The Response of Employees to Severance Incentives

The University of California's Faculty, 1991–94

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ABSTRACT

In response to huge budgetary shortfalls in the early 1990s, the University of California offered its older and longer-service employees financial inducements to leave. This paper analyzes the responses of UC's faculty to three waves of buyout incentives. It is estimated that an individual presented with 10 percent higher severance benefits has a 7–8 percent higher probability of quitting. However, quit probabilities are very difficult to forecast with accuracy. This casts doubt on arguments that maintain that buyouts are superior to employer-initiated layoffs as a mechanism to effect large employment changes.

I. Introduction

When organizations make large and discrete cuts in their employment, they may either mandate extensive layoffs or induce employees to quit by offering them severance payments. Layoffs are claimed to engender morale problems among retained employees that deter them from undertaking company-specific human capital investments. On the other hand, employee buyout programs raise potential adverse selection problems: on the one hand, more "able" workers with better alternative employment opportunities may accept the monetary inducements and quit the organization; and, on the other hand, because each worker's reservation price is private information, the buyout program will involve the payment of rents to some, perhaps many, employees. Moreover, the cost reductions of such programs are uncer-

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tain because quit responses of employees to the financial incentives offered are difficult to forecast. Hence, even though some economists have lauded "efficient buyouts" as a "refined" alternative to the "blunt instrument" of layoffs,[1] because of informational asymmetries, management have tended to prefer layoffs.

The principal objective of this paper is to determine the validity of these two objections to employee buyout programs—that they are plagued with adverse selection difficulties and that the quit response of employees is difficult to forecast. Both of these issues identify the severance rate as the key issue in employee buyout programs. The adverse selection problem concerns the composition of the severances while the forecasting question concerns the response of employees to the severance benefits offered. Hence, in answering these questions, this paper focuses upon the programs' severance rates (or, equivalently, the acceptance or quit or take-up rates). Of course, the severance rate and its composition across employees with different salaries and severance benefits are central to any calculation of the monetary costs and benefits of these programs.

The employee buyout programs studied here are those implemented by the University of California (UC) in the early 1990s. The sharp recession in California at the end of the 1980s induced a large drop in state revenues and, as a result, the state's funding of the University of California was cut by about $300 million in 1991–92 over the previous year. The persistence of the recession into the 1990s kept the pressure on the UC system to cut costs. The University adopted a number of measures to reduce expenditures in line with the drop in revenues, but in terms of the cost savings involved the most important actions were the programs to induce the separation of some of its faculty and staff.

The severance payments were drawn from the University of California Retirement Plan (UCRP) so that the buyouts were characterized as early retirement programs.[2] The use of the retirement fund to finance these severance payments draws attention to the fact that the research in this paper is relevant to another very important class of issues, namely, the ability of universities to make adjustments in its faculty in an age no longer characterized by mandatory retirement.[3] There have been a number of studies concerned with the future age distribution of university faculty and with the impact of the end of mandatory retirement on that distribution.[4] The research here is germane to these issues because adjustments in pension benefits are likely to constitute a principal instrument for universities to induce older faculty to retire.[5]

1 These quotes are taken from Lazear (1995, p. 45) who uses them in the context of mandatory retirement although the logic of the argument applies to the employer-initiated separations considered here.

2 At the time that the University's operating budget was in critical condition, UC's pension fund was extremely well funded yet, by statute, income could not be moved from the pension fund to the current operating budget. Although *money* could not be moved, *people* can be induced to move from current payrolls to receiving pension income. This is the basic logic of the program.

3 The amendments in 1978 to the Age Discrimination in Employment Act (1967) raised the age of the protected class to 70 years but still permitted universities to require its faculty to retire at that age. However, further amendments in 1986 to the Act stipulated the end of mandatory retirement in universities by 1994.

4 See, for instance, Ashenfelter and Card (1996), Bowen and Sosa (1989), and Rees and Smith (1991).

5 A survey by the National Education Association (1994) found that, of 44 states responding, 17 had offered some early retirement incentive program in the previous five years to employees in public education. Respondents in only six of the states described the programs as "successful" although it is not clear what was meant by this. A useful review of such programs at universities up until the mid-1980s is contained in Chronister and Kepple (1987).

The appeal of this instrument is greater if the costs of alternative financial inducements can be predicted with confidence and if the least productive faculty respond to these incentives and quit the university. The experience of the University of California's three separate employee buyouts can inform these issues.

It needs to be stressed that this is a study of separations, however, not of retirement. Many employees did not retire from the labor force; indeed, a number remained employed in the UC system (although they had different job titles and the university had no obligation to reemploy them). The analysis here would be relevant if the buyouts were offered to employees aged in their thirties instead of their fifties and sixties. It would be just as relevant if UC had floated bonds to finance the buyouts instead of using the retirement fund.

