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Predicting teacher retention behavior: Ex ante prediction and ex post realization of a voluntary retirement incentive offer

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ABSTRACT

Teacher retention and retirement decisions are increasingly affected by retirement benefits as the date of retirement eligibility approaches. As part of an effort to rein in operating costs, Chicago Public Schools sought to induce earlier retirement of senior, hence costlier, teachers by offering a voluntary retirement incentive that would be implemented only if enough teachers indicated their willingness to accept it. We used a structural model to predict teacher willingness to take the incentive, and later, when the number of teachers signing up was realized, we compared predictions to the outcomes. We found that the predicted number of willing takers would be less than required to implement the incentive, and this proved true. Further, the predictions were similar to the patterns of takers by age and year of service, though some differences were apparent. We discuss implications for using structural modeling to inform policy design.

1. Introduction

Policymakers are often required to set policy on short timetables without the benefit of rigorous, empirically-based policy analyses, such as those based on experimental or quasi-experimental approaches. Structural models are grounded in microeconomic theory, incorporate variables and parameters describing the structure of individual decision-making, and can be estimated using panel data. This approach enables predictions of proposed policy and can facilitate the shaping of policy by policymakers.

In the context of labor economics, structural models have been developed to understand workers' responsiveness to Social Security as they near retirement (Gustman & Steinmeier, 2005; van der Klaauw & Wolpin, 2008; French & Jones, 2011), decisions of federal civilians and military service members to separate from their current employment (Asch, Mattock & Hosek, 2015; Mattock, Hosek & Asch, 2016; Knapp, Hosek, Mattock & Asch, 2016b; Hosek, Nataraj, Mattock & Asch, 2017), and more recently retirement and separation decisions of primary and secondary school teachers (Knapp et al., 2016a; Ni & Podgursky, 2016; Ni, Podgursky & Wang, 2021, 2022; Knapp, Hosek, Mattock & Asch, 2018). Given the reliance of these models on their chosen structure, if the specification is wrong, then use of the model's predictions in shaping policy may lead to spurious results. The broad consensus in the literature is that there are few evaluations of the accuracy of structural models in predicting counterfactual outcomes (Keane & Wolpin, 2007; Pathak & Shi, 2021) and this has led to skepticism by some of their use in policymaking (e.g., Angrist & Pischke, 2010, in the context of industrial organization). This is heightened for issues associated with retirement decision-making that may reflect choices over the lifecycle and where some policy incentives may not be salient to a worker.

A goal of these models is to provide ex-ante predictions, and efforts in recent years have focused on approaches for building confidence in a model's predictions, also known as model validation (Keane & Wolpin, 2007; Heckman, 2010). The most convincing validation exercises in economics have used data other than what the model was estimated on (i.e., external validation) and use randomized social experiments or large regime shifts. These opportunities are rare and none to our knowledge have pertained to teachers. Examples in education include Todd & Wolpin (2006) and Pathak & Shi (2021). Todd & Wolpin (2006) validate a model of parental decisions about fertility and child schooling using a randomized social experiment in Mexico, and Pathak & Shi (2021) validate a model of school demand using a regime shift in Boston

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that altered where applicants can apply under school choice. With regard to retirement, Lumsdaine, Stock, & Wise (1992) estimate retirement behavior in a Fortune 500 firm using data before the introduction of a one-time retirement incentive similar in nature to what we study here, and use data after the incentive to assess the predictive validity of their model. In the context of retirement, Lumsdaine, Stock, & Wise (1992) represent the rare study in the retirement literature that compares an ex-ante model estimate to ex-post outcomes using regime change for the sample. The reason predictive models of retirement are rarely assessed is that policy changes are infrequent (e.g., Social Security was last significantly modified in 1983) and most retirement policy changes are implemented for new workers, requiring decades to determine if model predictions were valid. Even then, a challenge is to control for other variables that have changed in the years after policy change. Given the lack of opportunities for this type of validation, more recent research has focused on the use of non-random holdout samples (Keane & Wolpin 2007 discuss the value of this approach). In the context of teachers, Ni & Podgursky (2016) and Ni, Podgursky & Wang (2021) use a holdout sample of earlier teacher cohorts that have alternative pension rules. These approaches are convincing but leave open the possibility that changes in the characteristics of teachers across the samples may limit the validity of the model's predictions for cohorts on which the model was estimated or future cohorts of teachers.

The novelty of our paper lies in the comparison of ex ante prediction to ex post outcomes on the sample of interest. We are able to leverage a regime change – a one-time voluntary retirement incentive (VRI) offered by Chicago Public Schools (CPS) in 2016. Unlike other papers, we developed and estimated the model (Knapp et al., 2016a) prior to the emergence of the policy and conducted the simulations prior to the realization of the outcome.[1] The only other paper to have followed a similar research design is Pathak & Shi (2021). As they note, the benefit of making forecasts before the new policy is introduced is that it guarantees that forecasts and hypotheses are in no way biased by the actual outcome. Our paper extends this previous work by focusing on teachers and being able to incorporate two additional elements that address the concern of the model's ability to address novel policies:

(1) the VRI was not part of the benefit structure the model was estimated on, so it is a novel rather than incremental regime change and it was unexpected, and
(2) if insufficient teachers committed to retirement when the VRI was offered, the VRI would not be implemented and teachers opting to retire could rescind their decisions, thereby revealing teachers for whom the incentive was pivotal.

The original model, reflecting the questions of the earlier study, focused on teachers who started their career in teaching. It was estimated on teachers age 22-30 at entry. Timely predictions for CPS prevented re-estimation of the model for all entry ages, leading to differential entry age being an additional dimension of out-of-sample predictions. Additionally, the data we use to estimate the model – individual, longitudinal CPS teacher data from the Illinois State Board of Education (ISBE) for teachers who started their career in CPS between 1979 and 2000 and going through 2012 – differs from the data used for our validation. Teachers eligible for the VRI were those eligible for retirement in the 2016-17 school year, and the data for this evaluation of the model's predictive validity was provided by CPS and covered only the 2016-17 school year. However, to make the initial prediction we had to use the sample on which we had estimated our model and forecast the change in sample composition based on expected inflow to and attrition from the relevant age range between 2012 and the 2016-17 school year. As policymaking can take years from conception to implementation, our research design mirrors how policy predictions from structural models can be used to inform and support policy reforms.

Applying the dynamic model of teacher retention behavior (Knapp et al., 2016a), we predicted that the VRI of $1,500 per year of service would have 588 takers out of 2,696 eligible teachers (Table 5.11, Knapp et al., 2018). The predicted 588 was far below the 1,500 required for actual implementation of the VRI. Of the teachers retiring, 73 percent would have retired without the incentive. That analysis identified a number of generalizable conclusions, a key one being that most teachers who could receive the VRI would have retired without the incentive, leading to substantial economic rents, and marginal teachers—those that retired because of the VRI—were likely to have retired within the next few years without the incentive. Herein lies one of the important contributions of the structural modeling approach: simulating counterfactual outcomes from the estimated model reveals complex interactions that, while potentially foreseeable, are often absent from the discussion of policy formulation.

Comparing the ex-post data to the predicted take rate and rescind rate patterns with respect to age and to years of service, we find the overall predicted rescind rate to be close to the observed rescind rate. However, the overall predicted take rate was below the observed take rate. The observed number of takers was 748 out of 2,600 eligible, higher than the 588 predicted takers but well below the 1,500 required to implement the VRI. This policy experiment was a success: the model was able to recognize the target number of 1,500 retirements as an infeasible objective when CPS had no alternatives for determining the likely impact of the policy. We also show that, as the model predicted, the take rate of the retirement incentive was heavily skewed towards teachers eligible for or close to eligibility for unreduced pension benefits, suggesting the model captures important dimensions of the retention decision. However, the underprediction of the take rate might lead to concerns of its validity in other contexts. We discuss factors that might account for the underpredicted take rate and estimate the pecuniary magnitude those factors would have to take on to explain the differential.

Our analysis of the ex-post results confirms the value of dynamic analysis and counterfactual predictions as a valuable tool for policy analysis, and it also points to limitations that might be addressed through timely collection and analysis of additional information before final policy decisions are made, or later as policy is being revised. This research has implications for novel policy evaluation and optimal incentive design beyond the offer of retirement incentives, particularly in ongoing efforts to cope with unfunded pension liabilities. It suggests that teacher retention modeling and policy simulation would have been valuable in guiding policy design and informing deliberations at early stages. At the same time, the model did not account for contextual factors at the time VRI was offered, and our exploratory simulation suggests that these factors were present and had the effect of increasing the take rate above what the model predicted. Thus, just as modeling, estimation, and simulation can be a valuable addition to policy formulation, a role for sensitivity analyses, expert judgment, and gathering additional information on situational factors remains.[2]

Section 2 discusses voluntary retirement incentives and provides background on CPS compensation. Section 3 discusses the dynamic model of teacher retention data, and Section 4 describes the data, the model's parameter estimates, and the close fit to the data (i.e., internal

[1] These simulations were presented to Chicago Public Schools staff during contract negotiations (before the VRI offer was agreed upon) and at the American Education and Finance Policy Annual Meeting in March 2017 before the outcome of the VRI offer was known.

[2] Pathak & Shi (2021) find that a heuristic based alternative model performed as well as their model prior to accounting for differences in auxiliary inputs. These auxiliary inputs had to be predicted in order to make the initial predictions, similar to how we had to predict the sample composition of the teachers that would be eligible for the VRI. After accounting for the realized auxiliary inputs, they find their model outperforms the heuristic models.

validity). Our analysis of the VRI is an ideal test of the model's external validity. Section 5 describes the approach to simulating the VRI policy to produce results on retirement and reproduces teacher retention predictions from Knapp et al. (2018). Section 6 compares our ex-ante predictions to realized outcomes, and Section 7 concludes with insights from the findings for retirement incentives, the use of structural modeling to evaluate prospective policies, and possible future research.

2. Background on CPS salary schedule, pensions, and the voluntary retirement incentive

2.1. Policy background

Many state and local public pension programs, including those for public school teachers, are underfunded. For instance, the U.S. average funded ratio for state pension plans in 2016 was 66 percent (Pew Charitable Trusts, 2018), and the Chicago Teachers Pension Fund (CTPF) is no exception. Its pace of decline into underfunding was dramatic. CTPF was more than 90 percent funded from fiscal year 1995 through 2003 and was over 100 percent funded in 1997 and 1998. But because of low contributions in the following years coupled with optimistic assumptions on asset returns, CTPF was less than 70 percent funded by 2010 and only 49 percent funded by 2013. Thus, in 2013 its assets covered only half of its actuarial liability (Chicago Public Schools, 2016).[3]

In response to this worsening situation, the State of Illinois enacted Public Act 96-0889 in April 2010. It required the Chicago Board of Education to make larger-than-usual annual contributions to CTPF beginning in 2014 to achieve 90 percent funding by the end of 2059. The impact was profound. CPS required contributions to CTPF jumped from $143 million in fiscal 2013 to $585 million in 2014, $634 million in 2015, and $635 million in 2016 (Segal Consulting, 2016).

