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*Pensions and Late-
Career Teacher
Retention*

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Abstract

Public school teachers retire much earlier than comparable professionals. Pension rule changes affecting new teachers can be used to close this gap in the long run, but any effects will not be observed for decades and the implications for workforce quality are unclear. This paper considers targeted incentive policies designed to retain experienced high-need teachers, of retirement age, as instruments to extend current teachers' careers. We use structural estimates from a dynamic retirement model to simulate the workforce effects of targeted late-career salary bonuses and deferred retirement (DROP) plans using administrative data from Missouri. The simulations suggest that such programs can be cost-effective, partly because long-term pension savings offset a portion of upfront program costs. More generally, we demonstrate the utility of using structural retirement models to analyze fiscal and workforce effects of changes to public sector pension plans, since the effects of pension reforms cumulate over many years.

1. Introduction

A large empirical literature finds substantial, persistent differences in teacher effectiveness within and between schools. High quality teachers have large effects not only on test scores, but also longer term outcomes such as matriculation to college and wages (Chetty et al., 2014). This highlights the importance of recruiting, cultivating, and retaining better teachers, particularly in low-performing schools. Similar concerns have been raised about the STEM teaching workforce, with emphasis as well on high-need schools.

The literature on the labor-supply responsiveness of teachers to financial incentives is mixed. Findings from Dolton and von der Klaauw (1995), Feng (2009), Glazerman et al. (2012), and Hanushek, Kain, and Rivkin (2004) imply inelastic labor supply, while studies by Clotfelter et al. (2008), Falch (2010), and Feng and Sass (2016) find somewhat larger labor-supply elasticities. However, in contrast to the mixed findings from research on the teaching workforce as a whole, studies of senior teachers consistently show a high degree of responsiveness to pension system incentives (Furgeson et al., 2006; Costrell and McGee, 2010; Brown, 2013; Fitzpatrick and Lovenheim, 2014; Ni and Podgursky, 2016; Knapp et al., 2016). Traditional teacher pension plans (i.e., final average salary defined-benefit) contain strong incentives designed to “pull” teachers to certain combinations of age or experience, and then “push” them into retirement. Retirement rates tend to spike at “full” and “early retirement” cells in age-experience grids. Moreover, when retirement incentives change across the cells in these grids, retirement rates change accordingly.

The elastic response of teachers to retirement incentives and the powerful “pull” and “push” incentives built into most retirement plans suggests an alternative route to teacher staffing in high-need schools or fields – namely, enticing senior teachers to postpone retirement by

altering the “push” incentives for retirement. To date there seems to be little recognition of the potential for such policies, as the empirical research on the effects of pension incentives on teacher quality and school performance is limited.¹ This is particularly relevant because available data suggest that, on average, teachers retire at relatively young ages compared to other professional workers (Harris and Adams, 2007).

In most private sector firms and in other areas of government employment, retirement benefits are seen as useful tools for reshaping the workforce and upgrading quality. For example, the US armed services has for decades manipulated retirement incentives to reshape the workforce to meet manpower requirements (Warner and Pleeter, 2001; Asch et al., 2015).² In the private sector, professionals are primarily covered by defined contribution (DC) pension plans, which do not have the “push” incentives for retirement that are typical of teacher plans. Nonetheless, private sector firms use bonuses and other tools to discourage or encourage retirements by senior professional staff.³

For administrators in traditional public schools, there is no ability to experiment with alternative retirement plans because educators in all of the school districts in a state are required to participate in the state’s teacher plan.⁴ This is in contrast to other dimensions of compensation policy, such as performance pay, where local experimentation is feasible (e.g., Dee and Wyckoff,

¹ Exceptions include Koedel et al. (2013) who study the effects of push and pull incentives on workforce quality, Fitzpatrick and Lovenheim (2014) who examine the effect of an early retirement incentive in Illinois on student test scores, and Chingos and West (2015) who examine the relationship between teacher quality and preferences for retirement plan structure.

² See also: <http://www.leatherneck.com/forums/archive/index.php/t-45263.html>.

³ For example, see <https://hbr.org/2004/03/its-time-to-retire-retirement>, <http://www.plansponsor.com/MagazineArticle.aspx?id=6442461355>, <http://www.mckinsey.com/business-functions/organization/our-insights/retaining-key-employees-in-times-of-change>.

⁴ Charter schools in 14 states are allowed to opt out of state teacher plans. However, there has been no research to date on the effect on teacher retirement behavior in charter schools that exercise that option (Olberg and Podgursky, 2011). A few cities (e.g., Chicago, NYC, St. Louis, Kansas City) have municipal teacher plans. In these cases all educators in district-operated schools are required to participate in the municipal plan.

2015; Yuan et al., 2013). While there is variation across states in the parameters or rules for teachers' defined-benefit (DB) retirement plans, there is essentially no natural experimentation with alternative retirement compensation models or policies. While some states have adopted DC and/or hybrid plans (i.e., a combination of DB and DC plans) for teachers in recent years, these new structures typically apply only for new hires and have not been in place long enough to assess their effects on retirement behavior.

In the absence of sufficient “regulatory space” to generate policy variation and data to undertake traditional evaluations, in this paper we take an alternative approach and use structural estimates from a Stock-Wise “option value” retirement model to simulate the workforce effects of alternative late career compensation schemes and changes to pension plan rules. We study the state of Missouri and focus on high-need teachers, which we proxy by a STEM teaching field. We consider the efficacy of policies designed to offset the powerful late career “push” incentives embedded in traditional teacher pensions plans. In particular, we focus on two policies that target STEM teachers: late career salary bonuses and deferred retirement (DROP) plans. The former are policies that can be implemented by individual school districts or statewide, while the latter would be statewide and require changes in the rules governing the pension plan. Our estimates suggest elastic labor supply responses to these policies, particularly for the DROP plans. The costs per incremental year of retained teaching may be justified if programs are targeted to effective and/or high-need teachers.

2. Patterns of Retirement and Pension Plan Rules

Before undertaking our examination of policy alternatives, it is useful to review some descriptive data on retirements. Harris and Adams (2007) use data from the 1992-2001 Current Population Surveys (CPS) to compare career attrition rates of teachers to those of accountants,

nurses and social workers. Despite the intensive focus in research on early-career teacher attrition (e.g., Goldhaber et al., 2011; Ingersoll, 2001), Harris and Adams show that early-career teachers behave similarly to early-career workers in comparable professions. The divergence between teachers and other professional workers comes later in the career: “teacher turnover is relatively high among older teachers reflecting the fact that they retire considerably earlier than other professionals” (Harris and Adams, 2007, p. 326). Using methods similar to Harris and Adams, in Figure 1 we compare the conditional mean age of retiring teachers in Missouri to the average retirement age for college-educated professionals from a more current CPS sample covering 2008-2014. Figure 1 makes clear that Missouri teachers retire at considerably younger ages than their non-teacher professional counterparts.

(Figure 1)

What factors drive high late-career attrition among teachers? While individual workforce participation decisions are caused by a variety of factors, pension plan incentives surely play an important role. Table 1 summarizes key pension plan rules in Missouri.⁵ The replacement factor is a multiplier that, when combined with years of service, gives the pension replacement rate. For example, a 30-year teacher in Missouri would retire with a 2.5 percent replacement factor, yielding a pension that replaces 75 percent (30×0.025) of the final average salary in retirement (where the final average salary is calculated as the average of the highest 3 years of earnings). In the Missouri plan there are three conditions under which teachers become eligible to collect unreduced pension benefits (i.e., eligible for “full retirement”): (1) the sum of age and experience is 80 or above (“Rule of 80”), (2) the number of in-system service years is 30 or above, or (3)

⁵ We restrict our analysis to teachers in the state retirement plan. This excludes teachers in the St. Louis and Kansas City school districts, who have their own municipal plans. The state plan covers more than 90 percent of Missouri teachers.

age is 60 or above with at least 5 years of service. The modal age of entry into teaching in Missouri is 24, which means that with continuous work a typical entrant would become eligible for full retirement benefits at age 52.

(Table 1)

Figure 2 shows the expected pension wealth accrual profile for a representative age-24 entrant in Missouri over the career cycle assuming continuous work. A projected earnings profile during work is generated using a wage function that is a cubic of experience, estimated on Missouri data. The figure shows the back-loading of pension-wealth accrual and highlights the sharp retirement incentives created by the plan rules. Pension wealth peaks for the representative teacher at the “rule of 80” notch and declines thereafter. Working past the peak yields a higher annual annuity but fewer years to collect it, with the effect of the latter dominating the effect of the former and thus lowering expected pension wealth.

(Figure 2)

This paper explores the efficacy of changing the “push out” incentives in a selective manner, for a targeted group of STEM teachers. School districts, particularly those with mostly low-SES students, regularly report difficulties in recruiting fully-qualified math and science teachers (Podgursky, 2010). Like Missouri teachers overall, the median retirement age for Missouri STEM teachers is 57 (Figure 1). One approach to reducing staffing pressures would be to lengthen the typical STEM-teacher career.