The data used in this paper describe all the University of California (UC) faculty offered financial incentives to quit their employment at UC. There were three separate buyout programs and this paper describes all three. The data are drawn from the payroll and fringe benefit files of the University and contain the sort of information typically contained in an employer's records. This means that we lack information on, for instance, an employee's health status and his income from sources other than UC (such as the income and activities of his spouse). This would be a serious drawback if the principal goal was to provide a full account of the factors affecting an employee's decision to accept a severance pay package. In fact, as already stated, one goal is the narrower one of assessing whether buyouts offer an efficient device for inducing separations, an argument which, turns on the ability of an employer to forecast the consequences of his buyout program. For this purpose, I have exactly the sort of information that any employer would have on his employees.

The paper proceeds by describing the buyout programs and by offering a simple characterization of them. I then describe the critical empirical features of the programs before reporting the consequences of fitting equations to describe the probability of individuals accepting the buyout programs.

II. The University of California Severance Programs

A. The Design of the Severance Incentives

UC's retirement program is funded by contributions from active employees, from the University, and from investment earnings. The pension is a defined benefit plan. An employee becomes eligible to receive pension benefits if he is at least 50 years of age and has worked for UC for five years or more (or, if hired before July 1989, has reached the age of 62 regardless of years of service). The benefits consist of (cost-of-living adjusted) annual payments that are proportional to an employee's highest UC salary over a three year consecutive period. The factor of proportionality rises with his years of service and his age at retirement.[6] Various health plans are

6. For those employees whose pension benefits are coordinated with Social Security, the salary relevant for the calculation of benefits is reduced by a fixed amount to recognize UC's contributions to Social Security. However, those who quit under the retirement incentive programs received an income supplement that, until age 65, offset the salary reductions

available to those who have quit. Pension payments are conditional on the individual having left regular employment at the UC system, but they will be paid if the individual works for other employers.

The employee buyout schemes were known as verips, Voluntary Early Retirement Programs The first verip (named Plus 5) was extended in the academic year 1990–91 and offered additional pension benefits to those faculty who agreed to quit employment by 1 July 1991. The second verip (named Take 5) was offered in 1992–93 and the resignation date was 1 January 1993 The third verip (named VERIP 3) was introduced in 1993–94 and the separation date was 1 July 1994. We shall dub these verips as, sequentially, *verip1*, *verip2*, and *verip3*. For the academic staff, an employee was eligible for *verip1* if the sum of his age and years of service was at least 80. For *verip2*, the eligibility requirements were eased: the sum of age and years of service needed to be at least 78 years. Finally, the employee's age plus years of service needed to be at least 73 to be eligible for *verip3*. Faculty who elected to accept the verips were not eligible to be rehired as career employees for five years.[7]

To understand the severance incentives, consider the following simple representation. Let y be the individual's UC annual salary relevant to the computation of his pension benefits.[8] Let p_0 be the employee's annual pension income in the absence of any verip while p_k is the annual pension income accompanying acceptance of *verip k* ($k = 1,2,3$). If a is the employee's age factor relevant to the computation of benefits (we shall note shortly how the age factor varies with years of age) and if m denotes his years of service, then for someone eligible to receive pension benefits $p_0 = a.m.y$.[9]

The severance incentives provided by the verips altered this formula for the computation of pension benefits. The general form for pension income accompanying acceptance of the verips was $p_k = (a + \Delta a)(m + \Delta m)\lambda y$ where Δa represented the additional age factor as a severance incentive, Δm was the additional years of service, and λ was the proportional increase in y.[10] The values of Δm and λ for the three verips and the additional years of age (not age factor) are shown in the top panel of Table 1 from which it is evident that the severance pay parameters were the same for *verip1* and *verip2* and that, in *verip3*, Berkeley's *verip3* incentives differed from

7. They could be rehired, however, as contract employees for "urgent business necessity" and this implied they could not be members of the UCRP If a faculty employee were rehired for teaching purposes only, a schedule relating his per quarter course payment to his pre-verip base salary was specified. For example, in each of the three verips, someone with a salary at time of verip acceptance of \$75,000–\$80,000 was to be paid \$6,500 for teaching one regular quarter course

8 This salary is called the "highest average plan compensation" and, for most employees, this will be their salary averaged over the most recent three years.