Under pressure to fund the increased pension contributions, and with decreasing systemwide enrollment, the Chicago Board of Education decided in May 2013 to close 49 underutilized elementary schools (de la Torre, Gordon, Moore, Cowhy, Jagesic & Huynh, 2015), decreasing operating expenditures in following years.[4] In July 2015 CPS laid off 1, 400 CPS workers mostly from operations, central office, and special education programs and cut $200 million from its budget (Schulte, 2015). The workforce, including teachers, was cut further in 2016 and 2017. CPS also sold bonds to obtain funds and, to save cost, refinanced existing bond obligations at lower interest rates.

In addition, the Board of Education sought fiscal relief from the state, arguing that CPS was treated unfairly. In 2016 the state contributed $3.7 billion to the Illinois Teacher Retirement System, which covers non-Chicago public school teachers, but just $12 million to CTPF. State legislation under consideration in 2016 would have increased the state contribution to CTPF to $215 million in 2017, but the legislation did not pass.[5] Legislators again addressed funding issues in 2017, this time passing an omnibus bill, Public Act 100-0465, with a set of fiscal reforms intended to address funding shortfalls and prevent Illinois' credit rating, already at junk bond status, from dropping further. The legislation included the $215 million for CPS in 2017 and similar relief in outyears. Henceforth, the state would pay the annual normal cost contribution to CTPF, yet the district was still responsible for digging CTPF out of its underfunding hole. In that regard, the legislation permitted an increase in the Chicago Board of Education's dedicated property tax levy from 0.383 percent to 0.567 percent, with the additional revenue earmarked for CTPF. Still, the Board of Education's required contribution stood at $539 million in 2018 and was projected to increase from there (GRS Retirement Consulting, 2018). Throughout these ups and downs, CPS was under pressure to reduce its operating costs in order to allocate revenue to the retirement contribution.

Challenging financial times, both for CPS and the pension fund, could lead teachers to expect further restraint or cutbacks in education spending, and the uncertain environment may have suggested to some that further layoffs and school closures were possible. Changing expectations may influence teacher decisions to retire as well as take a retirement incentive when offered.

2.2. CPS teacher salary schedule

Teacher salaries increase with their level of education and effort to obtain more education. The beginning salary in the 2015-2016 school year was $50,653 for a teacher with a bachelor's degree, $54,161 for a teacher with a master's degree, $55,916 for a teacher with 15 hours of additional study beyond a master's degree, $57,670 for a teacher with 30 hours of additional study beyond a master's degree, and $59,424 for a teacher with 45 hours of additional study beyond a master's degree.[6] Each of these education levels has up to 16 steps that reflect additional years of experience, with the top end of the scales, "step 16," having salaries of $85,920, $89,534, $91,339, $93,146, and $94,952, respectively. Teachers that begin with a bachelor's degree often obtain a master's degree within a few years, and those with a master's degree often study beyond it.

2.3. CPS pensions

Chicago teachers and administrators in our period of study are covered by the CTPF Tier 1 retirement plan, a defined benefit pension system. We refer to teachers and administrators as "teachers" for short. CPS opted out of Social Security, and CTPF is the sole source of pension benefits accumulated through CPS employment. CTPF offers retiree health insurance, with retired teachers participating in Medicare since 1986. It has features typical of most teachers' pensions in the U.S. (Hansen, 2010) and similarities with the defined benefit plans of government employees and military personnel. Knapp et al. (2016a) summarizes details of the retirement plan.

Participants must contribute 9 percent of their salary to CTPF, and CPS contributed 7 percent of salary on behalf of teachers during the time period we study, leaving 2 percent to be paid directly from the participant's salary. Teachers vest in CTPF Tier 1 after five years of service in CPS. The normal retirement age is 55 for a teacher with 33.95 years of service, 60 for a teacher with 20 years of service, and 62 for a teacher with fewer than 20 years of service.

Teachers are eligible to receive the full retirement benefit at the normal retirement age. The full benefit equals $B = M \times YOS \times FAS$, where M is the pension multiplier, YOS is the total number of covered years of service in CPS, and FAS is the final average salary. The multiplier was incremented by years of service before 1998 and has been 2.2 percent since then. Together, the multiplier and years of service determine the fraction of the final average salary that is received as a retirement benefit. For example, with a 2.2 percent multiplier and 20 years of service, the benefit for a teacher at the normal retirement age of

[3] Fiscal years for CTPF are from July-June, e.g., FY2016 covers July 2015-June 2016.

[4] A school is "underutilized" when enrollment is below 80 percent of capacity. Nearly 12,000 students were displaced, and 93 percent of them enrolled in schools with higher performance ratings (de la Torre et al., 2015).

[5] But, with other funds also in weak condition, e.g., Chicago Municipal Employees' Annuity Fund had a funded liability of only 25 percent, the governor vetoed the bill and called for more comprehensive pension reform (Offerman, 2016a, 2016b). The Illinois Senate overrode the governor's veto on this bill and the House adjourned without a final vote on the measure.

[6] We use information on teacher salaries from the 2015 – 2016 CPS salary schedule for 208-day employees for the typical school year to provide background information on the structure of salaries by education, age, and years of service.

60 is 44 percent (20 × 2.2 percent) of final average salary. CTPF calculates the final average salary for Tier 1 teachers as the average of the four highest consecutive years of earnings within the most recent 10 years of service. This is the last four years of earnings for most teachers. The final average salary is nominal; it is not adjusted for inflation or subsequent increases in the CPS salary schedule. For teachers retiring at the end of their work life, final average salary is likely only a few percentage points less than if salary were adjusted for inflation.[7]

A teacher with at least 20 years of service may retire early between ages 55 and 60, but the retirement benefit is reduced by 6 percent for each year short of normal retirement age. A teacher with 30.95 years of service can retire at age 57 instead of age 60 but with 18 percent less, or 0.82 times the normal-age benefit. Because normal retirement age changes based on years of service, a 57-year-old teacher with 31.95 years of service would have his or her benefit reduced by only 12 percent given that he or she would be eligible for a full pension with only two more years of service, bringing total years of service to 33.95.

Once begun, retirement benefits are adjusted for inflation. The annual cost of living adjustment for CTPF Tier 1 teachers is 3 percent. The cost-of-living adjustment (COLA) starts one year after retirement, or at age 61, whichever is later, and the COLAs are compounded.[8]

Summarizing, Tier 1 teachers vest after five years of service, may receive full benefits at age 55 with 33.95 years of service, at age 60 with 20 years of service, or at age 62 with less than 20 years of service. Early retirement is possible with some benefit reduction. Benefit amount is determined by a typical defined benefit formula, $B = M \times YOS \times FAS$, and final average salary is in nominal terms as of the years it was earned. Retirement benefits have an annual COLA of 3 percent.

2.4. CPS voluntary retirement incentive

The VRI was offered in the 2016 – 2017 academic year to teachers eligible to retire at the end of the fiscal year, June 30, 2017. If implemented, the VRI would pay a lump sum of the VRI rate times years of service in CPS, and a VRI rate of $1,500 per year of service in CPS was settled in CPS negotiations with CTU. However, the VRI would not be implemented unless at least 1,500 teachers signed up for it by March 31, 2017, and if it were not implemented the teachers who had expressed a willingness to accept it could rescind their commitment to retire.

Because the pension amount depends on years of service, a teacher induced to retire by the incentive would have fewer years of service than otherwise expected, hence a lower pension benefit than otherwise. Still, the pension would be received for more years. Similarly, for teachers who could retire early, the decrement to the pension might be greater if retirement were sooner than otherwise expected. Finally, VRI was a one-time offer. There was no plan to offer a voluntary retirement incentive in future years, nor had there been such a plan in the past.

Separately, CPS considered whether to hire teachers to replace the retiring teachers. Hiring would decrease budget cost savings but help to maintain the teacher workforce and prevent increases in class size.

3. Dynamic retention model for CPS teachers

We relied on the dynamic retention model (DRM) of teacher retention behavior, previously estimated in Knapp et al. (2016a), to predict the number of teachers willing to accept a VRI and retire. We extended the model to incorporate policy transitions necessary to simulate teacher retention from a VRI.

3.1. Model overview

The DRM is an empirical behavioral model of retention decision making over a career with a given employer. Individuals are assumed to be rational and forward-looking, taking into account expected future earnings from the employer, their own preference for employment with that employer relative to the external market, and uncertainty about future events that could cause them to value their current service more or less, relative to their external opportunities. Each period, teachers make a decision to stay if the teacher's expected value of staying ($V^S_{a,t}$) and an idiosyncratic random shock from teaching (ε^c_t) exceed the expected value of leaving ($V^L_{a,t}$) and an idiosyncratic random shock from nonteaching (ε^e_t):

$$V^S_{a,t} + \varepsilon^c_t > V^L_{a,t} + \varepsilon^e_t$$

Examples of idiosyncratic random shocks are changes in teaching assignments, transfer opportunities, external job offers, or tied moves (e.g., when a partner's job location changes). The shocks are assumed to be drawn from an independently, identically distributed type 1 extreme value distribution. Leaving teaching is assumed to be an absorbing state – once teachers leave, we assume they cannot return. Continuing teachers can revisit the choice between teaching in CPS and external opportunities in each future period until either retirement from the labor force, which is presumed to be at age 66, or retirement from CPS, which for many teachers is at 34 years of service when retirement benefits attain their maximum value.

The value of staying depends on a teacher's expected earnings in each year of CPS service and the teacher's taste for teaching in CPS relative to the external market. Taste represents the monetary equivalent of the individual's preference for teaching in CPS relative to an external job (nonteaching), along with any persistent difference in the individual's expected earnings in CPS versus in an external position. The model uses estimated earnings-age curves to represent the expected teacher salary and external salary.[9] An individual might believe his or her expected salary to be persistently higher or lower than those curves, and the net effect of these perceived differences enters into taste. In effect, taste is a person-specific fixed effect. It is unobserved, and we assume it has a normal distribution among teachers entering teaching at the beginning of their work career. Mathematically, the expected value of staying is

$$V^S_{a,t} = \gamma^c + EC_t + w^c_t + \beta E_t\left[\max\left(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1}\right)\right] \qquad (1)$$

where:

- γ^c is individual taste for CPS teaching relative to an external position, where $\gamma^c \sim N(\mu, \sigma^2)$
- $EC_t = \max\left\{\psi - \frac{\psi t}{12}, 0\right\}$ is an early career taste function for CPS teaching relative to an external position that fades over the first 12 years
- w^c_t is CPS teacher average annual earnings at time t (and experience in CPS is also t)
- β is the personal discount factor
- $V^S_{a+1,t+1}$ is the value of staying as a teacher in CPS at age $a+1$ and time $t+1$
- $V^L_{a+1,t+1}$ is the value of leaving teaching in CPS at age $a+1$ and time $t+1$

[7] The lack of an inflation adjustment can make a large difference to a teacher who leaves CPS after 10 years of service at age 35 and claims CPS retirement benefits at age 62. At an inflation rate of 2 percent per year, each dollar of final average salary at age 35 has an inflation-adjusted value at age 62 of $0.58, a 42 percent decrease.

[8] The COLA for Tier 2 teachers, those hired in 2011 or later, was much lower at 1.25 percent in 2017 (GRS Retirement Consulting, 2018).

[9] We used earnings-age curves as computed in Knapp et al. (2016a). These are described in greater detail in the next section.