The careers of current teachers could in principle be extended with changes to pension rules that incentivize later retirements (e.g., impose a minimum age for full benefits of 62 or 65, reduce the generosity of the formula factor, etc.). However, legally it is difficult to change pension rules for incumbent teachers (Monahan, 2010). Thus, when reforms of state and local

pension plans occur, including teacher plans, they focus on changes for new teachers. However, the effect of such policies on retirements will not be felt for several decades. We focus instead on a set of voluntarily policies that could be enacted in the near term and provide incentives for teachers to postpone retirement. In order to assess the effects of such incentive policies we need a behavioral model of retirement.

3. Analytic Framework

We model teacher retirements following Ni and Podgursky (2016), who, in turn, use the general framework developed by Stock and Wise (1990) to estimate a structural model that explains the recurring decision to work or retire at later stages of the career cycle. The model incorporates the “option value” of continued work at any given point in the career. The term “option value” is used in this context because in a DB plan the retirement decision is made only once and cannot be reversed. Thus, each year a teacher compares the value of exercising the option (retiring) versus continuing to work and exercising the retirement option at a future date.

In the model, a teacher's expected utility in period t is a function of expected retirement in year m (with $m=t, \dots, T$, where T is an upper bound on the teacher's lifetime). In period t , the expected utility of retiring in period m is the discounted sum of pre- and post-retirement expected utility:

$$E_t V_t(m) = E_t \left\{ \sum_{s=t}^{m-1} \beta^{s-t} [(k_s(1-c)Y_s)^\gamma + \omega_s] + \sum_{s=m}^T \beta^{s-t} [(B_s)^\gamma + \xi_s] \right\} \quad (1)$$

where $0 < k_s < 1$ captures the disutility of working, Y is income while working in real dollars, B is income during retirement in real dollars (i.e., the pension benefit), and c is the teacher's contribution rate to the pension plan. Teacher preferences for current versus future income are captured by the discount parameter β and risk aversion (and the inverse of intertemporal

elasticity of substitution) is reflected in γ . This specification assumes that the disutility of work, k_s , changes monotonically with age: $k_s = \kappa \left(\frac{T_0}{age} \right)^{\kappa_1}$, where $T_0 = 65$ is the maximum age observed in the sample in the first year and κ, κ_1 are parameters to be estimated.

Uncertainty enters the model through the random variables ω_s and ξ_s , which reflect unobserved factors that influence the utility of teaching and retirement. We assume that the unobserved innovations in preferences for teaching relative to retiring, $v_s = \omega_s - \xi_s$, follow an AR(1) process:

$$v_s = \rho v_{s-1} + \varepsilon_s \quad (2)$$

where ε_s is iid normal $N(0, \sigma^2)$, introducing two more parameters to be estimated (ρ, σ).

In previous work, Ni and Podgursky (2016) estimated this model on a panel of Missouri teachers using administrative data from the Missouri Department of Elementary and Secondary Education (MODESE) linked to retirement data from the state teacher pension plan (MOPSRs). Their data panel included teachers aged 47-59 in 2002 who were followed through 2008. Ni and Podgursky (2016) used data on teacher salaries, age and experience – and the pension plan rules shown in Table 1 – to project values of Y and B forward for each teacher in each year. These projections facilitate estimation of the optimal retirement age for each teacher, which maximizes expected utility per Equation (1). Data and source code from Ni and Podgursky (2016) are provided online with their published article.

The resulting parameter estimates in Ni and Podgursky (2016) are plausible. For example, the estimated subjective discount rate is 3.5 percent. The disutility of work versus leisure (retirement) grows with age, teachers are notably risk-averse, and shocks to preferences strongly persist, which likely reflects persistent (but unmeasured) personal and household factors such as health and marital status. More importantly, the model provides excellent out-of-sample

fit in describing teacher responses to a series of pension enhancements enacted in Missouri between 1995 and 2001.

Our current work builds on Ni and Podgursky (2016) by extending the analytic framework to evaluate policy proposals designed to extend teachers' careers. Equations (3) and (4) below show augmented version of Equation (1) for the bonus and DROP policies we evaluate, respectively. All repeating variables and parameters are as defined in Equation (1).

A bonus b to incentivize retention in period q , $t \leq q < m$, modifies expected utility per Equation (1) as follows:

$$E_t V_t(m) = E_t \left\{ \sum_{t \leq s \leq m-1, s \neq q} \beta^{s-t} [(k_s(1-c)Y_s)^\gamma + \omega_s] + \beta^{q-t} [(k_q((1-c)Y_q + b))^\gamma + \omega_q] + \sum_{s=m}^T \beta^{s-t} [(B_s)^\gamma + \xi_s] \right\} \quad (3)$$

The new term in Equation (3), $(k_q((1-c)Y_q + b))^\gamma$, captures the dollar value of the bonus in the year of eligibility.

We also consider DROP policies that allow a teacher to collect a partial or full pension while working. The modified version of Equation (1) under the DROP policies, with the DROP in period m and separation in period $m+1$, is as follows:

$$E_t V_t(m) = E_t \left\{ \sum_{s=t}^{m-1} \beta^{s-t} [(k_s(1-c)Y_s)^\gamma + \omega_s] + \beta^{m-t} [(k_m(Y_m + \alpha B_m))^\gamma + \omega_m] + \sum_{s=m+1}^T \beta^{s-t} [(B_s)^\gamma + \xi_s] \right\} \quad (4)$$

where B_s is the pension benefit from retiring in period m , collected in period s . The new term in Equation (4), $(k_m(Y_m + \alpha B_m))^\gamma$, captures the features of the DROP plan – namely, the value of the annuity during years of work under the DROP plan, B_m , is multiplied by the replacement rate, α , and no pension contributions are taken from salary during DROP-covered years.

As noted above, we focus our analysis on a newer cohort of Missouri teachers from 2011 in STEM fields. While we could in principle re-estimate Ni and Podgursky's model on our

newer, STEM-focused sample, we choose to apply the previous estimates for the parameters in Equation (1) from their study out-of-sample to improve the validity of the exercise and speak to the generalizability of the model. It is important to acknowledge that our use of out-of-sample parameter estimates assumes that the underlying teacher preference parameters are stationary over time, and hold for STEM teachers (i.e., preferences do not systematically differ between STEM and non-STEM teachers near retirement). The out-of-sample predictions of the model for our new sample of STEM teachers, shown below, suggest that this assumption is reasonable.⁶

Table 2 shows the parameter estimates for the model applied in our analysis. They are the same as in Ni and Podgursky with the exception of an updated estimate of σ . The update is because the variance of v_s , which reflects the many unmeasured personal and household factors that affect teachers' propensities to retire, is expressed in dollars and must be brought up-to-date for our sample to reflect real salary growth.⁷ The appendix provides additional analytic details about the process of conducting policy simulations with the model.⁸

4. Out-of-Sample Forecasts

To evaluate the efficacy of the model initially, we use the estimated parameters shown in Table 2 to predict retirement patterns of the 2,131 STEM teachers in Missouri aged 48-65 in 2011 who have at least five years of experience. We track our sample of STEM teachers forward

⁶ In a consequential policy application it may be beneficial to re-estimate the model for the target population. That said, if the target population is small and teacher preferences in this regard are fairly stable across teacher types, as is suggested by our study (at least within Missouri), precision gains from using a larger sample could offset any losses associated with using a less-targeted group for estimation. Moreover, even if the model is re-estimated for a new target population, it would be critical to investigate out-of-sample fit along the lines of what we show below for our newer sample of STEM teachers.

⁷ Ni and Podgursky (2016) estimate $\sigma=3660$ for the sample starting in 2002 and $\gamma=0.72$. We assume the salary grows by 2.5% annually in real terms. Thus, for the new sample starting in 2011, we use $\sigma = 3660 \times 1.025^{(2011-2002) \times 0.72}$ (see Ni and Podgursky (2016) footnote 13 for more details on the adjustment on σ). This adjustment is necessary because the error is additive to the utility of salary.

⁸ An important issue addressed in the appendix is sample censoring driven by the fact that some teachers with idiosyncratic preference errors are more likely to have retired before reaching our sample window. Section II of the appendix describes a novel approach to correct for this censoring in the simulation sample.

in time for three years through 2014 to evaluate retirement behavior, comparing model predictions to observed outcomes. Table 3 provides descriptive information about the sample.

To quantify the statistical significance of the mismatch between predicted and observed quantities, two types of errors merit attention. One is sampling error that affects the estimated parameters of the structural model. This is the usual basis of confidence bands. The width of the confidence band is a function of the standard errors of the estimated parameters. Because of the prohibitive time cost of simulations using multiple parameters on a large number of teachers in this study, we only use the point values of the estimated structural parameters in our simulations, ignoring this type of error.