9. As an example, for someone aged 60 years (for whom the age factor is 2 41 percent) with 25 years of service credit and whose y is \$80,000, his p_0 is (0.0241)(25)(\$80,000) = \$48,200 The product of a and m is constrained not to exceed one hundred percent

10 Each verip also offered "transition assistance" of three months' salary. (In the case of *verip1*, it was 1.07 times three months' salary) Compared with a worker's annual salary over the remaining years of his working life and with his annual pension over his lifetime, this transition assistance represents a very small amount and I neglect it in this summary statement of the severance incentives

Table 1
Values of Parameters in Computing Verip Severance Incentives

	Verip Severance Incentives		
	Δm	λ	Additional Years of Age
verip1	5	1.07	0
verip2	5	1.07	0
verip3 except Berkeley	5	1.07	3
verip3 for Berkeley	6	1.07	2

Mapping from Age to Age Factor, *a*

Age in Years	Age Factor, *a*	Δa Corresponding to Three More Years	Δa Corresponding to Two More Years
50	1.09%	0.21%	0.13%
51	1.16	0.22	0.14
52	1.22	0.28	0.16
53	1.30	0.30	0.20
54	1.38	0.32	0.22
55	1.50	0.30	0.20
56	1.60	0.30	0.20
57	1.70	0.71	0.20
58	1.80	0.61	0.61
59	1.90	0.51	0.51
≥60	2.41	0	0

those of the other UC campuses.[11] The mapping from age to the age factor, *a*, is given in the bottom panel of Table 1 where the column labeled "Δa corresponding to three more years" indicates the accelerated age factors offered to faculty in *verip3* except for those at the Berkeley campus while the column labeled "Δa corresponding

11. The reason for offering different severance terms to Berkeley faculty was that "there are concerns that the campus has a disproportionately large number of professors who would elect to retire For that reason, a slightly different plan will be offered to Berkeley faculty to minimize retirements" (from "Intercom Special, Newsletter for the Office of the President, University of California," June 18, 1993). As we shall see shortly, the severance incentives at Berkeley were less attractive to faculty at ages younger than 58 years compared with those offered to faculty at other campuses, but (contrary to the stated goals of the program) *more attractive* to faculty at 58 years or older. Behind the distinct treatment of Berkeley in *verip3* was a struggle among the campuses for different *verip3* terms

Table 2
Severance Incentives by Years of Service, Age, and Verip

	Service Years			
Age	20	25	30	35
		Verip1 and *Verip2*		
Any age	0.34	0.28	0.25	0.22
		Verip3 except Berkeley		
51	0.59	0.53	0.49	0.45
54	0.65	0.58	0.54	0.51
56	0.59	0.52	0.48	0.45
57	0.90	0.82	0.77	0.73
58	0.79	0.72	0.67	0.64
59	0.70	0.63	0.58	0.55
60 or more	0.34	0.28	0.25	0.22
		Verip3 for Berkeley		
51	0.56	0.49	0.44	0.40
54	0.61	0.54	0.49	0.45
56	0.56	0.49	0.44	0.41
57	0.55	0.48	0.44	0.40
58	0.86	0.78	0.72	0.68
59	0.76	0.68	0.63	0.59
60 or more	0.39	0.33	0.28	0.25

to two more years'' identifies the accelerated age factors in *verip3* offered to Berkeley faculty.[12]

Define $B_k(= p_k - p_0)$ as the monetary bonus accompanying acceptance of *verip* k and express this as a fraction of the pension income in the absence of the verip incentive, p_0. This is the severance incentive, S_k:

$$(1) \quad B_k/p_0 = S_k = (\lambda - 1) + \lambda[(a.\Delta m + m.\Delta a + \Delta m.\Delta a)/a.m].$$

Evidently, the severance incentive varied across individuals by age and years of service. It is useful to illustrate these values of S_k by age, years of service, and verip. Thus, for *verips1* and *2* where Δa was zero, some representative severance incentives, S_k, are given in the top panel of Table 2. *Verip3*'s severance incentives for all UC campuses except Berkeley and then for Berkeley are listed in the middle and bottom panels, respectively, of Table 2.

12. These retirement age factors are those effective 1 July 1992 Because *verip1* did not offer accelerated age incentives, the pre-July 1992 age factors are not relevant to our analysis. The age factors vary by months for people of the same age in years The values of the age factors in the text are those corresponding to someone whose birthday coincides with the retirement date (that is, for someone exactly the specified age)

The values of S_k in this table suggest the following conclusions about variations in the severance incentives:

1. In *verips 1* and 2, the severance incentive was independent of age. In *verip3*, the severance incentive changed nonmonotonically with age.
2. At ages younger than 60, *verip3* provided greater incentives for an employee to quit than *verips 1* and *2*. At ages 57 to 59, *verip3*'s severance incentives were more than double those for *verip1* or *verip2*. For faculty with 20 years of service, values of S reached up to 0.90 for those at UC campuses other than Berkeley, a substantial severance incentive. Recall that, to be eligible for *verip3*, the sum of a faculty member's age and service had to be 73 years. Thus, at 57 years of age, he needed merely 16 years of service to be eligible.
3. In all three verips, the severance incentive fell with years of service. The decline was greater at lower years of service than at higher years of service.
4. In *verip3*, compared with the other UC campuses, the severance incentive for Berkeley was lower at ages less than 58 years while Berkeley's incentive was higher at ages 58 or more.[13]

B. The Decision to Accept the Severance Payment

The inducements provided by a buyout will depend, of course, not only on an individual's earnings at his current employment compared with his alternative income opportunities, but also on his future earnings, those of his spouse, their savings, his discount rate, his length of life, and so on. Many of these variables are unobserved not only by the researcher, but also many are not known with certainty by the individual faced with the severance pay option. We restricted the analysis to variables that are actually observed and that could be used easily by the personnel office of any firm to forecast the acceptance rates of a severance program.