- $E_t[\max(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1})]$ is the expected value at t of being able to choose “stay” or “leave” in $t+1$, depending on which has a higher realized value

We estimate the mean and standard deviation of the taste distribution at entry; the taste distribution evolves over teachers’ careers because of selective retention which depends in part on taste. In addition, the value of staying as a CPS teacher includes the value of the option to leave at a later date. The option value comes from being able to revisit the stay/leave decision in each future period. Although the idiosyncratic shocks that will be realized in future periods are not known in the current period, there is value in being able to choose between staying and leaving in each future period as compared to committing in the current period to a certain length of stay, or certain time of departure, in the future. Like taste, the idiosyncratic shock is unobserved, but we assume it follows an extreme value distribution with zero mean, and we estimate the standard deviation of the distribution (λ).

Choices made in the current period affect the value of choices in the future. A teacher choosing to stay in CPS adds a year of service, moving closer to retirement eligibility and increasing retirement benefits, thereby influencing the value of staying in CPS in the future. Similarly, past choices affect the value of staying at CPS in the current period.

The value of leaving includes expected earnings in the external market, plus CPS retirement benefits if any, plus the idiosyncratic shock.[10] An individual who leaves CPS might remain in teaching, obtain work in a different occupation, work full- or part-time, or leave the labor force. Consistent with Knapp et al. (2016a), we use the earnings of full-time workers with a bachelor’s degree, excluding teachers, in the Chicago metropolitan area to represent external earnings. The value of leaving does not include a term representing preference for external work, non-pecuniary factors, or person-specific differences between the individual’s own expected wage and the representative expected wage, because these factors are subsumed in the taste for teaching. In addition, in the 2016-17 school year, the VRI is a one-time cash incentive that is paid if the teacher leaves teaching in that year. Mathematically, the expected value of leaving is

$$V^L_{a,t} = w^e_a + VRI_t + \sum_{s=a+1}^{A} \beta^{s-a} w^e_s + R^c_{a,t} \tag{2}$$

where:

- w^e_a is average annual earnings in the external market at age a
- VRI_t is the value of the voluntary retirement incentive, equal to $1,500 times t years of service in the 2016-17 school year and zero otherwise
- $\sum_{s=a+1}^{A} \beta^{s-a} w^e_s$ is the present value of future external earnings through period A
- $R^c_{a,t}$ is the present discounted value of retirement benefits accrued for a teacher leaving at age a and with t years of service in CPS

In total, there are five parameters to be estimated – mean and standard deviation of taste (μ, σ), the parameter of the early career taste function (ψ), the personal discount factor (β), and the scale parameter of the idiosyncratic taste factor (λ).

Given uncertainty in the model, we define the probability of a teacher continuing to teach at age a at time t as

$$Pr_{a,t}(Stay) = Pr\left(V^S_{a,t} + \varepsilon^c_t > V^L_{a,t} + \varepsilon^e_t\right)$$

which forms the theoretical basis of a likelihood function that is then estimated.

An innovation of Knapp et al. (2016a) was the inclusion of incumbent teachers (i.e., those already employed at CPS) in the first year of the data allowing the model to cover the entire career of CPS teachers. Many new entrants in our data will not have accumulated the required age and years of service between the first and last year of our data (1992 and 2012, respectively) to be eligible to retire, implying that the data would not include retention decisions over likely retirement years. Consequently, we adapted the DRM to allow inclusion of incumbent teachers in the estimation sample. To do this, we derived expressions for the posterior taste distribution of the teacher population conditional on years of service, then developed career retention likelihoods for incumbent teachers given their years of service when first observed in the data. The model is estimated by maximum likelihood conditional on the assumption that the idiosyncratic error follows a type 1 extreme value distribution in a process that is now standard in the economic literature using dynamic discrete choice models (Train, 2003; van der Klaauw & Wolpin, 2008; Arcidiacono & Miller, 2020). Since the purpose of this paper is to examine the external validity of a previously estimated model, we refer interested readers to Appendix A for additional detail on the model and retention likelihoods and Knapp et al. (2016a) for additional details regarding model formulation and estimation.

4. Data and parameter estimates

4.1. Chicago teacher retention data

Data on CPS teachers used for the ex-ante analysis come from the Teacher Service Record (TSR) database of the ISBE. The data include a unique identifier which allowed us to create a teacher-level retention profile for each teacher. In Knapp et al. (2016a), we used the data to identify entering cohorts of teachers and observed teacher age, total creditable years of service, breaks in service, salary, and exit from teaching in Chicago. We analyzed CPS teacher retention for teachers who were aged 22 to 30 when they entered CPS. The original sample restriction to this age group reflected the earlier paper’s focus on how retirement incentives shape teachers’ careers, so the focus was on teachers starting their career as a teacher. Teachers who enter CPS at later ages might have begun teaching in a different school district or become a teacher after another career. As a result, entrants at a later age might reflect a different population.[11]

The estimation sample combined teachers that entered CPS in years 1992 to 2000 and were aged 22 to 30 at entry, along with incumbent teachers in 1992 who started their teaching career in CPS between 1971 and 1991 and were aged 22 to 30 at entry. The final year of data is 2012. In the 1992 to 2000 entry cohorts, eighty percent of the entrants were women and the average age of entrants was 26. At entry, 88 percent had a bachelor’s degree and 11 percent had a master’s degree or higher. By

[10] We also considered including the potential Social Security benefit, but we chose to omit it in the final analysis. Since CPS does not contribute to Social Security, a teacher would have to leave by a certain age in order to accumulate the minimal ten years of Social Security contributions in order to qualify for these benefits. In addition, these benefits are reduced due to the Government Pension Offset, a special rule applied to public sector workers, like those in CPS, who do not contribute to Social Security while working in the public sector. When we included Social Security in the model, we assumed that individuals completely internalized the structure of these benefits. However, it was clear during the model’s estimation that either these benefits are not valued at the same level as other compensation or teachers did not fully internalize the structure of Social Security, because the inclusion of it substantially reduced the fit of the model by inducing simulated behaviors at odds with those observed in the data. Omitting Social Security from the model assumes that teacher’s do not internalize the structure of Social Security in making their decision of whether or not to stay in CPS.

[11] Timely predictions for CPS prevented re-estimation of the model for all entry ages, leading to differential entry age being an additional dimension of out-of-sample predictions.

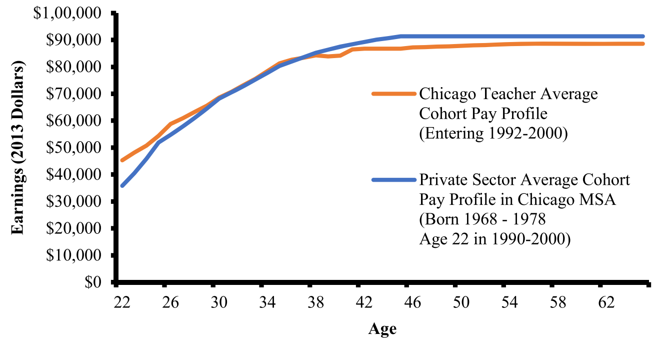

Fig. 1. Teacher and Non-Teacher Earnings Profiles

Table 1
Retention of Retirement-Eligible Teachers Under the Baseline and Under Alternative VRI Amounts

Parameter	Estimate	Standard error
Mean of taste, μ	-8.61	1.44
Standard deviation of taste, σ	49.78	1.17
Shock scale, λ	68.29	1.61
Personal discount factor [β]	2.86 [0.946]	0.0331
Early career taste factor, ψ	69.42	3.01

Source: Table reproduced from Table 6.1 in Knapp et al. (2016a).
Notes: In estimating the personal discount factor, the parameter is transformed using a logit function to bound it between zero and one during estimation. The value reported in square brackets is the transformed estimated corresponding to the parameter β in the model.

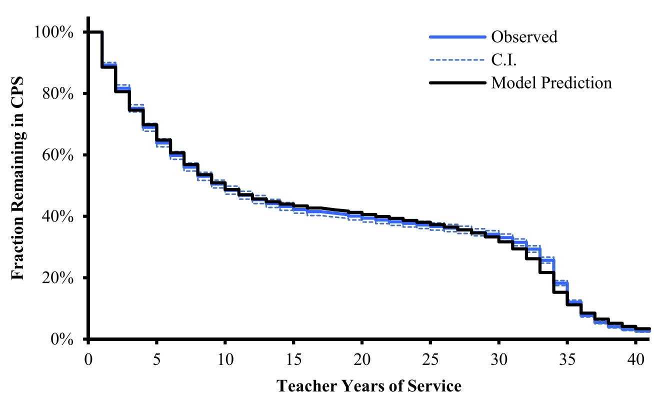

Fig. 2. Observed and Predicted Teacher Retention

2012, 42 percent had a bachelor's degree and 58 percent had a master's degree or higher. The 1992 incumbents were on average 41 years old in 1992, 77 percent were women, 59 percent had a bachelor's degree and 41 percent had a master's degree or higher. In 2012, 36 percent had a bachelor's degree and 64 percent had a master's degree or higher.

4.2. Teacher and non-teacher earnings by age

In Knapp et al (2016a), we estimated teacher earnings with TSR data from 1979 – 2012. The first step was to estimate cross-sectional earnings profiles by ordinary least squares with a piecewise linear specification in years of service interacted with degree level, bachelor's or master's, for full-time teachers. This accurately approximated the salary schedule for each calendar year. We used these results to create earnings profiles by entry cohort. For a given entry cohort Y, first-year earnings came from predicted earnings for the first year of service in year Y, second-year earnings came from predicted earnings in the second year of service in year Y+1 cross-sectional pay profile, and so on until the individual reached 34 years of service or fiscal year 2012, the last observed year. Earnings after 2012 were projected using the nearest cohort's earnings growth for the unobserved years of service (in terms of age).[12] Earnings were discounted to 2013 dollars using the annual averages for the consumer price index-urban (CPI-U) of the Bureau of Labor Statistics. Predicted earnings increased rapidly in the first 20 years of the career and flattened afterwards.

We used Current Population Survey data for 1962 – 2014 to construct teachers' expected earnings profiles for non-CPS employment. We estimated a Tobit model for earnings as a function of year, birth-cohort, educational attainment, and metropolitan location, accounting for top-coding for high earners. The estimated model was used to predict earnings profiles by cohort for individuals with a bachelor's degree working in the Chicago metropolitan statistical area (MSA). We froze earnings at age 45, as the model would otherwise predict earnings to decrease. The predicted decrease likely resulted from selection out of working at older ages.

The non-teaching earnings profile is similar to that for teaching. The starting salary for a young worker is lower in non-teaching but grows faster at first. Teacher and non-teacher earnings are nearly equal over ages 28 to 38 and continue growing to the mid 40s. From then to age 65 teacher earnings were about $87,000 to $88,600, and non-teacher earnings were $3,000 to $4,000 higher. The resulting earnings profiles were averaged for a representative cohort, i.e., age 22 in 1990 – 2000 and are presented in Fig. 1.

4.3. Parameter estimates

We use the DRM parameters that were estimated in Knapp et al. (2016a) and as presented in Table 1. All parameter estimates are statistically significant. The parameters for the mean and standard deviation of taste, shock scale, and early career taste factor are denominated in thousands of dollars. Fig. 2 shows that the estimated model fits the teacher retention data well. It accounts for high early-career attrition and the drop in retention at 34 years of service.