The second type of sampling error stems from the draws of preference errors for each teacher. Aggregate quantities – e.g., the teacher survival rate in 2015 – are also affected by this type of error. Aggregation of the retirement decisions for all STEM teachers based on a draw of the preference errors yields an estimate of survival rate in each year. We obtain 10,000 predicted survival outcomes in each year from sets of preference errors for each teacher, aggregate over all teachers in the simulation sample, and plot a 95% confidence band for the overall survival rate based on the empirical distribution. Because our confidence bands do not take the first type of error into account, they are conservative.

Data on actual and predicted survival rates for our sample are presented in Figure 3 along with 95 percent confidence bands. Over the three-year period, 31.3 percent of the STEM teachers retire. Overall, the model does a good job fitting employment survival for this out-of-sample group. Figures 4 and 5 report the age distributions of retired and non-retired STEM teachers over this period. Non-retired teachers are those who had not retired by 2014. The model provides an excellent fit to the age distribution of both groups. Figures 6 and 7 report experience distributions

for retirees and non-retirees. Here the fit is not as good as for age. The model over-predicts retirements in the 25-30 year experience range and correspondingly under-predicts in the same range for non-retirees. Nonetheless, for nearly all age and experience groups, the actual values fall within the conservative 95 percent confidence bands.⁹

(Figures 4-6)

5. Simulated Effects of Retention Policies

We use the model to examine the effects of two different incentive policies, retention bonuses and Deferred Retirement Option Plans (DROP). Two key design aspects for a retention bonus or DROP policy are: (1) which teachers are offered an incentive, and (2) how large is the incentive and for how long. There are several factors that determine the efficiency of the incentives. One issue is that the policy will generate a weak behavioral response if the teachers who are offered an incentive would have continued working even in its absence. Moreover, for the policy to be cost effective, it must be the case that a group of teachers with a sufficiently high probability of retirement can be identified. Otherwise the incentives will largely accrue to infra-marginal teachers who would have kept working anyway.

It must also be the case that the retirement behavior of at least some of these retirement-prone teachers can be changed – that is, there must be some teachers at the margin such that a retention incentive can convince them to continue teaching. As the dollar value of the incentive gets larger, more and more teachers will respond. However, the higher the value of the incentive, the more expensive each marginal and infra-marginal payment becomes.

⁹ The model fit is similar for the full sample of 2011 Missouri teachers (comparative results omitted for brevity), which is consistent with STEM teachers having similar preferences to the larger workforce.

Note that a retention incentive not only affects teachers directly targeted in the retirement window, but may also affect teachers who enter the retirement window in the future and have lingering effects after the incentive period (depending on the structure of the incentive). The cumulative effects of the “pull” toward incentive eligibility is a nonlinear function of the size of the award. The efficient incentive size (per teacher) depends on all of these tradeoffs. . .

For both the retention-bonus and DROP policies, we identify experience cells at which retirement rates are particularly high to intervene in an effort to minimize infra-marginal payments. Given the parameters of the Missouri plan, this leads us to focus on an experience level of 32 years. As can be seen in Table 1 and Figure 2, there is a formula-factor bump that comes with completing the 31st year of service in Missouri. Empirically, this results in a retirement spike after the completion of that year (Koedel, Ni and Podgursky, 2014).

5.1 Selective Retention or Longevity Bonuses

The first policies we consider are single-payment retention bonuses of \$5,000 and \$10,000 paid to STEM teachers who attain 32 years of experience. Again, the bonuses are designed to retain STEM teachers working in the retirement window by partially offsetting the “push” incentive of the pension plan. An advantage of the bonus policies we consider is that they can be implemented independently by a single district, or statewide. They would not need to be coordinated with the pension plan. We assume that bonuses are for one year only and do not enter base pay, which means that they do not enter into the calculation of the retirement annuity (i.e., they are not part of the salary used by the pension fund to compute final benefits).

Table 4 reports the simulated effect of the bonus policies for our cohort of STEM teachers. We use the structural model to simulate retirements over thirty years under permanent, single-year bonus policies. Over the 30-year window, nearly all of these teachers will have

retired. The column labeled “baseline” shows that we would have expected 13,759 additional years of teaching from this cohort in the absence of any retention policies, and teachers would have retired with average experience of 26.7 years. .

(Table 4)

Columns two and three of Table 4 report the effect of two different one-time bonuses, of either \$5,000 or \$10,000, paid to all STEM teachers who attain 32 years of experience. Because the bonus policies are permanent, all teachers know that they will receive the bonus if they reach the relevant threshold in the future. This allows the implementation of the bonus to affect work/retirement decisions for teachers leading up to the incentivized experience level.

The table shows that a \$5,000 bonus yields 61 additional teaching years from this cohort. The average gross cost per additional year is \$73,083, which arises from several sources. First are the bonus payments themselves. The bonuses are paid to marginal teachers, who would have retired without the bonus, and to infra-marginal teachers, who would have worked anyway. Second, working in the opposite direction, there is a decrease in total pension wealth for marginally retained teachers because they forgo pension payments while working (Figure 2). There is a partial offset of the pension savings owing to induced retention prior to the bonus, which raises pension wealth a little. Finally, there is the salary earned by the retained STEM teachers while they continue working. All of these factors are accounted for in our gross cost estimates.

When the dollar value of the bonus doubles from \$5,000 to \$10,000, the increase in retained STEM teaching years more than doubles, from 61 to 141, and the average cost per year drops slightly. The reason is that as the bonus increases, retention rises for teachers at all experience levels (seen most clearly in Figure 9 below). However, the bonus is only paid to

teachers who hit the Experience = 32 benchmark. Some of the less experienced teachers who are retained as a result of the bonus will ultimately exit before they ever collect due to other reasons (e.g., alternative job offers, health, unexpected mobility). These marginal years are “free” in that the teachers contributing them will never collect the bonus. The larger the incremental pool of pre-eligibility retained teachers (i.e., with experience less than 32), the larger will be the ratio of free to compensated years, hence the lower costs. Increasing the size of the bonus raises this ratio. However, an oversized bonus is inefficient because the number of marginal teaching years has a limit and a higher bonus amount results in higher payments to all teachers.¹⁰

Net costs of an incremental year (row 5) are much lower than gross costs (row 4) because they account for the foregone cost of replacing a retained experienced teacher – namely, the cost of a novice teacher. For our net cost calculations we assume that the size of the teaching workforce does not change as a result of the policy. Thus, if a STEM teacher retires, she is replaced by a novice; and if she does not, the replacement cost is forgone. Row 5 of Table 4 incorporates the cost of novice replacements by showing the cost of an additional retained year of experienced teaching net of the replacement salary of a novice.¹¹ This is our best estimate of the actual cost of an additional year of teaching from the bonus policies. For the \$5,000 and \$10,000 bonuses this ranges between roughly \$36,000 and \$39,000. Finally, the last two rows of the table reports the elasticities of additional experienced years of teaching with respect to the gross and net costs. The simulated gross and net elasticities are about 1.5 and 3.0, respectively, and are similar for both the \$5,000 and \$10,000 bonuses.

¹⁰ That is, the cost curve is U-shaped with respect to the size of the bonus (result not shown for brevity).

¹¹ In the case of a marginally retained teacher the district saves the salary of the novice teacher who wasn't hired that year, but it does not save the hiring and recruiting costs since the retained teacher will eventually need to be replaced. It merely postpones the latter costs. We do not incorporate the modest savings due to postponed recruiting into our calculations and note that the net cost estimates we report in Table 4 are biased slightly upward as a result.

5.2 *Selective DROP Plans*

The next three columns of the table report the effects of selective DROPs. The DROPs permit employees to retire and begin collecting all or part of their pension annuities and continue working for a limited period of time, per Equation (4). From the date that the teacher enters the program forward she no longer contributes to the pension plan, nor does she accrue additional service. The annuity payments are usually put into an escrow account while the teacher continues to work, and become available with interest when she stops (i.e., discontinues covered employment).¹²

While most states do not have DROP plans, several have implemented them. For example, teachers in Arkansas for many years have had the option of participating in a DROP plan where they receive roughly 70 percent of their pension annuity and can continue to work full time for up to ten years.¹³ Similarly, Florida teachers can retire, have their annuity deposited in an escrow account, and continue in full time employment for up to five years, after which they terminate employment and collect their accumulated annuity payments plus interest.¹⁴ The Louisiana teacher retirement system also provides a DROP option for retirement eligible teachers for up to three years.¹⁵

Although several states offer or have offered this option for educators, in every case of which we are aware, it is an untargeted program. That is, it is available to all retirement eligible

¹² Unlike retention bonuses, which could be implemented independently and at the district or state level, DROP plans are implemented statewide. Interestingly, while Missouri teachers do not currently have a DROP plan, policymakers have taken a small step in that direction by permitting retired teachers in “critical shortage” areas (as defined by a district) to take full time covered employment for up to two years and continue collecting their retirement annuities. Many other states have similar “critical shortage” waivers pertaining to post-retirement full time work. Unfortunately, we have no data on the usage of such provisions in Missouri.

