frozen.

[80] I assume that respondents and their employers contribute at the same rate in all years. I rely on the RAND HRS files which convert respondent reports of own and employer contributions to percentages of earnings.

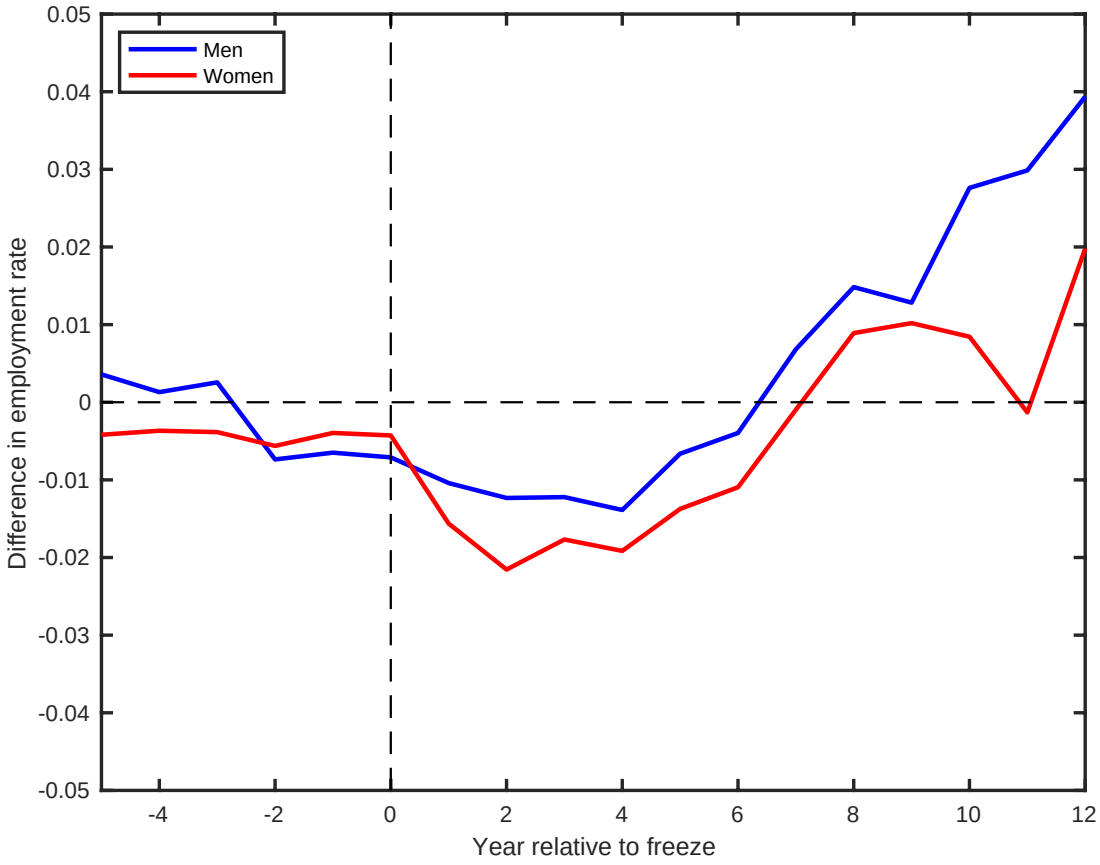
[81] All three components (i.e. DB wealth, earnings, and DC wealth) are converted to 2010 dollars. I do not account for taxes in these simulations because online tax calculators cannot be used within the restricted setting in which pension data are accessed.

[82] By preventing future growth in the nominal value of benefits, DB freezes have the effect of lowering the present value of DB wealth in each year subsequent to the freeze, thereby generating negative future accruals. This is because benefits stay fixed but the horizon over they can be collected falls.

calculations for different values of a^F to obtain different post-freeze paths of total compensation.