Early career taste is no longer a factor after twelve years of service, and from then on mean taste increases over the career because of selective retention, with higher-taste teachers more likely to stay. The standard deviation of taste is $49,780 at entry, and it too decreases over the career because of selective retention.

The shock scale parameter estimate is $68,290. (The mean of the shock parameter is zero.) The standard deviation of the shock is $\pi/\sqrt{6}$ (= 1.28) times this amount, or $87,585, which is about equal to the annual salary of a senior teacher. To put this in perspective, in September 2016 a teacher with 20-24 years of service and at age 40-44 had a salary just above $85,000 and had a mean taste of about $30,000 (Fig. 6.2, Knapp et al., 2016a). The teacher would also value the opportunity to choose between teaching and nonteaching in the next year. This teacher, then, could face a negative teaching shock of 1.3 standard deviations of the shock distribution, or a positive external shock of the same magnitude, and would choose to remain in teaching. The personal discount factor is estimated at 0.9457, implying a willingness to trade $100 in compensation next year for $94.57 in current compensation. This is equivalent to a personal discount rate of 5.74 percent.

5. Policy simulations

To compare ex ante predictions to ex post outcomes, we first predict

[12] We estimated the teacher earnings regressions in terms of years of service rather than age because the TSR data include years of service information. The Current Populations Survey had age but not years of service. To put both profiles in the same units, the predicted earnings profile for teachers is expressed in terms of age.

Table 2
Retention of Retirement-Eligible Teachers Under the Baseline and Under Alternative VRI Amounts

Fiscal year	Baseline	$1,000 per year	$1,500 per year	$2,000 per year	$3,000 per year	$5,000 per year
2017	2,696	2,696	2,696	2,696	2,696	2,696
2018	2,266	2,166	2,108	2,046	1,909	1,608
Retirements	430	530	588	650	787	1,088
Change in retirements from baseline		100	158	220	357	658

Table 3
Illustrative Calculations of Net Present Value of Staying vs. Leaving

Years of Service	Age							
	55	56	57	58	59	60	61	62
20	161,170	99,206	86,012	74,020	63,165	53,366	50,291	46,023
21	179,936	116,579	77,987	65,894	55,134	45,641	43,656	40,541
22	199,807	135,170	69,587	57,422	46,787	37,633	36,772	34,844
23	221,445	155,603	88,799	49,140	38,614	29,780	30,024	29,265
24	205,370	177,988	110,034	41,143	30,701	22,161	23,483	23,862
25	189,179	160,024	132,880	62,930	22,703	14,466	16,874	18,402
26	173,185	142,245	113,361	86,686	14,849	6,900	10,379	13,039
27	157,542	124,796	94,150	65,761	39,794	**-433**	4,089	7,851
28	142,461	107,875	75,432	45,290	17,620	**-7,393**	**-1,874**	2,944
29	127,868	91,413	57,141	25,214	**-4,193**	**-30,891**	**-7,552**	**-1,720**
30	61,363	76,303	40,110	6,301	**-24,945**	**-53,438**	**-30,216**	**-5,668**
31	**-7,308**	8,056	24,296	**-11,488**	**-44,673**	**-75,063**	**-52,069**	**-27,763**
32	**-76,352**	**-60,712**	**-44,179**	**-26,703**	**-62,053**	**-94,581**	**-72,069**	**-48,272**
33	**-144,209**	**-128,534**	**-111,965**	**-94,449**	**-75,934**	**-110,957**	**-89,304**	**-66,416**
34	**-205,854**	**-190,689**	**-174,659**	**-157,714**	**-139,801**	**-120,866**	**-100,850**	**-79,691**
35	**-155,036**	**-142,935**	**-130,144**	**-116,622**	**-102,329**	**-87,220**	**-71,248**	**-54,364**

Notes: Cell entries are in dollars. Authors' calculations. Negative values are in bold for ease of reading.

the effect of the VRI on teacher retention and on the CPS budget. The DRM can be used to simulate the retention decisions of an entering cohort of teachers. For each simulated teacher, a stay/leave decision is made in each year of service until the teacher leaves. This produces a retention profile for the teacher.

The DRM can also be used to simulate the retention decisions of the CPS teaching workforce from one year to the next. Since a teacher with more years of service is likely to have a greater taste for teaching, each teacher's probability of continuing in CPS is based on his or her years of service and current age at the simulation's base year. Total retention for the workforce from the base year to the next year represents the population weighted sum of the simulated retention decisions. Simulating retention decisions is done under current pay and retirement conditions and under alternative conditions such as changes to retirement benefits, enabling a comparison of retention under current policy versus the VRI that was offered as well as a range of less- and more-generous VRI policies. In particular, the VRI was an unanticipated, one-time offer to retirement-eligible teachers. Because it was unanticipated, it could not affect retention decisions in years prior to the year in which it was offered. Because it was a one-time offer rather than an offer available for several years, there was no reason to consider the optimal year to retire under the VRI policy; either take it in the year it was offered or forego it forever. In the DRM, the VRI payment appears in the value function for a non-CPS position, e.g., a job elsewhere, in the first year after leaving CPS. The VRI is an incentive to retire, and its attractiveness to a teacher depends not only on the amount of the VRI payment but also on the extent to which the teacher's pension is lower than if the teacher were to retire later without receiving the VRI.

A VRI has multiple theoretical effects. It can be expected to increase the number of retirements in the year it is offered. Consequently, it will also decrease the number of retirement-eligible teachers retained in the following years relative to baseline retention. Therefore, we simulate not only the immediate impact on retention—that is, the number of VRI takers—but also the impact in subsequent years. When simulating a VRI offer, retirement-eligible teachers are offered a VRI in a specific academic year, and only in that year. In years after that academic year, the simulation reverts to the ex-ante policy (no VRI). With this extension of the simulation code, it is possible to compute the impact of VRI in the year it is offered and in subsequent years.

Related to this, VRI eligibility depends on pension-claiming eligibility and the VRI payment depends on years of service. The VRI can influence only those teachers who are retirement-eligible in the academic year when it was offered. Teachers with more years of service (hence a larger VRI) have a greater incentive to leave, while teachers with a penalty for early claiming have a greater incentive to stay. The simulation accounts for variation in a teacher's incentives to stay or leave in response to the VRI's design based on their age and years of service.

Finally, policymakers wanted to know how the VRI affects the operating budget. This requires computing the cost of the VRI, which depends on the specific amount paid to each taker, the number of takers, and the costs avoided in future years as the retirees in the year the VRI is offered may be replaced by new teachers who are lower paid. A valuable feature of the simulation is its capability to predict the number of teachers that would have retired in the absence of VRI. The number of additional teachers induced to retire by the VRI can then be calculated, as can the total payments to teachers receiving a VRI payment that would have retired without it, known as economic rents.

5.1. Predicted VRI effect on retention

We used the DRM to simulate the number of teachers who would retire under the VRI offer of $1,500 per year of CPS service and under a range of other rates including a baseline of no VRI. Before the simulations could be run, however, we needed to project our ex-ante teacher data, which ended in 2012, to 2017, the year the VRI was offered. The projection provided an estimate of the number of teachers on hand in 2017 and the number eligible to retire. Those eligible to retire were the target population of the VRI when it was offered in 2017. We later compared this number to the actual count in 2017 using data given to us by CPS in 2018.

Based on the projection using ex ante data, the number of retirement-

Table 4
VRI Rate (Dollars per Year of Service) at Which the Net Present Value of Staying vs. Leaving Is Zero

Years of Service	Age							
	55	56	57	58	59	60	61	62
20	8,059	4,960	4,301	3,701	3,158	2,668	2,515	2,301
21	8,568	5,551	3,714	3,138	2,625	2,173	2,079	1,931
22	9,082	6,144	3,163	2,610	2,127	1,711	1,671	1,584
23	9,628	6,765	3,861	2,137	1,679	1,295	1,305	1,272
24	8,557	7,416	4,585	1,714	1,279	923	978	994
25	7,567	6,401	5,315	2,517	908	579	675	736
26	6,661	5,471	4,360	3,334	571	265	399	501
27	5,835	4,622	3,487	2,436	1,474		151	291
28	5,088	3,853	2,694	1,617	629			105
29	4,409	3,152	1,970	869				
30	2,045	2,543	1,337	210				
31		260	784					
32								
33								
34								
35								

Source: Authors' calculations.

eligible teachers was 2,696. Our simulations, reported in Table 2, indicated that the VRI of $1,500 per year would induce 588 of them to retire, leaving 2,108 continuing to teach. At baseline (VRI = $0), the simulation predicts that there would have been 430 retirements. Thus, adding the VRI increased the number of retirements by 158 (= 588 – 430). Because the VRI would be payable to all retiring teachers but only 158 additional teachers were induced to retire, a rent would be paid. Table 2 also shows predicted retirements of 787 with a VRI of $3,000 per year and 1,088 with a VRI of $5,000 per year. In the VRI range considered in the table, predicted retirements are in each case below the required number, 1,500.

To better understand the low responsiveness to a VRI, we made two further calculations. First, we computed the present discounted value of leaving versus continuing to teach by age and years of service; this was done at baseline (VRI = $0). Second, for the many instances where the value of continuing was greater than the value of leaving, we computed the VRI rate necessary to make the value of leaving as high as the value of staying, at which point the teacher would be indifferent to staying versus leaving, i.e., accepting the VRI and retiring from teaching. The net present discounted value of staying versus leaving is shown in Table 3, and the VRI rate needed to drive the net present discounted value to zero is in Table 4.

The present discounted values assume that a retiring teacher would begin drawing a retirement benefit from CTPF immediately and that the now-former teacher would work at an external job through age 66, as assumed when estimating the DRM.[13] A teacher not retiring could continue to teach through age 66,[14] receive the teacher salary and the monetary equivalent of the taste for teaching, and would, upon retirement, receive a retirement benefit reflecting the additional years of service in CPS. For teachers with 20, 25, 30, and 35 years of service in the VRI decision year, the average values of taste are $30,706, $33,164, $36,415, and $49,246, for instance. The latter value is quite high because only teachers with the highest taste continue to teach after maxing out their retirement benefits and forgoing benefit receipt for each year in which they continue teaching. The calculation used a teacher salary of $88,602 and an external salary of $91,393.

The table reveals nonlinear relationships between years of service and age. For instance, at 25 years of service the net value of staying decreases from ages 55 through 60, increases to age 62. The nonlinearity reflects the non-random selection of teachers remaining in teaching and the complex interactions between age and years of service that are reflected in the pay schedules and the pension, e.g., the 6-percent per year penalty for retiring early becomes smaller as the teacher ages toward 60. This points to the importance of doing detailed calculations of the net value of staying when simulating the effect of the VRI on retirement.

Table 4 shows the VRI rate per year of CPS service needed to offset the positive amounts in Table 3. The VRI rates are of course higher in the cells for years of service 20 to 25, which are where the net value of staying (Table 3) is higher. The blank cells in the table indicate that no VRI is needed because the net value of staying is negative. As can be seen, in many cases with 20 to 30 years of service and ages 55 through 57 a VRI rate above $3,000 per year is needed. By comparison, for 24 or more years of service and age 60 or more, a rate of $1,000 is enough. However, at a common eligibility condition for retirement, namely, 20 or more years of service and age 60, a VRI rate of $2,668 per year is needed; many teachers who could retire would otherwise prefer to continue teaching.