In this spirit, write individual i's probability of accepting the offer of verip k as prob$(A_{ki} = 1)$ and let this depend upon the ratio of the income offered by the verip, p_{ki}, to the individual's income from current UC employment (y_i): prob$(A_{ki} = 1) = F[\alpha \ln(p_{ki}/y_i)]$, where α is an unknown (positive) parameter indicating the sensitivity of the acceptance rate to the ratio of severance income to work income, and ln denotes the "natural logarithm of". Call p_{ki}/y_i individual i's "replacement ratio," that is, the fraction of individual i's current salary that *verip k*'s severance income will replace. From Equation 1, $p_k = p_0(1 + S_k)$ and, approximately, $\ln[p_0 (1 + S_k)] = \ln(p_0) + S_k$ so the probability of individual i accepting *verip k* may be written:

(2) $\text{prob}(A_{ki} = 1) = F[\alpha \ln(p_{0i}) + \alpha S_{ki} - \alpha \ln(y_i)]$

Equation 2 maintains that, holding constant individual i's preverip pension income, p_0, and his current earnings, y, the probability of *verip k*'s severance pay offer being

13 This is because, at age 58 and older, Δa is the same for Berkeley faculty and for faculty elsewhere at UC while Δm is greater for the faculty at Berkeley. At age 60 and beyond, $\Delta a = 0$ so the severance incentive is simply $S_3 = (\lambda - 1) + \lambda(\Delta m/m)$ and Δm is greater for faculty at Berkeley than for faculty at the other UC campuses.

accepted depends positively upon the severance incentive, S. The attractive feature of Equation 2 is that it isolates the incentive, S, that an employee buyout program can manipulate to affect the inducement to quit. Indeed, once the value of α is determined, the impact of such severance pay programs on quits can be ascertained simply by entering values of S into Equation 2. When α is known, quit rates in the absence of a verip can be forecast by setting S to zero in Equation 2.

Equation 2 suggests an estimating equation that relates the acceptance probability, prob (A_{ki} = 1), to the severance incentive, S, holding constant an individual's pre-verip pension income, p_0, salary, y, and perhaps other variables, denoted here by X.[14]

$$\text{(3)} \quad \text{prob}(A_{ki} = 1) = F[\alpha_0 + \alpha_1 \ln(p_{0i}) + \alpha_2 S_{ki} + \alpha_3 \ln(y_i) + \eta X_i]$$

What variables might be included in X? One would be controls for the age of the individual: age is relevant for those contemplating retirement from the work force because work-leisure preferences vary by age. Among those intending to remain in the labor force, however, younger faculty may assess their opportunities for reemployment more favorably than older faculty. Moreover, if the relevant characterization of the choice involves income and savings over an individual's lifetime, then the length of life (related to the individual's current age) would figure prominently in that calculation.[15]

We shall also consider controls for the academic department in which individual i works and his UC campus. Deciding to leave an academic department may depend upon whether and how many of your colleagues are also doing so. As a result, even among people of the same age with the same financial incentives, we may expect variations in acceptance rates by department and campus.[16]

Once both age and academic department are held constant, variations in salary across faculty are associated (in part) with differences in their productivity. Therefore, Equation 3 addresses the adverse selection question posed by employee buyout programs. In the UC's compensation structure, more productive faculty occupy higher "steps" in a given rank and a higher salary accompanies these higher steps. Holding constant age and academic department, those faculty who are more productive tend to earn a higher UC salary.[17] Therefore, after controlling for age and depart-

14. Equation 2 would suggest, of course, that, in Equation 3, $\alpha_1 = \alpha_2 = -\alpha_3$

15 Some studies of employee buyout programs (for example, Hogarth 1988) construct present values of earnings and pensions simply by multiplying current earnings and current pension income by a "present value factor" that is a nonlinear function of age. This method of constructing present values of these variables is equivalent to my procedure of using current salary and current pension income and controlling for age with a vector of age dummies (as we will below)

16. As noted in the introduction, I lack information on variables that from previous research are known to be relevant in accounting for quit decisions For instance, because the data I use in estimating Equation 3 are from UC's payroll and benefits records, I do not know the full personal wealth of the individuals nor whether their spouses are working and, if so, at what wage We do not know the state of the individual's health although it should be noted that faculty accepting a verip are entitled to the same health insurance benefits as if they were employed. In other words, I am restricted to using variables typically available to a firm's benefits and payroll office and we view our procedure as the type of analysis that an enlightened benefits office would undertake

17. UC uses three principles for raising salaries, a merit system of rewarding performance on an occasional basis, a quasi-civil service understanding that a person will not be "held back" in step advancement and salary increases if his work is satisfactory; and a cost-of-living adjustment that affects all salaries independent of productivity. The first of these works toward a correlation between salary and productivity while

ment, a pervasive adverse selection problem will be exhibited by a positive effect of y_{ik} on the verip acceptance decision. That is, adverse selection among quits will be revealed if severance rates are greater among higher paid faculty provided differences in age and academic department are accounted for.