G Supplementary tables and figures

Figure G1: Impact of freezes on employment by gender (56-64 year-olds)



Notes: This figure shows the time path of the treatment effect of the freeze on employment rates for men and women separately. Workers are 56-64 years-old at the time of the freeze.

Table G1: Pre-period summary statistics split by age group (without propensity score re-weighting)

Variable	50-55			56-64			65-70		
	Comp. mean	Diff.	p-value	Comp. mean	Diff.	p-value	Comp. mean	Diff.	p-value
Worker characteristics									
Age	52.5	0.002	0.90	59.6	0.034	0.29	67.0	-0.011	0.68
Male	0.466	0.034	0.30	0.478	0.032	0.38	0.478	0.030	0.50
High school	0.226	0.005	0.77	0.231	0.000	0.99	0.288	0.006	0.75
Some college	0.329	-0.011	0.24	0.314	-0.010	0.26	0.292	-0.007	0.42
College or more	0.391	0.002	0.93	0.394	0.007	0.80	0.315	0.004	0.87
White	0.793	0.020	0.28	0.819	0.027	0.16	0.824	0.042	0.05
Black	0.093	-0.009	0.24	0.081	-0.013	0.05	0.074	-0.016	0.05
Hispanic	0.065	0.001	0.95	0.052	0.000	0.99	0.051	-0.006	0.46
Other race	0.049	-0.013	0.11	0.048	-0.014	0.09	0.051	-0.020	0.06
Earnings ($)	61,610	2051	0.61	62,240	1,243	0.73	48,130	-3915	0.10
Tenure at $l-5$	7.6	-0.817	0.07	8.2	-0.898	0.04	8.2	-0.760	0.07
Retired	0.020	0.002	0.17	0.054	0.004	0.23	0.188	0.008	0.50
In labor force	0.966	-0.003	0.16	0.930	-0.005	0.23	0.783	-0.010	0.49
Switched $l-5$ employer	0.034	0.025	0.01	0.030	0.024	0.02	0.027	0.006	0.07
Pension and firm characteristics									
Log DB pension wealth/active participant	10.18	-0.037	0.91	10.27	-0.077	0.82	10.5	-0.028	0.87
Log DB pension accrual/active participant	7.73	-0.205	0.52	7.80	-0.264	0.41	7.98	-0.325	0.05
Pension plan claim age	62.7	-0.015	0.96	62.7	0.036	0.89	64.2	0.137	0.41
Log firm size	8.46	0.066	0.90	8.32	0.079	0.88	7.42	-0.273	0.55
Fraction workforce ≤ 45	0.584	0.007	0.63	0.570	0.005	0.74	0.553	-0.015	0.27
Fraction workforce [46,50]	0.146	-0.003	0.50	0.142	-0.001	0.68	0.136	0.000	0.99
Fraction workforce [51,55]	0.124	-0.002	0.60	0.128	-0.002	0.69	0.122	0.002	0.64
Fraction workforce [56,60]	0.086	-0.001	0.89	0.094	0.000	0.94	0.095	0.005	0.21
Fraction workforce [61,65]	0.041	0.000	0.98	0.045	0.000	0.96	0.061	0.005	0.20
Fraction workforce [66,70]	0.011	-0.001	0.62	0.012	-0.001	0.66	0.021	0.001	0.55
Fraction workforce ≥ 71	0.007	-0.001	0.46	0.008	-0.001	0.59	0.012	0.002	0.38
Comparison group workers	383000			373000			77000		
Treated group workers	60000			66500			11000		
Comparison group firms	7700			8600			4600		
Treated group firms	1500			1700			900		

Notes: Unless otherwise noted, statistics reported in the table average over the five year period preceeding any freeze activity. Pension wealth per active participant is computed as the present value of the liability owed to active participants divided by the number of active participants. Tenure is understated because the LEHD does not capture the complete history of an employer-employee relationship when states enter the dataset after a given employee-employer relationship is established. P-values for the difference between treatment and control groups are obtained by regressing the statistic of interest on a indicator variable for treatment status and clustering standard errors at the firm-level.