Tables 3 and 4 thus indicate that the number of VRI takers will depend on the distribution of retirement-eligible teachers by age and years of service. Generally speaking, those who are incentivized to retire would have likely retired within a few years without the VRI.

The additional retirements induced by the VRI have dynamic implications for the CPS teacher workforce. The increased outflow of teachers decreases the size of the workforce relative to baseline. CPS could make up all or part of the decrease by hiring replacement teachers. Cost savings would be greatest if this were done by hiring start-of-career teachers who have the lowest salary. One approach would be to hire teachers in 2018 to replace the VRI takers in 2017. This would cause a surge in hiring in 2018 followed by lower hiring in the following years than would have occurred to replace teachers retiring under the baseline.

5.2. Implications for costs and cost savings

A $1,500 VRI is predicted to induce 158 additional retirements. If all retiring teachers were replaced to maintain the size of the teaching workforce, new teacher hiring in 2018 would be 158. In future years, hiring is predicted to be less than it otherwise would have been because many of the teachers who are induced to retire in 2018 would have retired in the near future, thus advancing the timeline associated with

[13] An external job here represents the next best alternative, and so could also be thought of as the value of leisure should the individual not continue to work.

[14] Because the additional years of teaching are deterministic in the table, the table calculations do not reflect the generality of the DRM where the teacher makes a stay/leave choice in each future year and the value function includes the option value of this choice. Consequently, the table calculations understate the value of staying in teacher. Still, the table usefully illustrates the difference in the present discounted value of the income streams from leaving with a VRI compared to staying.

Table 5
Salary Cost at Baseline and with VRI of $1,500 per Year in 2017, Including New Hires (Millions of Dollars)

Fiscal year	Salary cost of teachers eligible to retire in 2017 at baseline	Salary cost of teachers eligible to retire in 2017 under VRI	Change in salary cost of teachers eligible to retire in 2017	Salary cost of replacement teachers at baseline	Salary cost of replacement teachers under VRI	Change in salary cost of replacement teachers	Cost of VRI	Budget change if retirees replaced	Budget change if retirees not replaced
2017	$245	$245							
2018	$206	$192	−$14.5	$21.4	$29.2	+$7.8	+$25.3	+$18.6	+$10.8
2019	$170	$160	−$9.6	$43.2	$49.1	+$5.9		−$3.7	−$9.6
2020	$137	$131	−$6.3	$64.1	$68.4	+$4.3		−$1.9	−$6.3
2021	$109	$105	−$4.0	$83.6	$86.9	+$3.3		−$0.7	−$4.0
2022	$84	$82	−$2.5	$102.4	$104.9	+$2.6		+$0.1	−$2.5
2023	$63	$61	−$1.5	$119.7	$121.7	+$2.0		+$0.5	−$1.5
Total			−$38.3			+$25.8	+$25.3	+$12.8	−$13.0

Notes: Negative values imply budget savings from VRI relative to baseline. Totals may differ due to rounding.

Table 6
Comparison of Observed and Predicted VRI Take Rates and Rescind Rates

	Observed, all entry ages	Observed, entry ages 22 – 30	Predicted, all entry ages	Predicted, entry ages 22 – 30	Predicted, entry ages 22 – 30, adjusted
Eligibles	2,600	783	2,696	783	783
VRI takers	748	233	588	194	265
VRI rescinders	231	73	158	55	71
Fraction of eligible taking	29	30	22	25	34
Fraction of takers rescinding	31	31	27	28	27

Notes: Columns 2 and 3 are based on data provided by CPS after the VRI was offered. Column 2 includes teachers at all entry ages, and column 3 limits entry ages to 22 – 30. Column 4 predictions are based on simulation using the teacher retention model and data from the estimation sample projected from 2012 to 2016; the same predictions appear in Table 2. Column 5 predictions use a simulation sample of teachers entering CPS at ages 22 to 30 and having the same size and age/year of service composition as in Column 3. Column 6 adjusts the simulation model to include an additional $1,500 per year of service incentive to leave teaching after the 2016 – 2017 academic year. Eligibles are teachers who, as of October 2016, were eligible for retirement at the end of the CPS fiscal year, June 30, 2017. VRI takers are eligibles who signed up for the VRI in the 2016 – 2017 academic year enrollment period which ended on March 30, 2017. Signing up indicated a willingness to receive the VRI and retire at the end of the fiscal year. VRI rescinders are those takers who chose not to retire at the end of the fiscal year, by which point it was known that fewer than 1,500 teachers had signed up for the VRI and it would not be paid.

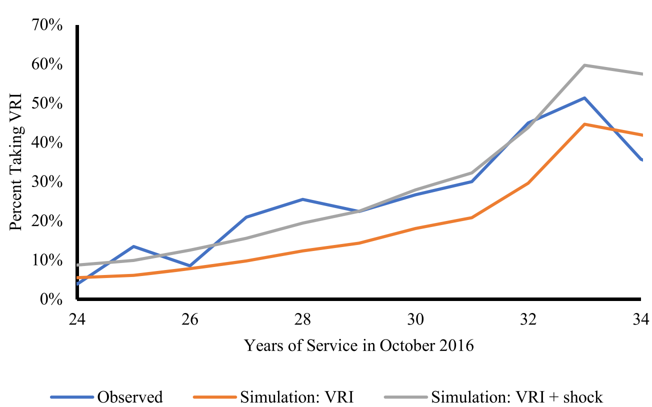

Fig. 3. Observed and Predicted VRI Take Rates by Years of Service
Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a $1,500 VRI per year of service. The VRI simulation corresponds to a $1,500 VRI per year of service and a $1500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only the continuous range of years of service are shown that include a number of eligible teachers with a sample size of at least 25.

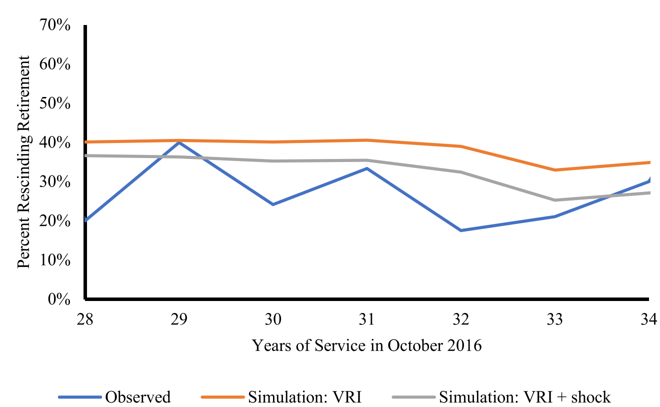

Fig. 4. Observed and Predicted VRI Rescind Rates by Years of Service
Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a $1,500 VRI per year of service. The VRI simulation corresponds to a $1,500 VRI per year of service and a $1,500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only the continuous range of years of service are shown that include a number of eligible teachers that took the VRI with a sample size of at least 10.

hiring of new teachers. However, new teachers are more likely to leave, requiring further hiring in 2019 and following years because new hires exhibit higher attrition than senior teachers. Further, as demonstrated in Fig. 1, the rapid increase in early career salaries reduces the cost savings from replacing senior teachers with junior teachers.

Table 5 shows the impact on salary cost. There are three parts to this: the decrease in salary cost among teachers eligible to retire in 2017, the increase in salary cost for the 2018 new hires, and the cost of the VRI. We find that when the $1,500-per-year VRI is accompanied by immediate full replacement, budget savings are negative—not only in 2018 but for the six-year period from 2018 through 2023. Instead, the VRI with replacement hiring would cost CPS $12.8 million. If instead there were no replacement hiring, there would be budget savings of $13.0 million.

This analysis highlighted three non-obvious conclusions (Knapp et al., 2018):

(1) most teachers who received VRIs would have retired without the incentive – demonstrated by the small net decrease in senior teachers in 2018 from the VRI (Table 2) and the comparatively large cost of the VRI in 2018 (Table 5, Column 8)
(2) marginal retirees were likely to have retired within a couple years without the incentive – demonstrated by the convergence in senior teacher salary costs (Table 5, Column 4)
(3) sharp increases in salary over the first years of teaching (see Fig. 1) narrowed the salary gap between junior and retiring teachers from which potential savings were supposed to derive if retiring teachers were replaced (Table 5, Column 7)

5.3. Potential limitations to external validity

The model parameters used for our predictions were estimated on teachers entering between the ages of 22 and 30, traditionally representing 45 to 50 percent of CPS teachers. Knapp et al. (2016a) chose this restriction for estimation purposes to limit the sample to teachers who started their career in CPS in order to ensure accuracy in years of teaching experience. For teachers entering CPS at older ages, we did not know whether they had previously taught or, if so, for how many years. CPS entrants over 30 are more likely to be individuals with a substantial work history outside of CPS, including transfers from other school districts or individuals pursuing teaching as a new profession. For simplicity, in making predictions regarding the VRI we assumed that all teachers' preferences, including those entering before age 22 and after age 30, reflected the model parameters estimated on teachers entering between the ages of 22 and 30. Additionally, the model was designed only to capture behavior through the 41st year of service and age 66. To the degree that preferences for older entrants into CPS differ from our assumption, the model's predictions for those individuals may be less accurate.

The model is also relatively simple. Consequently, it may not capture some theoretical tradeoffs. For example, the form of period-specific utility equates utility with pecuniary measures, allowing everything to be interpreted in terms of present value dollars. When combined with the intertemporal tradeoff of expected future utility pathways (via the expected value functions), the period-specific utility function highlights the tradeoff of current and deferred compensation conditional on the discount factor for the teacher population. However, this comes at the cost of understanding tradeoffs between pecuniary and non-pecuniary forms of income, which may differ between some groups (e.g., by gender). Other simplifications include the use of constant teacher and external earnings profiles. While the model includes a factor (i.e., the taste factor) that captures persistent differences between teacher and external earnings profiles, if there is a time-varying differential impact on pay across particular groups of teachers, the exclusion of these characteristics may lead to biased predictions. Future work applying the model to inform differential impacts on particular groups would require additional flexibility in the structure of the model (e.g., through additional model parameters based on groups of interest) as well as data with richer individual-level demographics. For our purposes using the model to evaluate a VRI for career teachers that is not targeted at a particular group, the key tradeoffs of retiring now versus later are well captured by our model.

6. Ex ante predictions versus ex post realizations

In 2018, CPS provided data on the number of teachers eligible for the VRI when it was offered in the 2016-17 academic year, the number who signed up for it in the enrollment period ending March 30, 2017, and the number of those teachers who chose not to retire but remained in teaching when it turned out that fewer than 1,500 teachers had signed up and therefore the VRI would not be paid.[15] Table 6 compares the values based on the CPS data to predicted values. The 2016-17 CPS data we use to evaluate the predictive performance of the model differs from the ISBE data used to estimate the model described in section 4, which covered 1979-2012.