This model of individual decision-making does not recognize the possibility that certain faculty might be offered assurances of higher than normal salary increases in subsequent years for rejecting a verip offer this year. In other words, one could imagine an institutional response to the verips that took the form of identifying some key faculty who would be assured of larger salary increases in future years if they did not take up the verip offer now.[18] Although this cannot be ruled out in particular instances, it could not have been a common situation as the UC budgetary problems were addressed not only by the employee buyout programs, but also by imposing tight restrictions on salary increases. Cost-of-living salary increases were withheld and one year saw a university-wide pay cut. In the data analyzed below, there is no statistically significant difference between the salary increases of those who rejected a previous verip and those newly eligible for the next verip. Hence, there is no evidence that, in the year following each verip, those who rejected the verip enjoyed larger salary increases than those who were not eligible for that verip.

III. Description of Data on UC Faculty

The data used in this analysis consist of all UC faculty eligible for the severance pay benefits. In other words, save for a handful of people with missing values on some key variables, we have the eligible UC population, not a sample of that population. Information is available on age, years of seniority, gender, ethnicity, department, and campus as well as the financial variables, salary and pension benefits in the absence and in the presence of the verips. Each individual's actual value of S is known.

Descriptive statistics in Table 3 on the eligible population by verip indicate that 1,963 faculty were eligible for *verip1*. Their mean age was 62 years, their mean years of service was 27 years, and almost 31 percent of those eligible accepted the *verip1* offers.[19] *Verip2*'s eligibility requirements were less stringent than *verip1*'s so

the second mitigates that relationship. The third factor is irrelevant to the issue of salary and productivity among UC faculty as it does not affect their relative salaries

18 When I put this argument to the people who ran the verips at the University of California, they were doubtful that the system of salary-setting at UC with its quasi-civil service procedures permitted much opportunity for verip-eligible faculty to be guaranteed much in the way of subsequent salary increases.

19. Differences across campuses suggest peer effects In *verip1*, acceptance rates were highest at Davis and lowest at Irvine, Davis' rate being almost 13 percent above Irvine's even though the average age of the faculty at Irvine was a little above that at Davis. Also, there are some striking differences in verip acceptance rates by academic departments There are some departments with consistently above average acceptance rates (such as the group consisting of Architecture, Planning, and Environmental Studies and also the group consisting of Languages and Classics) and others consistently below (such as the group Chemistry and Pharmacy and also the group English and Comparative Literature). There is no apparent relationship between verip acceptance rates and seniority even though the retirement incentives are related to seniority. This is because other factors (such as age and earnings) affecting the probability of verip acceptance are correlated with seniority and confound any simple relationship between acceptance and seniority

Table 3
Characteristics of Those Eligible for Severance Incentives by Verip and Age

	#	Percent	Mean Earnings $'000s	Median Earnings $'000s	Mean Age	Mean Service Years	Percent Accepted
Verip1							
All ages	1,963	100	86.27	79.98	62.2	27.0	30.8
Ages 50–54	43	2.2	79.56	77.83		27.3	7.0
Ages 55–59	568	28.9	80.90	75.71		26.2	6.0
Ages 60–64	726	37.0	85.28	78.79		26.9	25.2
Ages 65–69	518	26.4	92.67	84.78		27.5	55.6
Ages 70+	108	5.5	93.16	86.56		29.8	89.8
Verip2							
All ages	2,024	100	90.00	82.68	60.4	26.4	17.8
Ages 50–54	156	7.7	82.18	78.76		26.3	1.3
Ages 55–59	772	38.1	85.61	79.73		25.9	4.0
Ages 60–64	714	35.3	90.10	82.09		26.7	27.2
Ages 65–69	343	17.0	101.23	93.53		26.7	34.4
Ages 70+	39	1.9	107.62	100.09		29.1	38.5
Verip3							
All ages	2,728	100	87.89	80.28	59.0	25.1	33.0
Ages <55	578	21.2	78.71	73.37		23.9	7.3
Ages 55–59	991	36.3	84.64	76.78		25.0	23.7
Ages 60–64	754	27.6	90.60	83.17		26.0	51.2
Ages 65–69	322	11.8	102.74	96.56		25.3	56.5
Ages 70+	83	3.0	108.52	99.47		25.7	67.5

Earnings are expressed in 1990–91 dollars.

a few more than two thousand faculty were eligible. Both average years of age and seniority are lower in *verip2* and the acceptance rate—almost 18 percent—is considerably lower than *verip1*. *Verip3* further lowered the eligibility requirements making 2,728 faculty eligible with lower mean age and seniority than the previous verips. With much more generous retirement incentives, however, *verip3*'s acceptance rate was 33 percent. In all three verips, acceptance rates rise with age.[20]

Table 4 suggests some systematic relationships in the verip acceptance decision through describing the differences between those accepting and rejecting each verip.