¹³ <https://www.artss.gov/members/teacher-deferred-retirement-option-t-drop/how-does-t-drop-work>

¹⁴ http://www.dms.myflorida.com/workforce_operations/retirement/members/deferred_retirement_option_program_drop

¹⁵ https://www.trsl.org/main/optional_programs/drop

teachers. We are aware of no cases of a targeted DROP but in principle there is no reason a targeted DROP would not be possible. Thus, in this section we simulate the effect of DROP plans for our sample of STEM teachers in Missouri.

We consider three DROP plans with different levels of annuity replacement while working. All three plans permit recipients to collect annuities for one year while working when they hit the experience benchmark (in our case 32 years), after which they must retire. The requirement to retire after one year is restrictive relative to DROP plans that have been implemented in practice, which as noted above flexibly allow for additional work for one-to-multiple years after DROP enrollment, but it is useful for head-to-head comparisons with the bonus treatments. Moreover, as we discuss below, our analysis highlights the targeting inefficiency of exit-year flexibility in previous DROP plans, which permits more infra-marginal take-up. We also note that even with the requirement of full separation after one-year, all three of the DROP plans we consider raise cohort retention rates.¹⁶

We consider cases where teachers collect 50, 70, and 100 percent of their regular annuity under the DROP plan. The former cases result in savings to the pension plan for marginally retained workers, and at the same time may be attractive to teachers because they permit significantly higher incomes during years of work under the DROP when partial retirement payments can be collected at the same time as salaries. The DROP programs are entirely voluntary and as such there should be no legal problems with this type of pension reform, as the experience with DROP plans in many states indicates.

The results from the DROP plans are summarized in the second vertical panel of Table 4. We focus our discussion on the 70 percent case because it is similar to an already existing plan

¹⁶ In unreported results we also simulate 2-year DROP plans, which unsurprisingly have larger effects on retention but are more costly. Net-price response elasticities for 1- and 2-year DROP plans are similar.

(i.e., Arkansas teachers). The 70 percent DROP plan yields an additional 122 years of experienced STEM teaching for our sample at an average net cost of \$11,040 per additional year. The elasticity of additional STEM years with respect to net costs is very high, at 10.35 (the gross cost elasticity is also non-negligible, at 2.52).

There are two reasons the net-cost elasticity is so high. First, and most importantly, the requirement that teachers commit to separation after one year forces many infra-marginal teachers (i.e., those who planned to stay past 32 years anyway) to self-identify and reject the DROP plan; no such deterrent is present with the bonus plans. To see why this is so important, imagine there is a group of teachers who strongly prefer teaching over retirement (a large positive value of v_s in equation (2)). These teachers would all collect the retention bonus. However, the DROP plan will be unappealing because it forces them to begin collecting the annuity at experience = 32 and quit teaching after the following year. The DROP plans thus more effectively target marginal teachers.

This aspect of our analysis highlights a strategic inefficiency of DROP plans that have been implemented in public policy thus far, as described above. Namely, beyond a general lack of targeting toward high-need teachers, available plans have allowed teachers to exit flexibly from the DROP each year within a window with a maximum of 3-10 years. This flexibility permits take-up from infra-marginal teachers who expect to retire within a wide post-eligibility range of experience, which will cover most teachers (empirically, few teachers work far beyond retirement eligibility) and obviates the efficiency gains from the revelation requirement of the restrictive DROP that we simulate.

The second reason for the cost-efficacy of the DROP plans is that at least for the partial-replacement plans, marginal teachers that are induced to remain give back substantial value in

terms of pension wealth. While the DROPs are still a net gain for individual teachers, per the clear behavioral response documented in Table 4 (and Figures 8 and 9 below), the pension “give back” of the partial replacement DROPs works to offset the wage gap between retained senior teachers and their potential novice replacements. For the 50-percent DROP, the pension savings essentially offsets the salary gap on average. This fact, combined with the low take-up of infra-marginal teachers, is what drives the especially low net cost per retained year of experienced teaching under that plan. Costs go up as the DROP replacement rate rises because pension savings per retention decline. However, the effect is partially offset because the more lucrative DROPs induce notable additional retention leading up to the incentive year, thus generating more than one year of retained experienced teaching for each DROP recipient (Figure 9).¹⁷

Figures 8 and 9 illustrate general differences in the effects of the DROP and bonus plans that we simulate. First, Figure 8 shows the distribution of years of experience at separation for the 2011 cohort, making clear that the effects of the DROP plans are more concentrated at 32 years of experience. All of the DROP plans produce a very sharp reduction in retirement for the year when experience = 32 and then sharp increases in retirement (i.e., actual workforce exit) when experience = 33, with no change relative to the baseline in subsequent years. The bonuses, by contrast, since they involve less remuneration for teachers, produce a more modest bump in retirements at experience = 32. The bonus plans also allow for some post-treatment “lingering,” i.e., retention beyond experience = 32. Such “lingering” is precluded by the structure of the DROP plans we simulate, in which teachers must retire after the one-year window.

(Figure 8)

¹⁷ The 50-percent DROP also generates an uptick in retention prior to the incentive year (Figure 9), but it is very small.

Figure 9 provides further insight into the effects of the bonus and DROP policies. Here we plot the percentage *change* in the cumulative density function (cdf) of experience as compared to the baseline with no retention incentive. The large spikes for the DROP plans are clearly visible, and the 70 and 100 percent DROP plans, and the \$10,000 bonus plan, notably raise teacher retention prior to the incentive year. The figure makes clear that it would be misleading to assess the effectiveness of any of the incentive plans, but particularly the plans with sizeable incentives, by just focusing just on the “treatment” years. In a dynamic framework, the programs affect retention decisions in other years as well.

(Figure 9)

5.3 Targeted Versus Untargeted Policies

It should be noted that in the case of either retention bonuses or selective DROP plans, targeting of the retention incentives is critical to cost efficacy. There are two aspects of targeting that are important. The first is targeting the incentives to selected teachers rather than all teachers. Retention bonuses aimed at all teachers are a very expensive way to retain STEM teachers, or any other subgroup that policymakers identify as particularly valuable. For example, in the context of the bonus policies, a \$10,000 retention bonus provided to both STEM and non-STEM teachers would raise the net cost of an additional STEM year from \$35,881 to \$600,055. A 70-percent DROP plan provided to all teachers would raise the cost of an additional STEM year from \$11,040 to \$356,298. While these policies would also generate additional retention among non-STEM teachers, if the objective is to increase STEM teaching capacity, an untargeted policy is very costly. This is an important caveat as policies like the ones we consider have historically been implemented without clear targeting toward teachers in high demand.

The second aspect of targeting, discussed above, is with respect to retirement peaks inherent to the system under intervention. In Missouri retirements are concentrated most strongly after the 31st year; plan rules in other states will generate different retirement spikes. As noted above, a \$10,000 retention bonus provided at 32 years of experience in Missouri has a net cost of \$35,881 per retained STEM year. The same bonus provided at 26 years of experience raises the net cost to \$43,923 because more infra-marginal payments are made.¹⁸

6. Conclusion

Traditional DB pension plans create strong “pull” and “push” incentives that concentrate teacher retirements at relatively early ages. Legal and political factors have prevented reform of these systems for incumbent teachers and the limited reforms that have occurred are focused on new teachers. The benefits of reforms for new hires will not be seen for many decades. In the meantime, policymakers have ignored the potential for improving the workforce by neutralizing the strong “push” incentives in teachers’ retirement plans in a selective manner through targeted retention incentives for late career teachers. Using administrative microdata from Missouri, we simulate the effects of two types of policies designed to postpone retirement for STEM teachers. We show that selectively neutralizing the “push” incentives for STEM teachers via a targeted DROP plan can yield additional teaching years by senior teachers for as little as \$1,269 per year (50-percent DROP). Retention bonuses are costlier, at \$35-38,000 per incremental year.

Are such policies worth the cost? If the incentives were targeted to the most effective STEM teachers, then these plans would comfortably pass a cost-benefit test, particularly since the counterfactual would be replacing a year of instruction by an exceptionally effective senior teacher with a year of instruction from a novice. For example, based on the estimates of Chetty et

¹⁸ Modeling a DROP plan at 26 years of experience is complicated by the fact that most teachers would not be eligible for regular retirement at this milestone. Thus we do not simulate such an option.

al. (2014), one year of instruction by a teacher in the 95th percentile (as compared to the mean) yields a discounted benefit of roughly \$212,000. If targeting based on teacher quality is not possible, the cost effectiveness of the policies we consider is less clear. But even with a quality independent policy, available evidence showing that experienced teachers are more effective on average than novices (e.g., Clotfelter et al., 2006) could support some of the lower-cost DROP options we consider. If a policy were targeted to improve equity as well – e.g., by focusing on experienced STEM teachers in high-poverty schools – the value of the equity benefits would further improve a cost-effectiveness calculation.