The CPS data indicated an overall population of 20,732 full-time teachers in October 2016, of whom 2,600 were eligible to retire at the end of the academic year and could sign up for the VRI (see Table 6, column 2). Of these, 748 did so, producing a take rate of 29 percent. Also, 231 of those signing up chose not to retire at the end of the academic year, i.e., rescinded. The observed rescind rate was 31 percent. We estimated our teacher retention model on teachers who entered CPS at ages 22 – 30, which made it relevant to consider the take rate and rescind rate observed for teachers who entered at the same ages. These are shown in column 3. There were 783 of these teachers in CPS in October 2016, and they had a take rate of 30 percent and a rescind rate of 31 percent, both of which were close to the rates for teachers entering at all ages. Column 4 presents predictions shown above in Table 2.

Our projected population of 2,696 of teachers eligible to retire was slightly larger than the observed count of 2,600. This is because the original model predictions were made for a teacher population in 2016-17 school year that was projected from our estimation data, which ended in 2012. The predictions for this population used all teachers on hand in 2012 regardless of the age of entry into CPS, and their retention to 2016-17 school year was predicted from the teacher retention model. The 2,696 teachers had a predicted take rate of 22 percent and a rescind rate of 27 percent. We also made predictions for a sample limited to teachers entering CPS at ages 22 – 30 and having the same size and age/year of service composition as the observed population in column 3. In this case, the take rate was predicted to be 25 percent and the rescind rate 28 percent. Thus, the predicted take rate for this most comparable sample was 5 percentage points lower than the observed take rate, while the predicted rescind rate was 3 percentage points lower than the observed rate.

In predicting the rescind rate, we assumed that the number of rescinders equaled the number of additional teachers induced by the VRI to indicate a willingness to retire. Teachers who were predicted to retire at baseline (VRI = $0) presumably would have gone on to do so, while the additional teachers who were willing to retire with the VRI were assumed not have done so after the VRI was withdrawn.

We consider reasons why the model had underpredicted the take rate. Increasing the take rate would require some combination of a decrease in the value of continuing to teach and an increase in the value of leaving, relative to the values predicted by the model at baseline, apart from the effect of the VRI. Furthermore, such changes, to be credible, need to be related to the environment facing teachers when the VRI was offered—the policy context.

What might drive such changes to the value functions? A decrease in the value of continuing to teach at baseline, beyond what the model predicted, could come from CPS's turbulent situation when the VRI was offered. As mentioned in section 2, there had been school closings and teacher layoffs, and the Board of Education continued to face large, required contributions to the pension fund in the neighborhood of $600 million per year even though the state would contribute the roughly $200 million annual normal contribution. As a result of this turbulence, teachers had reason to expect a continuing austere and uncertain environment. Further, the added teachers willing to accept the VRI and retire (i.e., those in addition to teachers who would have retired without a

[15] Eligible teachers were identified based on their projected years of service in CPS and age at the end of the 2016-17 school year. Rescind rates were identified by teachers still teaching in October 2017 but who had in 2016-17 indicated their willingness to receive the VRI and retire.

VRI) may have re-evaluated the value of not teaching as they thought about retiring. They might have made plans for travel, family time, volunteering, and so forth, which for some served as a commitment device to continue on the path to retire at the end of the school year, and with plans perhaps becoming less abstract and more concrete as time passed, their estimate of the expected value of being retired from teaching might have increased.

To understand the monetary magnitude of the average uncertainty required to match the observed take up rates, we incorporated a common shock for all teachers in that year. We assumed the shock is measured in the form of an additional monetary incentive per year of service to leave teaching that was felt in the VRI offer year in addition to the VRI and paid regardless of the VRI offer. We found that an additional $1,500 per year of service would increase the predicted take rate from 25 percent to 34 percent, but slightly decrease the predicted rescind rate from 28 percent to 27 percent, which is below the observed rescind rate of 31 percent (see Table 6, column 6 versus column 3).[16]

Fig. 3 illustrates the take rate by years of service in October 2016. The model predictions accounting for the VRI capture the trend in the willingness to take the VRI with respect to years of service but are uniformly lower than the observed take rate. The additional incentive to leave teaching after the 2016-17 school year is represented by an additional $1,500 shock that is incurred regardless of the VRI offer. In this case, the take rate tracks the observed rate well, including the peak take rate at 33 years of service.[17] The four-percentage point discrepancy in Table 6 between the observed take rate (column 3) and the take rate in the adjusted prediction (column 6) is driven in large part by individuals with years of service in excess of 35 years, for whom the model predicts retirement. These individuals' incentives may not be well identified by the model if in fact their non-pecuniary taste for teaching is exceptionally high.

Fig. 4 shows the rescind rate by years of service in October 2016 conditional on taking the VRI. The observed rescind rate is relatively volatile but has a slight downward trend consistent with longer serving teachers being less likely to change their mind about retirement. The model's predicted rescind rates exhibit a smoother decline with age but occur at a higher rate. This rate is somewhat reduced when the $1,500 shock is added to the VRI. The model does a reasonable job of capturing the differences in the rescind rate by year of service, but consistently over predicts. The observed volatility suggests that the factors contributing to the decision to rescind a VRI and continue teaching are not fully captured by the model (e.g., teachers becoming attached to the idea of retiring once they have expressed a willingness to take the VRI).

In Appendix B, we extend the comparison of the observed versus predicted take and rescind rates to cover the entire sample (teachers entering at all ages) and also investigate age differences. The results in Fig. B.1 are similar to those observed in Fig. 3 in that our model does a good job of capturing the trend in take rates by years of service and that incorporating the additional incentive to leave teaching leads the predicted take rates to match the magnitude of the observed take rates. With the expanded sample, now incorporating older entrants, we observe a difference in rescind rates – they are generally higher for those with fewer years of service (Fig. B.2). In examining differences in take and rescind rates by age (Fig. B.3 and Fig. B.4), the model does a good job of capturing age-related patterns in take rates, with the magnitude also matching after an additional incentive to leave after the 2016-17 academic year is introduced.

To better understand the observed volatility in the rescind rate by year of service, it would be ideal to survey eligible teachers to understand what factors contributed to their decision, including their beliefs and preferences. In the context of a choice between a defined benefit and defined contribution system, Brown & Weisbenner (2014) find respondent attitudes about risk/return tradeoffs, financial literacy, return expectations, and political risk are important determinants of that choice and that respondent beliefs about plan parameters were often incorrect. It is possible that the rescind "choice" may similarly be guided by incorrect beliefs. At present, limited empirical evidence and survey data provide no guidance on teacher's beliefs and preferences regarding their pay, pensions and retention decisions. Until more comprehensive quantitative data are available, structural models used to set compensation policy should consider sensitivity analyses to determine the extent to which the predicted outcomes change across a range of parameter values and possible re-estimation of the model with different specifications of the objective function. In the case of a VRI, we considered an additional monetary incentive as a proxy for unobserved or unmodeled behavioral factors. This modelling choice for sensitivity analysis was driven by the nature of the VRI having a monetary value and being a novel element of the decision-making process. In other settings, what constitutes a sensitive dimension may differ. For example, the margin of sensitivity for the external validity of Pathak and Shi's (2021) model was in the input data (the analogy here would be an incorrect prediction of the 2016-17 teacher sample based on our 2012 data). At present, our review of the literature suggests that tests of external validity have all but replaced sensitivity analyses in published structural modeling papers of retirement decision-making. Yet such tests are not always feasible or timely.

Overall, our model did an excellent job of predicting a novel policy. The dominant discrepancies between the model's predicted take rates occur at ages outside its predictive range (i.e., working past 40 years of service or after age 66) or generally outside of what would have been observed for the model's estimation sample (e.g., teachers eligible for retirement but with less than 20 years of service, implying they became CPS teachers sometime after age 30). For the predicted rescind rates, we found an overall decline with age and years of service, though with some volatility across age and years of service. While the model was able to capture the decline with age and years of service, it did not replicate the larger, observed volatility. There apparently are unobserved factors important in the rescind decision but not captured by the model. Future research combining administrative and survey data with an experiment on compensation policy may provide insight on how teachers perceive such a decision.

7. Conclusions

Many school districts and local governments use or consider using voluntary retirement incentives (Galvin, 2016). The intent is to decrease the payroll cost of their workforce, decrease retirement fund liability, decrease workforce size without layoffs, or a combination of these outcomes. Given the substantial amount of underfunding among state pension systems – recently only seven had a funding ratio of 90 percent or greater (Jacobs, Doherty & Lueken, 2017) – it is likely that districts and states will continue to use retirement incentives to restructure their workforce. This research evaluates one example of a voluntary retirement incentive offered to teachers in Chicago, yet the lessons from it seem more widely applicable. Additionally, we predicted the effects of a novel compensation incentive before it was offered, and we evaluated the accuracy of the predictions with data that became available only after the offer was made.

We predicted that the VRI offer of $1,500 per year of CPS service, agreed on with the teacher union, would fall well short of the target of 1,500 retirees. When data became available on the number of teachers

[16] The additional incentive of $1,500 is also consistent with the predicted take up rate in Table 2 from a $3,000 VRI being close to the observed rate. In Table 2 and our earlier work, we presented findings for VRIs up $5,000, and the qualitative consequences were the same.

[17] Individuals with 33 years of service in October 2016 will reach the maximum experience that contributes to their pension by the end of the school year. Recall that 33.95 years of service is the maximum experience that contributes towards the pension, significantly reducing the incentive to continue teaching after the 34th year.

who signed up, we compared ex post outcomes to ex ante predictions. The model accurately predicted the pattern of take rates by age and year of service but under-predicted the overall take rate. Despite the under-prediction, the model correctly predicted that the target of 1,500 takers would not be met.

The contributions of our paper lie in demonstrating the usefulness of structural dynamic models to predict the effects of policy under consideration but not yet implemented, and, through its comparison of ex ante predictions to ex post outcomes, in encouraging future analyses to include timely consideration of contextual factors that can affect decision-making in ways either not captured by model structure or in data used for estimation. The comparison reveals that the predictions were largely accurate, and, given the ex-post data, indicate that the predictions would have been a good basis for policy decisions. However, the differences between ex-ante predictions and ex-post outcomes highlight the limitations of the model and the data available for analysis. We theorize that the ongoing financial struggles of the school district and the act of preparing for retirement may have encouraged more teachers to accept the VRI and not rescind the decision to retire, even when the VRI was not paid. It would have been useful to survey teachers about their decision to express willingness to accept the VRI and retire, and the factors that later led them to rescind their decision. Our approach of considering an additional monetary incentive as a proxy for unobserved or unmodeled behavioral factors that may affect the sensitivity of the response can be applied prior to a policy's implementation. Using this approach, researchers can demonstrate the sensitivity of the model's predictions to factors that may augment or weaken the incentives of the VRI (or alternatively, another policy under consideration).

Sensitivity analyses are valuable by exploring a model's parameter space and determining whether its conclusions are robust, but such analyses do not favor either upside or downside changes. We therefore also advise gathering information about the context of decision-making not captured by the model. In our case, financial turbulence, a reality, and a mind-set shifting toward a life of retirement, a conjecture, both work toward not rescinding the decision to accept the VRI and retire.