20 I have sought to obtain information on UC's forecasts (made at the time the programs were devised or announced) of each verip's acceptance rate I have been unsuccessful. I have been given various "scenarios," but nothing that represents the projected take-up rate that surely must have been calculated or conjectured when each verip's particular terms were determined One document calculating the possible cost consequences of *verip2* describes a "worse case scenario" where the takeup rate for faculty is 20 percent Other scenarios are 33 percent and 25 percent I infer from this that *verip2*'s actual rate of about 18 percent was substantially below the central tendency of projections

Table 4
Differences in Age, Earnings, and Pension Income Between Those Accepting and Rejecting Each Verip

	verip1		*verip2*		*verip3*	
	Accepted	Rejected	Accepted	Rejected	Accepted	Rejected
Total						
Mean age	65.6	60 7	63.6	59.7	61.9	57.6
Mean earnings	82.66	87.88	84.38	91.22	85.16	89.24
Mean p_0	52.36	42.92	52 45	41.24	46.69	35.15
Mean S	0.184	0.193	0.191	0.197	0.417	0.472
Mean p_0 $(1 + S)/y$	0.752	0.632	0.759	0.613	0.769	0.623
Aged 50–54						
Mean S	0.184	0.185	0.184	0.194	0.486	0.481
Mean $p_0(1 + S)/y$	0.446	0.429	0.448	0.413	0.439	0.443
Aged 55–59						
Mean S	0.193	0.194	0.197	0.197	0.609	0.551
Mean $p_0(1 + S)/y$	0.536	0.531	0.580	0.530	0.729	0.633
Aged 60–64						
Mean S	0.188	0.193	0.188	0.197	0.325	0.349
Mean $p_0(1 + S)/y$	0.724	0.689	0.778	0.729	0.822	0 792
Aged 65–69						
Mean S	0.184	0.196	0.195	0.205	0.374	0.351
Mean $p_0(1 + S)/y$	0.783	0.753	0.776	0.738	0.777	0.790
Aged $\geq$ 70						
Mean S	0.172	0.117	0.195	0.174	0.340	0.381
Mean $p_0(1 + S)/y$	0.799	0.888	0 778	0.812	0.790	0.749

Earnings and pension income are expressed in thousands of 1990–91 dollars

Those rejecting the verips tended to be about four or five years younger on average, to have one or two years less seniority, and to have between $4,000 and $7,000 higher average annual earnings than those accepting the verips. Upon controlling for age, the earnings differences between those accepting and those rejecting the verips become sharper. For instance, among those aged 55–59 years, the average earnings of those who rejected *verip1* were almost nineteen thousand dollars greater than those of the same age who accepted *verip1*.

Perhaps most striking of all the lines in Table 4 are those that report the mean values of the replacement ratio, $p_0(1 + S)/y$. The reasoning offered in Section II suggested this would be a key variable in helping to account for the decision to accept a verip. Among all eligible faculty, in each verip, the replacement ratio is approximately 0.75 for those accepting a verip and approximately 0.62 for those rejecting a verip, about a 13 percentage points difference.

Table 5
Descriptive Statistics on the Monetary Variables Affecting Severance

	All Three Verips Combined	*verip1*	*verip2*	*verip3*
Fraction Accepting verip	0.278	0.308	0.178	0.330
Mean S	0.299	0.190	0.196	0.454
Mean p_0	42.26	45.83	43.23	38.96
Mean y	79.89	86.27	90.00	87.89
Number of observations	6,715	1,963	2,024	2,728

The values of p_0 and y are expressed in thousands of 1991 dollars.

IV. Quantifying the Impact of Severance Incentives on Quits

The framework above suggested that the probability of an individual accepting a verip and quitting UC employment depends on his severance incentive, S, his earnings, y, and his pre-verip pension income, p_0. We now report on the consequences of relating each faculty member's acceptance decision to the monetary severance incentives offered him or her. Table 5 provides information on the key monetary variables in our analysis. The average value across all three verips of the severance incentive, S, is 0.30, but its average *verip3* value is more than twice its average value in *verip1* and *verip2*. Not only is the value of S higher in *verip3*, but it displays much more individual variation than it does in *verip1* and *verip2*.[21] This would suggest that *verip3* would offer a better opportunity to measure the impact of S on the quit decision. The average values of p_0 tend to be lower with each subsequent verip. This is the consequence of successively easing the eligibility requirements for each verip and changing the population of eligible faculty.