The problem that the bonus and DROP policies we evaluate are designed to ameliorate is that teachers in high-need fields retire at young ages relative to their professional counterparts. This is the product of strong incentives built into teachers' final average salary DB pension plans across the nation (Costrell and Podgursky, 2009). Despite major fiscal problems in these plans in many states, and policy shifts in a handful of states, there is currently no indication of a broad shift away from this structure of retirement benefits for teachers. Moreover, even in states where reforms have been undertaken, they do not affect incumbent teachers. Thus, working within the constraints of the current plans, states might consider exploiting teachers' powerful retirement incentives in a strategic manner to improve workforce quality. This strategy has been used for decades by the U.S. military and might have benefits for public schools as well.

Aside from the specifics of this particular policy simulation, this exercise shows the value of using structural retirement models to assess the effects of pension system reforms. Many states and municipalities face intense fiscal pressures to restructure their pension plans. Given the long time horizon over which these changes reshape the workforce, and the fact that existing pension plans provide almost no scope for experimentation, assessing the workforce effects of

pension reforms cannot make use of the traditional tools of policy evaluation. Micro-simulation exercises such as the one in this paper can help policymakers make more informed decisions with regard to pension plan reform.

Appendix

I. Details on the Structural Policy Simulations

There are four main steps in using the estimated parameters of the structural model for policy simulations.

1. Structural Estimates

We rely on the Ni and Podgursky (2016) parameter estimates based on a 2002-2008 panel of Missouri teachers aged 47-59 in 2002. The likelihood is computed from the following: the expected gain from retirement in period m over retirement in the current period t is

$$G_t(m) = E_t V_t(m) - E_t V_t(t) = g_t(m) + K_t(m)v_t,$$

where $g_t(m)$ is the difference in the expected utility from the flow of salary and pension benefits

between retiring in period m and current period t , $K_t(m) = \sum_{s=t}^{m-1} \pi(s|t)(\beta\rho)^{s-t}$ is a positive valued

function of the model parameters, and $K_t(m)v_t$ is the expected difference in the preference

errors between retiring in period m and period t based on the information in period t . There are

three sources of uncertainty in the model: uncertainty of future earnings and benefits (which we

ignore here because teachers' salary schedules are fixed), uncertainty of survival, and uncertainty

in the aforementioned preference shocks. To make survival uncertainty explicit, for a teacher

alive in period t we denote the probability of survival to period $s > t$ as $\pi(s|t)$. We can then write

$$g_t(m) = \sum_{s=t}^{m-1} \pi(s|t)\beta^{s-t}(k_s(1-c)Y_s)^\gamma + \sum_{s=m}^T \pi(s|t)\beta^{s-t}(B_s)^\gamma - \sum_{s=t}^T \pi(s|t)\beta^{s-t}(B_s)^\gamma.$$

Let $m_t^\dagger = \text{argmax } g_t(m)/K_t(m)$, be the year among all possible choices of m that maximizes

$\frac{g_t(m)}{K_t(m)}$. Then the probability that the teacher retires in period t ($G_t(m) \leq 0$ for all $m > t$) is:

$\text{Prob}\left(\frac{g_t(m_t^\dagger)}{K_t(m_t^\dagger)} \leq -v_t\right)$. The MLE of model parameters maximizes the joint probability of each

teacher retiring in the year she is observed to retire. See Ni and Podgursky (2016) for further details, along with the source code provided with their published article.

2. *Out-of-sample goodness of fit*

The parameters of the structural model describe basic teacher preferences, e.g., preferences regarding current versus future income (their discount rate), intertemporal substitution of consumption (that measures the desire to smooth income over time), and age dependent preferences for leisure versus work. They also include estimates of parameters pertaining to the nature of the statistical errors in the data (e.g., the variance of the errors that capture the missing data relevant for retirement decisions, such as health and spousal variables; and the persistence of the errors). The key feature of these parameters and the stochastic structure of the model is that they are independent of any particular set of pension rules or retirement incentives. The simulations in this paper are conducted under the assumption that these basic parameters are stable over time and do not differ between STEM and non-STEM teachers.

In order to test whether the assumption of pension-rule and sample independence is reasonable, we conducted a series of out of sample forecasts described in the text and Figures 3-6. The out-of-sample forecasts for 2011-2013 STEM teachers were developed as follows. For each STEM teacher we drew a pre-set number (10,000) of preference errors given by the AR(1) process in equation (2) and simulated the binary decisions (1=retire, 0=stay) in period t based on the inequality:

$$\frac{g_t(m_t^+)}{K_t(m_t^+)} \leq -v_t. \quad (1a)$$

where $\frac{g_t(m_t^+)}{K_t(m_t^+)}$ depends on the data, pension rules and retention incentives. The simulated frequency of retirement decisions for each teacher in each period is the predicted retirement probability.

Because the quantities of interest are aggregate variables (e.g., the fraction of all teachers in 2015 who choose not to retire), for goodness of fit we compare the aggregate quantities such as the survival rate in 2012 with the actual values. Averaging over all teachers yields the point prediction of the survival rate, which can be compared with the observed rate. Similar methods are used for the age and experience distributions of retirees and non-retirees.

3. Confidence Bands

We report “confidence bands” pertaining to latent preference errors. As note earlier, these bands differ from conventional confidence bands because the latter account for uncertainty in the parameter estimates due to sampling error. In this paper we conduct the out-sample exercise for a fixed set of parameter estimates obtained from Missouri teacher data for 2002-2008, as shown in Table 2. Our bands do not account for the uncertainty in those estimates due to the sampling errors. Instead, they only simulate uncertainty due to simulated preference errors implied in the Missouri 2011-13 data. We use the averages of the statistics (e.g., for retirement rate of a given year) from a large number of simulations of the preference errors. The bands show the critical values of a 95 percent confidence band using our conservative approach.

4. Policy simulations

After establishing satisfactory out-of-sample fit, we use the structural estimates to simulate quantities of interest for our sample of STEM teachers under the different retention incentives. For each policy under consideration we replicate the procedure used for out-of-

sample simulation described above. The only difference lies in the values of the function $g_t(\cdot)$, which depends on the policy under consideration. . .

II. Sample Selection Bias Correction

The forward-looking model described in (1) applies to the population of all employed teachers who are making retirement decisions. In that population, we assume that the preference uncertainty variable v_s is centered on zero. However, if we draw a given sample of retirement-eligible or near-eligible teachers (in our case, teachers with age between 48 and 65 and at least five years teaching experience), we will tend to oversample teachers with positive values of v_s , because teachers with negative values are more likely to have retired before reaching our sampling window. As a consequence the model will tend to over-predict retirement rates in the early years of the panel. Here we describe a novel approach to correct for this censoring in the simulation sample.

In the option-value model, the retirement condition for teachers in each year is shown by the inequality in appendix equation (1a). The preference shock v_s follows an AR(1) process in text equation (2). The key question is how to assign the initial value v_1 . The sample in the initial year, 2011, includes all teachers aged 48-65 in that year. Thus, the dataset includes teachers who were eligible for retirement but who chose to stay, but excludes those who chose to retire prior to 2011 (i.e., $t=1$). For the "stayers" in 2011 we know that $\frac{g_t(m_0^+)}{K_t(m_0^+)} > -v_0$, which implies that the initial value v_1 differs from the unconditional stationary distribution $N(0, \sigma^2/(1 - \rho^2))$. Drawing the initial value v_1 from the unconditional stationary distribution without taking this sample selection bias into account will result in over-predicting retirement in the initial years.

We adjust for sample selection bias using the following procedure: suppose a teacher in the 2011 sample was eligible to retire J years prior to 2011 and chose to stay. We back-track the retirement decision in each of the J years. We draw v_{-J} from $N(0, \sigma^2/(1 - \rho^2))$, and generate v_t for $t=-J+1, \dots, 0$ based on the AR(1) process in equation (2). If the draws of v_t prior to 2011 satisfy $\frac{g_t(m_t^\dagger)}{K_t(m_t^\dagger)} > -v_t$, for $t=-J, \dots, 0$ (i.e., the draws imply the teacher did not retire by year 2011), we then keep the draws of v_0 , and draw v_t for $t=1, \dots, T$ based on equation (2). We repeat this procedure until the number of kept draws reaches a pre-set number (10,000) and then compute the retirement probabilities by year.

Table 1. Key Teacher Pension Plans Rules.

<u>Missouri (PSRS)</u>	
Replacement Factor	2.5% if Exp \leq 30 2.55% if Exp $>$ 30
Eligibility - Regular	Age 60 & Exp \geq 5, OR Exp 30, OR Age & Exp \geq 80,
Eligibility - Early	Exp 25, OR Age 55 & Exp \geq 5
<u>Social Security</u>	No

Source: Pension plan reports. Note that Missouri PSRS does not cover teachers in Kansas City and St. Louis – who are covered by separate plans – but covers all teachers in the state.

Table 2. Out-of-Sample Parameter Estimates from Equation (1).

Parameter	Estimate
β	0.965
κ	0.640
κ_1	0.976
γ	0.716
σ	4295.1
ρ	0.643

Notes: This table replicates information from column (1) of Table 3 in Ni and Podgursky (2016), with the exception of the estimate for σ , which is updated for our sample to account for real wage growth as described in the text. The parameter estimates come from the model shown in Equation (1), estimated on a sample of Missouri teachers aged 47-59 in 2002 over a sample period 2002-08. Standard errors are in parentheses.