Several implications of our analysis go beyond the evaluation of retirement incentives. When the VRI was first considered, stakeholders did not have a credible means to predict take up and therefore were not equipped to consider alternative levels of generosity or alternative targets to trigger VRI implementation. As the outcomes and the predictions showed, the VRI was too low to reach the target, and a goal of 1,500 was unlikely to be achieved even under favorable circumstances. It is important to develop tools to help policymakers understand the interrelationship between the structure and level of compensation and the size and composition of their workforce. Experimental methods are not suitable if there is not enough time or money to conduct an experiment. Traditional approaches using quasi-experimental methods to identify behavioral responses require that a similar policy has been implemented in the past. Structural modeling, where the underlying elements of decisions are put in a logically consistent, estimable theoretical framework, is well suited to meeting the needs of policymakers for guidance in choosing among novel policy options that are intended to yield a behavioral response. This study has demonstrated that a structural model can be effective at producing theoretical responses and empirical estimates that are consistent with behavioral outcomes. The study also demonstrates that these models are not immune to coinciding circumstances. Future theoretical and empirical research could clarify circumstances in which behavioral responses are likely to deviate from a structural model and characterize those circumstances (e.g., are complex compensation offers less likely to evoke a behavioral response?). Finally, future research could use structural models to design policies that accomplish multiple stakeholder objectives, such as reforming pension plans to reduce costs while also minimizing the impact on workforce retention.

Disclosure Statement of David Knapp

I have no relevant or material financial interests that relate to the research described in this paper. Some of the data used in the study are proprietary to the Chicago Public Schools (CPS) system. These are the data on individual teacher choices indicating their willingness to accept the voluntary retirement incentive. We obtained institutional review board (IRB) approval to use the data. The CPS reviewed the study prior to its release and approved its dissemination. Funding for this research was provided through RAND Venture Funds, which are generated from a combination of gifts from RAND supporters and income from operations.

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Appendix A. Dynamic Retention Model

A.1. Model for Entrants into CPS at the Beginning of Their Career

The value of staying to teach in CPS for a teacher of age a at time t is $V^S_{a,t} + \varepsilon^c_t$, where $V^S_{a,t}$ represents the expected value of staying and ε^c_t is a random shock. The expected value of staying is

$$V^S_{a,\ t} = \gamma^c + EC_t + w^c_t + \beta E_t\left[Max\left(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1}\right)\right] \quad \text{(A.1)}$$

where:

- γ^c is individual taste for CPS teaching relative to an external position
- $EC_t = \max\left\{\psi - \frac{\psi t}{12}, 0\right\}$ is an early career taste function for CPS teaching relative to an external position that fades over the first 12 years
- w^c_t is CPS teacher average annual earnings at time t (and experience in CPS is also t)
- β is the personal discount factor
- $V^S_{a+1,t+1}$ is the value of staying as a teacher in CPS at age $a+1$ and time $t+1$
- $V^L_{a+1,t+1}$ is the value of leaving teaching in CPS at age $a+1$ and time $t+1$

- $E_t[\max(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1})]$ is the expected value at t of being able to choose "stay" or "leave" in $t+1$, depending on which has a higher realized value

The value of leaving teaching in CPS at age a and time t is $V^L_{a,t} + \varepsilon^e_t$, where $V^L_{a,t}$ is the expected value of leaving and ε^e_t is the random shock. The expected value of leaving includes external earnings and CPS retirement benefits, if any. Thus,

$$V^L_{a,t} = w^e_a + VRI_t + \sum_{s=a+1}^{A} \beta^{s-a} w^e_s + R^c_{a,t} \tag{A.2}$$

where:

- w^e_a is average annual earnings in the external market at age a
- VRI_t is the value of the voluntary retirement incentive, equal to \$1,500 times t years of service in the 2016-17 school year and zero otherwise
- $\sum_{s=a+1}^{A} \beta^{s-a} w^e_s$ is the present value of future external earnings through period A
- $R^c_{a,t}$ is the present discounted value of retirement benefits accrued for a teacher leaving at age a and with t years of service in CPS

Consistent with policy, Eq. (A.2) assumes that to claim CPS teacher retirement benefits, the individual must have left CPS.[18] Also, in $R^c_{a,t}$, t is the time period as well as the number of years of service in CPS. The notation could be extended to have separate clocks for the time period and for years of service.

An individual decides to continue teaching in CPS at age a and time t if the value of staying is greater than the value of leaving, i.e.,

$$V^S_{a,t} + \varepsilon^c_t = \max\left\{V^S_{a,t} + \varepsilon^c_t, V^L_{a,t} + \varepsilon^e_t\right\}$$

This expression is not an expected maximum but a simple maximum because the shocks in t have been realized and are known to the decision maker. Thus, the probability of staying a teacher in CPS at age a at time t is

$$Pr_{a,t}(Stay) = Pr\left(V^S_{a,t} + \varepsilon^c_t > V^L_{a,t} + \varepsilon^e_t\right) = Pr\left(\varepsilon^e_t < \varepsilon^c_t + V^S_{a,t} - V^L_{a,t}\right)$$

Assuming the shock terms have an extreme value distribution with zero mean and scale parameter λ, the probability of staying has a closed-form expression (Train, 2003):

$$Pr_{a,t}(Stay) = \frac{e^{\frac{V^S_{a,t}}{\lambda}}}{e^{\frac{V^S_{a,t}}{\lambda}} + e^{\frac{V^L_{a,t}}{\lambda}}} \tag{A.3}$$

We do not observe individuals' tastes for teaching in the CPS or random shock terms. Instead, we assume they are each distributed according to known types of probability distributions with unknown parameters that we estimate using available data. Specifically, we assume individuals' tastes for teaching in CPS are normally distributed and the random shocks have an extreme-value type 1 distribution. Given these distributional assumptions, we can derive choice probabilities for each alternative at each decision year and the cumulative choice probabilities or survival probabilities for an entering cohort at each decision year, and then write an appropriate likelihood equation to estimate the parameters of the model. These include the standard deviation of the probability distribution for the shock terms, the mean and standard deviation for the distribution of taste for teaching in the CPS for new-entrant teachers at entry, and the discount factor.

We next present the choice probabilities, the cumulative retention probabilities, and the likelihood equation. The extreme-value distribution, $EV[a, b]$, has the form $\exp(-\exp((a-x)/b))$ with a mean of $a + b\Gamma$ and a variance of $\pi^2 b^2/6$ (or a standard deviation of $\frac{\pi b}{\sqrt{6}} \approx 1.28b$), where Γ is Euler's Gamma (approximately 0.577), a is the location parameter, and b is the scale parameter. We assume the shock terms have a zero mean and scale λ, implying that they have the extreme-value distribution $EV[-\Gamma\lambda, \lambda]$, i.e., $a = -\Gamma\lambda$ and $b = \lambda$. Both ε^e_t and ε^c_t have an extreme value distribution. With this information, the expected value of the maximum has a closed form:

$$\begin{aligned} &E_t\left[Max\left(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1}\right)\right] \\ &= \int\int Max\left(V^S_{a+1,t+1} + \varepsilon^c_{t+1}, V^L_{a+1,t+1} + \varepsilon^e_{t+1}\right) d\varepsilon^c_t d\varepsilon^e_t \\ &= \lambda\ ln\left[e^{\frac{V^S_{a+1,t+1}}{\lambda}} + e^{\frac{V^L_{a+1,t+1}}{\lambda}}\right] \end{aligned}$$

[18] In some public defined benefit systems, it is possible to retire and begin collecting retirement benefits, but continue working as a part-time or contract employee after a certain time away. In Texas, for example, a retiree can return to work after a 12-month break and continue to draw retirement benefits. In September 2020, a district had to contribute 15.2 percent of salary to the Texas Retirement System, which contrasts to contributions for non-retired teachers where the state contributes 7.5 percent, the member 7.7 percent, and the school district 1.6 percent. The district may reduce the teacher's salary to cover part of the 15.2 percent (Texas Classroom Teachers Association, 2022). In CPS, a retiree may return to work and continue receiving retirement benefits. This must be as a temporary and non-annual employee for CPS and/or one or more Chicago charter schools, and the employee may work no more than 120 days per year or earn more than a total \$30,000 per year from any employer(s) (Chicago Teachers' Pension Fund, 2022). A return to work could be handled in our model by altering the choice in the *Emax* expression so that in periods when a teacher is eligible for retirement, based on age and years of service, the choice is between continuing as a teacher, retiring for an external position or to leave the labor market, or retiring to return as a part-time employee in the school district. We do not model returning retirees but treat them as leavers.

Substituting this into the expected value of staying (equation A.1), we have

$$V^S_{a,t} = \gamma^c + w^c_t + \beta\lambda\ ln\left[e^{\frac{V^S_{a+1,t+1}}{\lambda}} + e^{\frac{V^L_{a+1,t+1}}{\lambda}}\right] \tag{A.4}$$

Thus, we have an explicit expression for the value function of staying, given (unobserved to the analyst) taste for teaching in CPS, γ^c. The expression for the value function for leaving, $V^L_{a,t}$, is straightforward and given in equation (A.2). The expressions on the right-hand side of (A.2) and (A.4) are used in model estimation when evaluating the probability that a teacher chooses to stay at age a and having reached time t, $Pr_{a,t}(Stay)$, which is given by equation (A.3). The probability of leaving at age a and time t is $1 - Pr_{a,t}(Stay)$.

Given independent shock draws in each period, the cumulative probability that a CPS teacher entering at time 0 with age a will stay through t - 1 may be written[19]

$$cumulativePr(Stay)_{a,t} = \prod_{s=0}^{t-1} Pr_{a+s,a+s+1}(Stay)$$

The cumulative probability that a CPS teacher who enters at age a stays for t – 1 years and leaves at t is

$$cumulativePr(Leave)_{a,t} = \prod_{s=0}^{t-2} Pr_{a+s,a+s+1}(Stay)\left(1 - Pr_{a+t-1,a+t}(Stay)\right)$$

These probabilities are conditioned on the unobserved taste parameter, γ^c. We assume the taste parameter has a normal distribution $g(\gamma^c)$ with mean μ and standard deviation σ. We use this information to formulate the expected cumulative probability of a given career path, or the likelihood of that path. Thus, for a teacher in our data who enters teaching at age a, stays through t – 1 and leaves at t, the likelihood of that career path is

$$\mathscr{L}_i(\mu,\sigma,\lambda,\beta) = \int_{-\infty}^{\infty} \prod_{s=0}^{t-2} Pr_{a+s,a+s+1}(Stay)\left(1 - Pr_{a+t-1,a+t}(Stay)\right) g(\gamma^c)d\gamma^c \tag{A.5}$$

The subscript i in $\mathscr{L}_i$ denotes the ith teacher. Similarly, if the individual stays through t and is then censored, the likelihood is

$$\mathscr{L}_i(\mu,\sigma,\lambda,\beta) = \int_{-\infty}^{\infty} \prod_{s=0}^{t-1} Pr_{a+s,a+s+1}(Stay) g(\gamma^c)d\gamma^c$$

Thus, the likelihood for the entire data sample, N, is given by

$$\mathscr{L}(\mu,\sigma,\lambda,\beta) = \prod_{i=1}^{N} \mathscr{L}_i(\mu,\sigma,\lambda,\beta)$$

A.2. Extending the Model to Include Incumbent Teachers

The discussion so far is relevant to a population observed at entry into teaching in CPS at the beginning of a career. Our data included new entrants from 1992 to 2000 followed to 2012; however, such a sample provides relatively few stay/leave events in the years a teacher becomes benefit eligible. To augment the sample, we extended the DRM model to allow inclusion of teachers who were incumbent in 1992, on whom we also had longitudinal data from then forward to 2012. The extension assumed their taste distribution at entry was the same as the taste distribution of the 1992 – 2000 new entrants. Under this assumption, we expressed their conditional taste distribution as of 1992 in terms of the new entrant taste distribution and the cumulative probability that individuals of a given taste, who entered in years before 1992, stayed until 1992. Like 1992 – 2000 new entrants, they were then followed forward to 2012 and in each year could choose to stay or leave.