A. *If All Three Verips Embody the Same Behavior*

First, we present the consequences of assuming the impacts of the severance incentives are the same in all three verips. Equation 3 is estimated by conventional maximum likelihood probit and the entries in Table 6 are the implied effects of increases in each right-hand side variable on the probability of verip acceptance evaluated at the mean value of the sample predictions. According to Column 1 of Table 6, an individual with a ten percent higher value of S will have an 8 percent higher probability of accepting a verip than another individual who has the same pre-verip pension

21. Thus, the standard deviation of S across all faculty in *verip3* was 0.157 whereas it was 0.044 and 0.046 in *verip1* and *verip2*, respectively. The difference between the values of S at the 75th percentile and at the 25th percentile was 0.219 in *verip3* whereas it was 0.041 and 0.036 in *verip1* and *verip2*, respectively.

Table 6
Estimated Differences in Verip Acceptance Probabilities (estimated standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(p_0)$	0.392			1.008	0.434	0.339
	(0.026)			(0.110)	(0.076)	(0.032)
S	0.795		0.450	0.754	1.415	0.608
	(0.042)		(0.034)	(0.054)	(0.357)	(0.071)
$\ln(y)$	−0.540			−1.186	−0.613	−0.486
	(0.038)			(0.103)	(0.096)	(0.041)
$\ln[p_0(1+S)/y]$		0.347				
		(0.026)				
$V2$					−0.194	−0.072
					(0.266)	(0.013)
$\ln(p_0).V2$					0.029	
					(0.094)	
$S.V2$					0.023	
					(0.451)	
$\ln(y).V2$					0.001	
					(0.111)	
$V3$					−0.083	0.022
					(0.235)	(0.019)
$\ln(p_0).V3$					0.005	
					(0.094)	
$S.V3$					−0.723	
					(0.381)	
$\ln(y).V3$					0.048	
					(0.115)	
X's?	Age, *C*, & *D*	Age, *C*, & *D*	Age, *C*, & *D*	Age & Seniority	Age, *C*, & *D*	Age, *C*, & *D*
−2*log likelihood	6,140	6,390	6,392	6,325	6,078	6,096

These estimates are fitted to 6,715 observations In the row X's?, C stands for the inclusion of campus dichotomous variables and D stands for the inclusion of department dichotomous variables In every column except for Column 4, dummy variables for each age are included In Column 4, fourth-order polynomials in years of age and years of seniority are included $V2$ and $V3$ denote, in turn, dichotomous variables for *verip2* and *verip3* "−2*log likelihood" means the negative of twice the maximized value of the likelihood function. If S, $\ln(p_0)$, and $\ln(y)$ are omitted from the verip acceptance equation, the value of −2* log likelihood is 6,590 when age, campus, and department dummies are included income, the same earnings, is the same age, and is in the same department and campus.[22]

The consequences of restricting the coefficients on the three components of the financial incentives (p_0, S, and y) to have the same absolute values are shown in Column 2 of Table 6. Though the values of the coefficients in Column 1 suggest that the effects on the verip acceptance decision of the three financial variables were roughly similar (taking account of the estimated standard errors), there is a significant loss (as measured by standard chi-square tests) in explanatory power in combining the three variables into one, the replacement ratio.

What is the association between the verip acceptance decision and the retirement incentive, S, not controlling for preverip pension income and earnings? This is answered in Column 3 of Table 6. The effects of S are considerably attenuated.[23]

It is important to note in these equations how the effects of the severance incentives, S, are identified. Recall from Section II above that the rules administering the verips specified S to vary by age, by years of service (seniority), by verip, and by campus (Berkeley being different in *verip3* from the other campuses). The estimates in Column 1 of Table 6 introduce age and campus as explicit dichotomous variables into the severance decision so the independent variation in S reflects its variation by seniority and by verip. Shortly, we shall examine each verip separately, but at this point we need to consider whether the measured effects of S are really a surrogate for the effects of seniority. That is, contrary to the implications of the estimates in Column 1 of Table 6, suppose the severance incentives measured by S really have no effect on quits and yet suppose faculty with different years of service (age held constant) are differentially inclined to accept the buyout programs. Then an association between quits and S may arise merely because S is correlated with seniority and because seniority is omitted from the equations whose estimates are reported in Column 1 of Table 6.[24]

To examine this possibility, we estimated Equation 3 by including years of seniority as well as years of age in the vector of variables X. Fourth-order (quartic) polynomials in years of service and years of age were specified. The consequent estimates of the effects of S are contained in Column 4 of Table 6: the impact of differences in S on the probability is very similar to that in Column 1.[25]