Table 3: Simulation Sample: Missouri STEM Teachers.

Sample Year	Number of Teachers	Age	Experience	Male
Base Year				
All 2011	2131	54.31	20.30	0.31
Retirement Year				
2011	238	58.27	25.21	0.31
2012	217	58.62	24.80	0.37
2013	213	59.27	26.57	0.35
Not Retired by 2013	1463	56.21	21.82	0.30

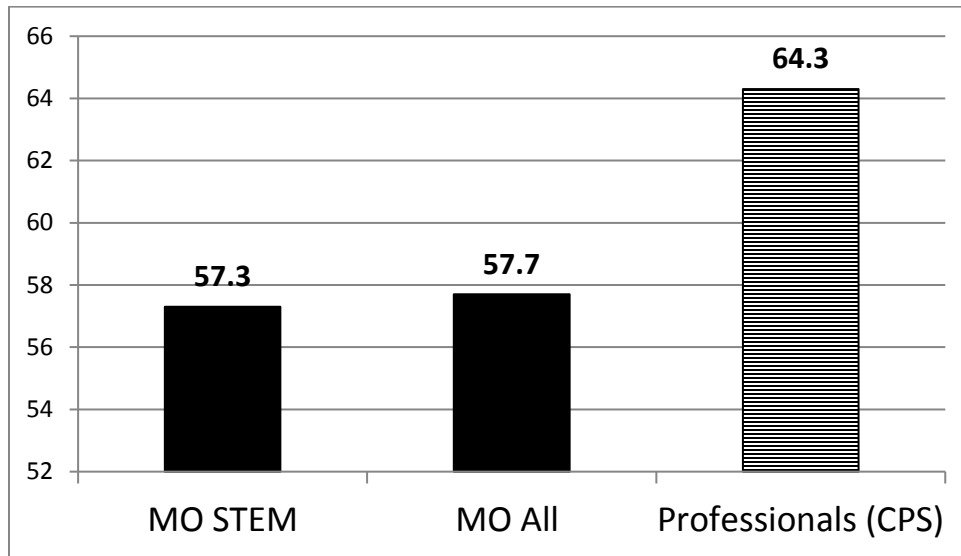
Source: Missouri administrative teacher records. Teachers 48-65 in 2011.

Table 4. Effects of Retention Bonuses and DROP Plan on STEM Teacher Retention.

	baseline	Retention Bonus at Exp =32		DROP at Exp 32 Percent of Annuity		
		\$5,000	\$10,000	50%	70%	100%
Total Additional Years of Teaching	13,579	13,640	13,720	13,649	13,701	13,809
Average Experience At Retirement	26.69	26.72	26.76	26.72	26.75	26.80
Additional Teaching Years (total minus baseline)	---	61	141	70	122	229
Average Gross Cost Per Additional Year	---	\$ 73,083	\$ 70,146	\$ 35,534	\$ 45,305	\$ 54,311
Average Cost Net of Novice Hire	---	\$ 38,818	\$ 35,881	\$ 1,269	\$ 11,040	\$ 20,046
Elasticity (Gross Cost)	---	1.56	1.63	3.21	2.52	2.10
Elasticity (Net Cost)	---	2.94	3.18	90.05	10.35	5.70

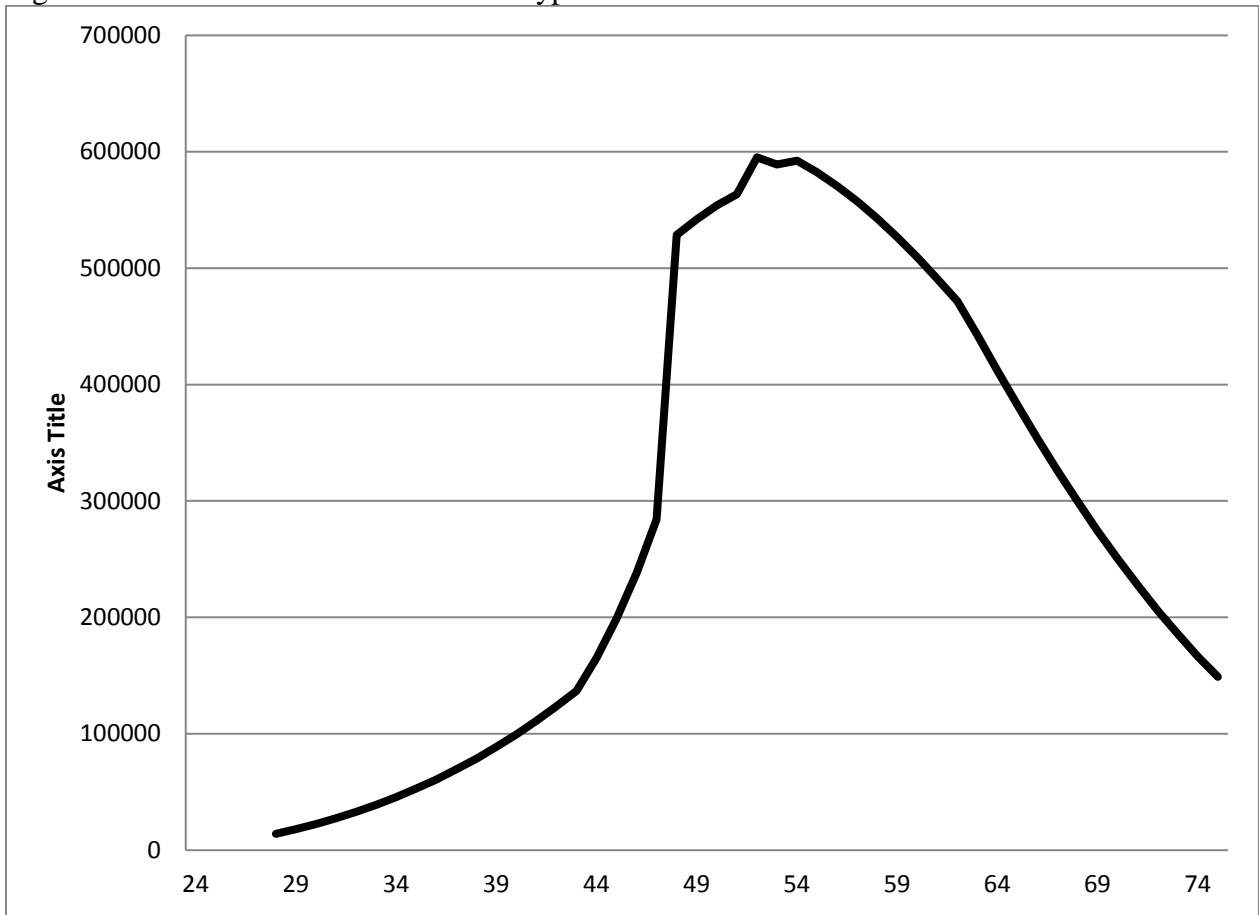
Source: Simulations from retirement model for the 2011 teaching cohort (n=2,131) over 30 years. We assume the cost of novice replacement of a retiring teacher is \$34,265. See text for details.

Figure 1. Mean Retirement Ages: Missouri Teachers and College-Educated Non-Teacher Professionals.



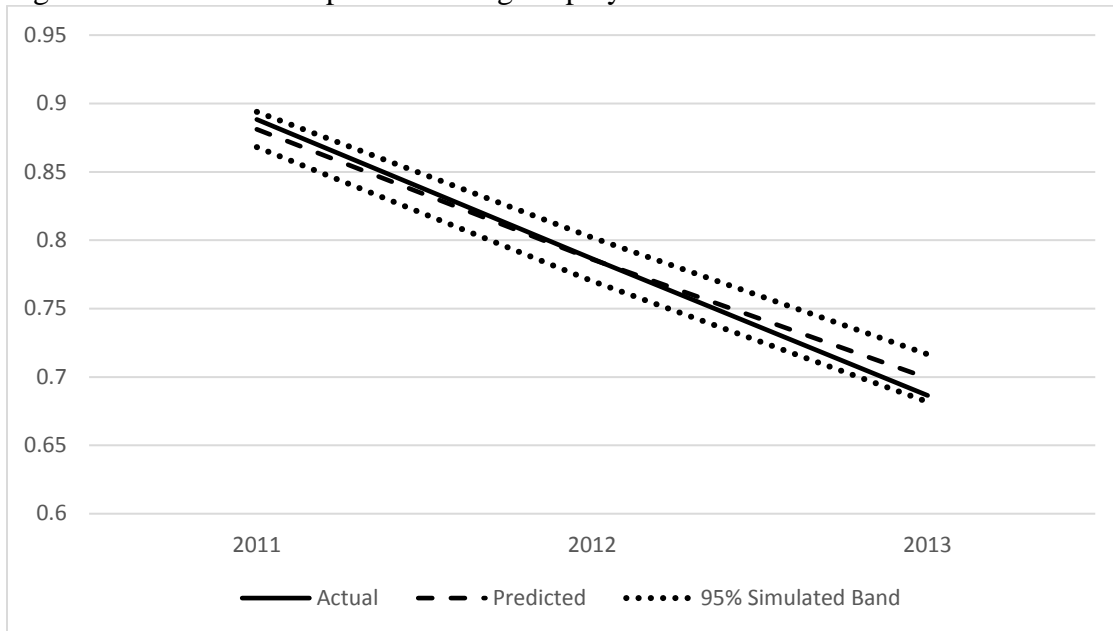
Notes: These are the conditional mean ages for teachers and college-educated (non-teacher) professionals, aged 50-65 who were employed in year t and left the workforce in year $t+1$. For MO this is the average for teachers employed 2008-2013; for the professionals, years 2008-2014.