The density of taste, γ^c, at the start of year of service t conditional on staying continuously from entry to t is

$$\begin{aligned} p(\gamma^c|s_0,s_1,\ldots,s_{t-1}) &= p(\gamma^c,s_0,s_1,\ldots,s_{t-1})/p(s_0,s_1,\ldots,s_{t-1}) \\ &= p(s_0,s_1,\ldots,s_{t-1}|\gamma^c)g(\gamma^c)/p(s_0,s_1,\ldots,s_{t-1}) \end{aligned} \tag{A.6}$$

Here, $p(s_0,s_1,\ldots,s_{t-1}|\gamma^c)$ is the probability that a teacher stays continuously to complete $t-1$ years of service (i.e., stays to the beginning of period t) given a particular value of taste drawn at entry into CPS. As before, the density of taste for new entrants is $g(\gamma^c)$. The denominator, $p(s_0,s_1,\ldots,s_{t-1})$, is the probability of staying continuously to complete $t-1$ years of service averaged over all values of taste, that is, taste is integrated out.

The DRM is a first-order Markov process, so the probability of staying in $t-1$ given that one has stayed continuously from entry through $t-2$ is just the probability of staying in $t-1$ given staying in $t-2$, and so forth. The expression in the numerator of (A.6) can then be written

$$p(s_0,s_1,\ldots,s_{t-1}|\gamma^c) = p(s_{t-1}|\gamma^c)p(s_{t-2}|\gamma^c)\ldots p(s_0|\gamma^c)$$

Also, the denominator in (A.6) is this probability averaged over taste:

$$p(s_0,s_1,\ldots,s_{t-1}) = \int_{-\infty}^{\infty} p(s_{t-1}|\gamma^c)p(s_{t-2}|\gamma^c)\ldots p(s_0|\gamma^c)g(\gamma^c)d\gamma^c$$

These results imply that (A.6) can be written as

[19] At entry, each teacher is assumed to decide to stay for the first period. In other words, when a teacher enters, it is assumed that the teacher has in effect decided to stay for the first period: $Pr_{a+0,1}(Stay) = 1$. Hence, the first stay/*leave* decision occurs at the beginning of the second period.

$$p(\gamma^c|s_0, s_1, \ldots, s_{t-1}) = \frac{p(s_{t-1}|\gamma^c)p(s_{t-2}|\gamma^c)\ldots p(s_0|\gamma^c)g(\gamma^c)}{\int_{-\infty}^{\infty} p(s_{t-1}|\gamma^c)p(s_{t-2}|\gamma^c)\ldots p(s_0|\gamma^c)g(\gamma^c)d\gamma^c}$$

The usefulness of this expression for the conditional probability of taste given some period of stay (left-hand side) comes from breaking it into a product of per-period stay probabilities of known form times the a priori taste distribution, also of known form (assumed to be normal), divided by an average value that can be computed from the same expressions.

Using the conditional density for taste of an incumbent teacher's years of service as of 1992, we can construct probability expressions for the incumbent's retention decisions in years from 1992 forward in the same fashion as done for new entrants, where the unconditional density of taste was used. For example, consider teachers who served continuously from entry and were making a stay/leave decision at the beginning of year of service 20 in 1992. These teachers began in 1973 and had already completed 19 years of service. The conditional taste distribution for these teachers is

$$\frac{p(s_{19}|\gamma^c)p(s_{18}|\gamma^c)\ldots p(s_0|\gamma^c)g(\gamma^c)}{\int_{-\infty}^{\infty} p(s_{19}|\gamma^c)p(s_{18}|\gamma^c)\ldots p(s_0|\gamma^c)g(\gamma^c)d\gamma^c}$$

In developing the likelihood for these teachers, this taste distribution was used in place of $g(\gamma^c)$ in (A.5) and their retention decisions were tracked from 1992 through 2012, the last period observed in the data set.

Appendix B. Comparisons for Full CPS Eligible Sample

In this appendix, we introduce additional figures that demonstrate the validity of the model predictions for the entire sample (not just teachers that enters CPS between the ages of 22 and 30). Fig. B.1 presents the relationship between years of service and take rates for the entire sample. As with Fig. 3, the model prediction does a good job of capturing the pattern of taking the incentive by years of service but does not capture the magnitude. In section 6, we introduce and discuss factors not incorporated in the model may incentivized teachers to leave CPS in the year of the VRI offer. Applying the same additional incentive to leave CPS in the year of the VRI offer, we find that the model generally captures both the magnitude of the take rate and the years of service trend.

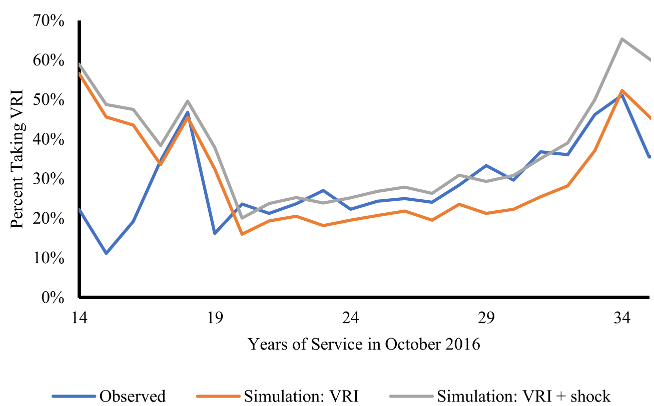

Fig. B.1. Observed and Predicted VRI Take Rates by Years of Service
Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a \$1,500 VRI per year of service. The VRI + shock simulation corresponds to a \$1,500 VRI per year of service and a \$1,500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only the continuous range of years of service are shown that include a number of eligible teachers with a sample size of at least 25.

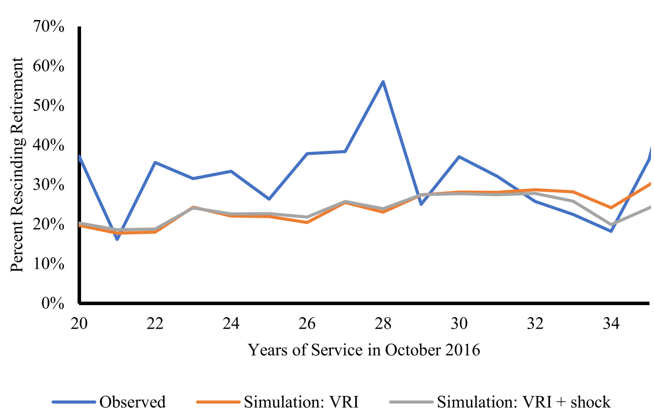

Fig. B.2. Observed and Predicted VRI Rescind Rates by Years of Service
Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a \$1,500 VRI per year of service. The VRI + shock simulation corresponds to a \$1,500 VRI per year of service and a \$1,500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only the continuous range of years of service are shown that include a number of eligible teachers that took the VRI with a sample size of at least 10.

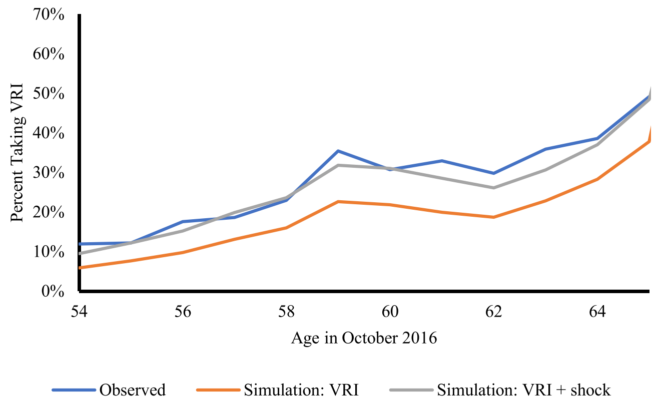

Fig. B.3. Observed and Predicted VRI Take Rates by Age

Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a $1,500 VRI per year of service. The VRI + shock simulation corresponds to a $1,500 VRI per year of service and a $1,500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only ages predicted by the model are shown (i.e., ages below 66). Individuals must be at least age 55 at the time of retirement to be eligible for the VRI.

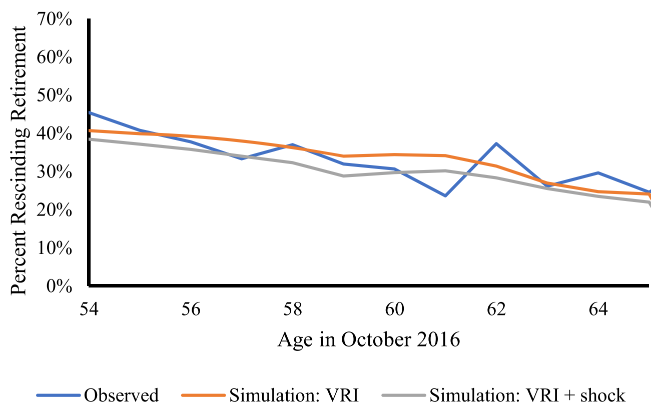

Fig. B.4. Observed and Predicted VRI Rescind Rates by Age

Notes: Sample is based on data provided by CPS after the VRI was offered. The VRI simulation corresponds to a $1,500 VRI per year of service. The VRI + shock simulation corresponds to a $1,500 VRI per year of service and a $1,500 shock incentive per year of service to leave teaching (regardless of VRI offer). Only ages predicted by the model are shown (i.e., ages below 66). Individuals must be at least age 55 at the time of retirement to be eligible for the VRI.

Fig. B.2 presents the relationship between years of service and rescind rates for the entire sample. As with Fig. 4, the observed rescind rate is volatile by years of service. In Fig. 4, we observed that the model generally over-predicted rescind rates for teachers entering between the ages of 22 and 30. However, using the entire sample, we see that the model under-predicts rescind rates among teachers with fewer years of service. We view this as reinforcement of the discussion in section 6 that unobserved factors contribute to the magnitude and volatility of rescind rates among teachers with fewer years of service. For example, teachers with fewer years of service may have limited retirement assets accumulated from work before teaching in CPS.

In additional to the years of service comparisons presented in Fig. B.1 and Fig. B.2, we introduce comparisons by age. Fig. B.3 presents the relationship between years of service and take rates for the entire sample. As with Fig. B.1 and Fig. 3, the model predictions capture the pattern of taking the incentive by years of service but do not capture the magnitude. Applying the additional incentive to leave CPS in the year of the VRI offer, we again find that the model generally captures the magnitude of the take rate as well as the age trend. The number of observed takers is greater at ages 61-63, which might suggest some interaction with the ability to claim Social Security benefits at age 62.

Fig. B.4 presents the relationship between age and rescind rates for the entire sample. Unlike Fig. B.2 and Fig. 4, the observed rescind rate is less volatile by age and exhibits a downward trend as in Fig. 4. It also does not over- or under-predict as substantially along the age dimension as it did with years of service.

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