Figure 2. Pension Wealth Accrual for a Typical Missouri Teacher.



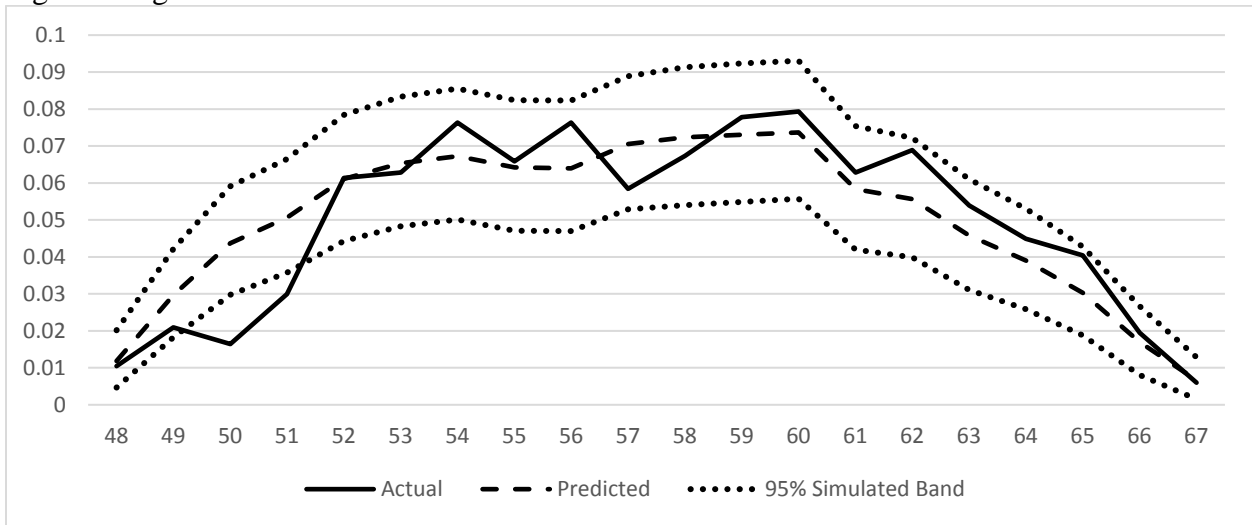
Source: Simulations based on pension rules in each state and estimates of entry and career growth in teacher salaries.

Figure 3. Percent of Sample Remaining Employed: Missouri STEM Teachers.



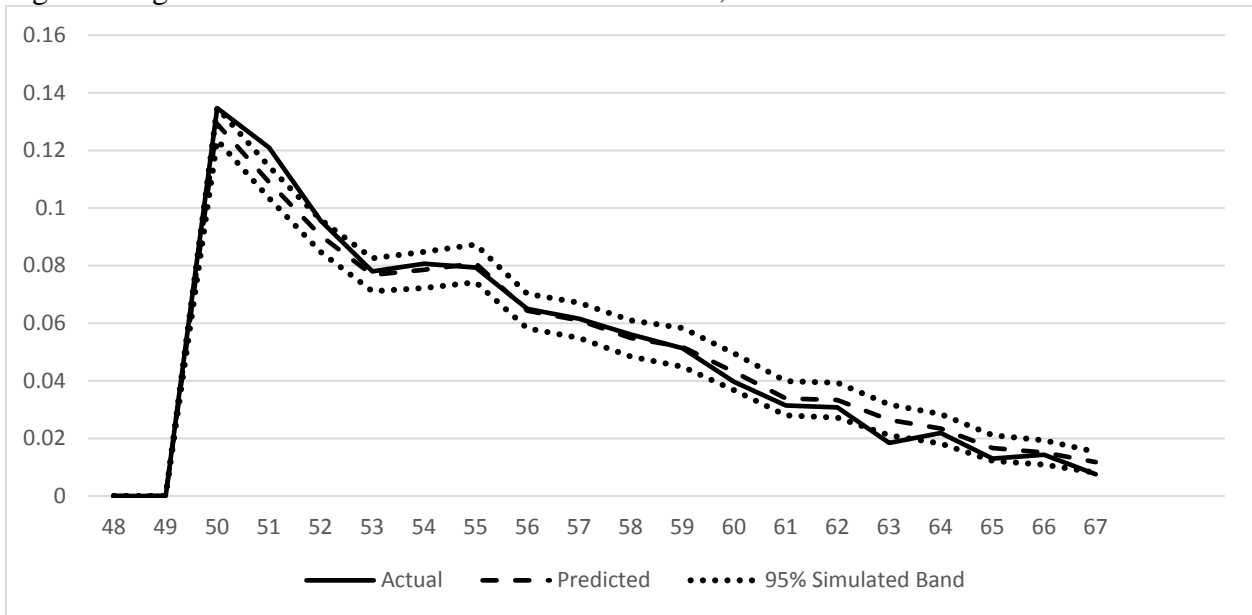
Note: The observed and predicted survival rates are for the STEM teachers in Missouri who were aged 48-65 and have who have or more years of experience in 2011. The predicted survival rates are based on simulated data from the structural model described in the text.

Figure 4. Age Distribution of Missouri STEM Retirees.



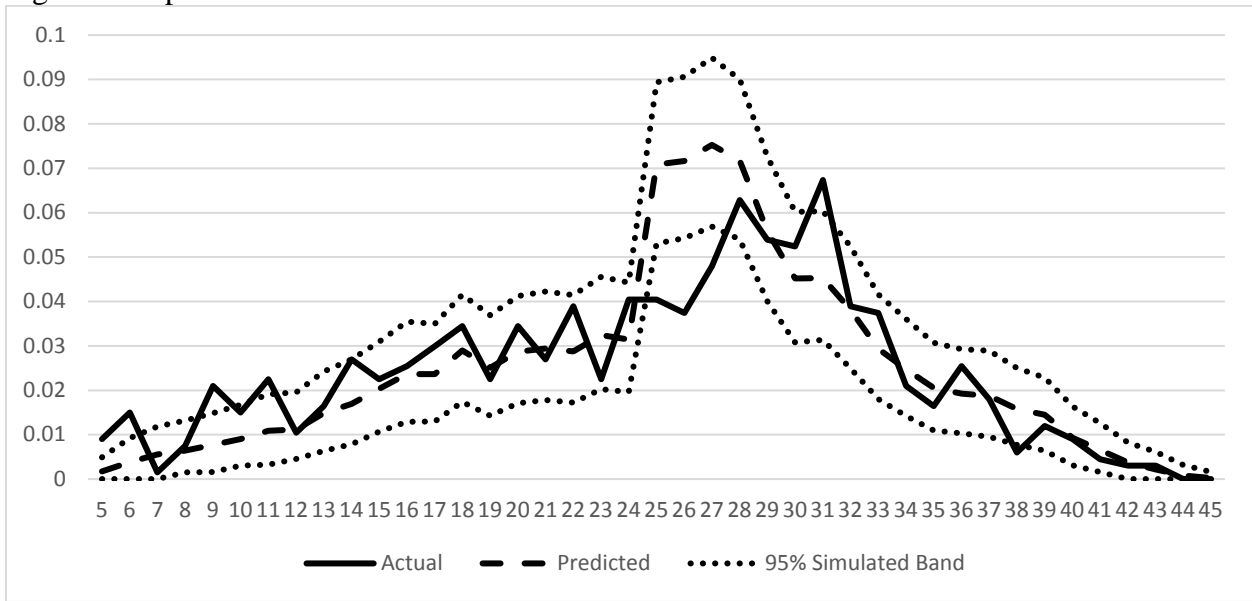
Note: The observed and predicted survival rates are for the STEM teachers in Missouri who were aged 48-65 and have who have or more years of experience in 2011. The predicted survival rates are based on simulated data from the structural model described in the text. The average age of retirees was 57.7. The predicted age was 57.0.

Figure 5. Age Distribution of Missouri STEM Teachers, Non-Retirees.



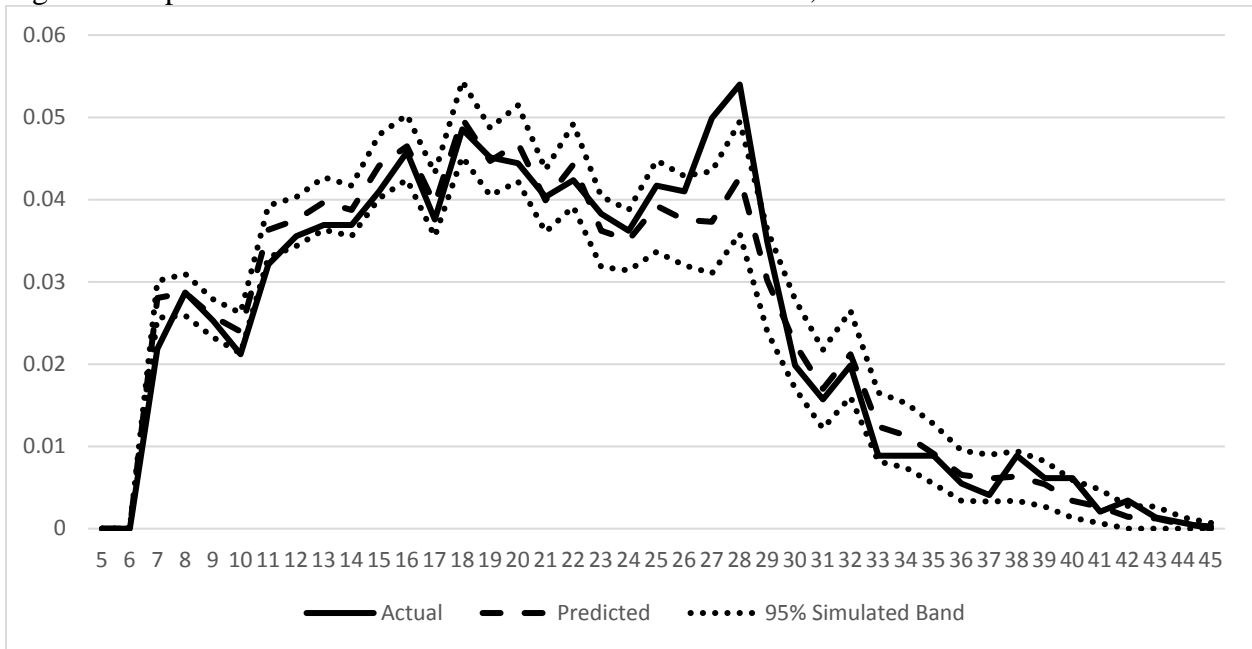
Note: The observed and predicted survival rates are for the STEM teachers in Missouri who were aged 48-65 and have who have or more years of experience in 2011. The predicted survival rates are based on simulated data from the structural model described in the text. The average age of non-retirees was 55.2. The predicted age was 55.5. Note that by definition it takes three years for a teacher to be classified as a non-retiree (i.e., didn't retire by 2014), which is why there are zero non-retirees at ages 48 and 49.

Figure 6. Experience Distribution of Missouri STEM Retirees.



Note: The observed and predicted distribution by experience at the time of retirement for MO STEM teachers aged 48-65 in 2011. The observed MO data from 2011-2013 are compared with simulated data from the structural model described in the text. The average experience of retirees was 24.5 years. The predicted experience was 25.7.

Figure 7. Experience Distribution of Missouri STEM Teachers, Non-Retirees.



Note: The observed and predicted distribution by experience for continued employment to the end of the period (2013). The observed MO STEM teachers aged 48-65 in 2008 are compared with simulated data from the structural model described in the text. The average experience of retirees was 20.8 years. The predicted experience was 20.4.

Figure 8: Distribution of Teaching Experience for Missouri STEM Teachers at Separation: Baseline and Alternatives.

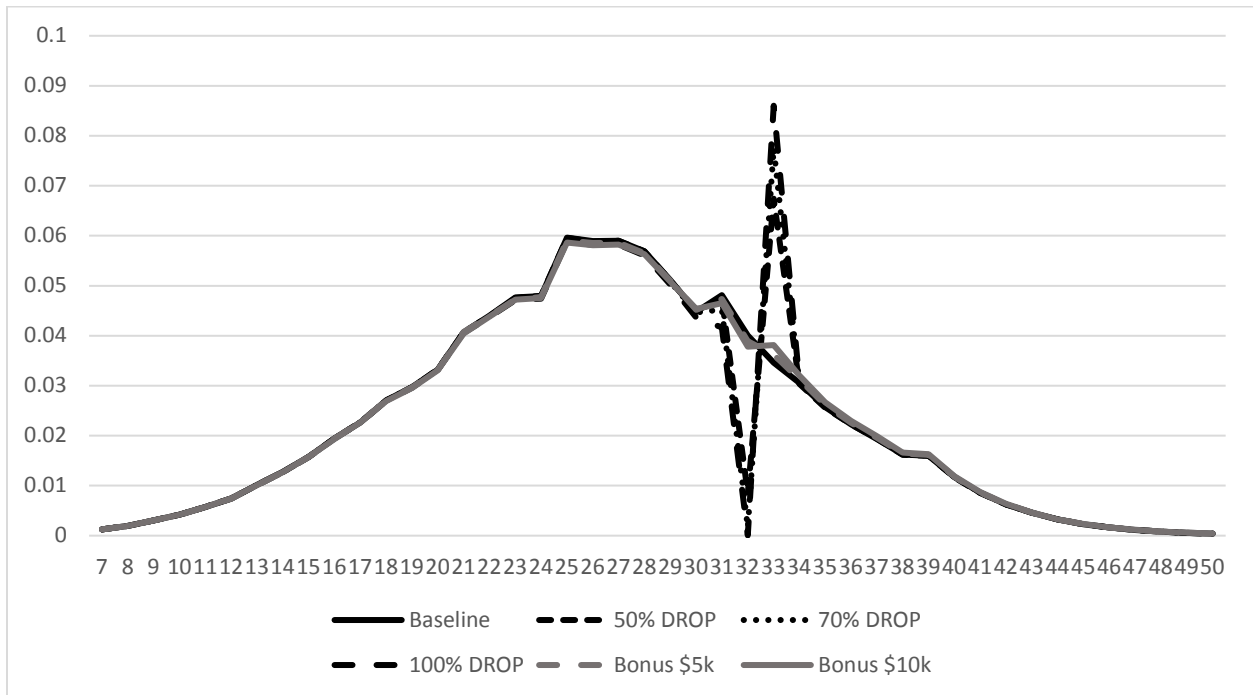
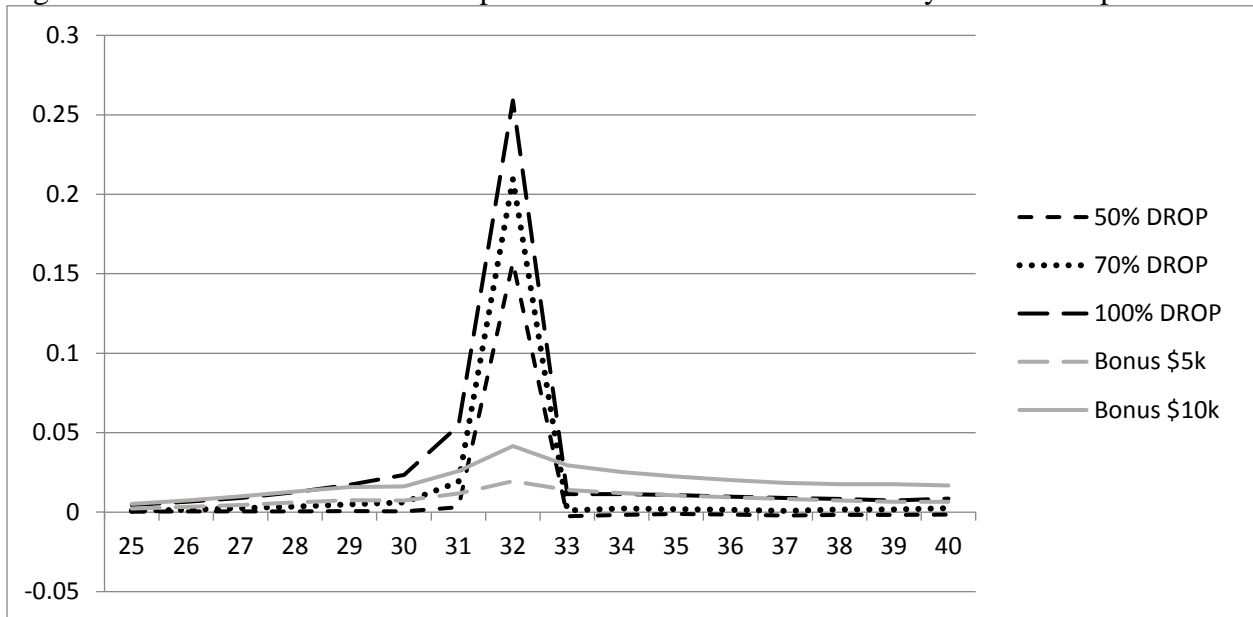


Figure 9: Increase in Cumulative Experience Function Over Baseline by Years of Experience



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