22 What age and campus patterns in severance rates are implied by the results reported in Column 1 of Table 6? After some erratic movement in the severance rates for ages 55 through 59, the severance probabilities rise with age and they display a particularly noticeable jump between age 59 and age 60 The campus differences in severance probabilities suggest Davis and Santa Cruz were distinctly more quit prone than the other campuses. Their severance rates are 7 and 8 percent higher than Berkeley's after accounting for the monetary, age, and department factors affecting severance We investigated whether women displayed a different quit propensity from men and whether different ethnic groups displayed dissimilar quit propensities. These differences were always small

23 A number of other specifications were studied. For instance, Equation 3 is additive in S and age In fact, the effect of separation incentives on quits may differ at different ages. When we allowed for this possibility, no systematic differences in the effect of S by age were detected

24. Recall that S falls with years of seniority while, in Column 1 of Table 6, S is positively correlated with the quit probability Therefore, if this argument in the text obtains, the quit propensity must fall with length of service (holding age and other variables constant)

25. One may go further than this and add dummy variables for *verip2* and *verip3* to the specification in Column 4 Upon doing so, again, the estimates suggest an important role for the severance incentives, S: an individual with a 10 percent higher value of S will have a 6 percent higher probability of accepting a

B. Different Severance Behavior across the Three Verips

The estimates reported in the first four columns of Table 6 embody the assumption that the responses to the severance incentives are the same in all three verips. This is unlikely to be the case for at least two reasons. The first concerns the changing expectations of the faculty and the other relates to the differences among the verips in the characteristics of the eligible population. Consider first the role of expectations.

At the time *verip1* was offered, there was no precedent for it in the UC system.[26] It was characterized as a singular, not-to-be-repeated, event. The faculty would have every reason to believe this was their only opportunity to take advantage of the special monetary incentives to quit. When the second verip was offered and offered on the same terms, it was impossible to argue that the severance program was unique and, indeed, given the continued financial pressure on the UC system, faculty might well wonder whether there would be yet another severance program. In other words, the expectations of the eligible population were quite different at the time of the second verip from the first. These expectations were likely to be different again at the time of the third verip when the UC administration went to considerable effort to persuade faculty that this was, indeed, the final severance program.[27]

A second reason to expect different responses among the verips to the severance incentives is that the characteristics of the eligible faculty were different in each verip. Not only were eligibility conditions loosened in each subsequent verip so altering the eligible pool, but also *verip2*'s eligible faculty consisted of those people who had been presented with identical severance financial incentives in *verip1*, and had rejected them. That is, when presented with the same financial incentives to quit, the distribution of *verip2*'s eligible faculty probably consisted of more people inclined to remain at UC than those in *verip1*. The situation is a little more complicated in *verip3* because the financial incentives to quit in *verip3* were more generous than those in the previous verips. However, *verip3* consisted of a number of faculty who had rejected at least one of the previous verips and thereby revealed themselves to be less quit prone (when faced with less generous monetary severance incentives than those in *verip3*) than those who had accepted one of those earlier verips. In

verip than another individual who has the same age, seniority, pension income, and earnings and observed in the same verip With respect to the estimates in Column 4, observe that while the estimated effect of S is very similar to that in Column 1, the estimated effects of pre-verip pension income and salary are much larger (in absolute value) although estimated more imprecisely The reasons for this are not difficult to fathom: in Column 4, the impact of differences in $\ln(p_0)$ and $\ln(y)$ on quits are those that hold constant variations in seniority (as well as age) whereas those in Column 1 do not hold seniority constant. In these equations that introduce seniority, estimated quit propensities tend to fall with seniority (holding age, S, $\ln(y)$, and $\ln(p_0)$ constant) although, on average, the decline is negligible. At the average value of the predicted probabilities, one more year of seniority is associated with one-half of one percent decline in the severance probability The seniority effect appears to be nonlinear with more seniority associated with declining severance probabilities at low levels of seniority and with more seniority associated with rising severance probabilities at high level of seniority.

26. There was an early retirement program for three months in 1980 for faculty at the California State University system, but this did not apply to the University of California.

27. After *verip3*, Kim (1995) conducted a survey of 233 verip-eligible faculty at UCLA He included in his survey a question asking faculty whether they expected another verip within the next three years. Those faculty expecting another verip were less likely to have accepted a verip and quit UC employment (although there is not enough information provided to quantify this difference)

devising *verip3*, the UC administration was well aware of this issue. Indeed, much more generous severance terms were designed for *verip3* because it was believed that many quit-prone faculty had already left employment so that substantially more attractive benefits would be needed to induce more quits.

One way of investigating the relevance of these issues is to fit the following equation to the data on all three verips:

$$(4)\quad \text{prob}(A_i = 1) = F\{\alpha_0 + \alpha_1 \ln(p_{0i}) + \alpha_2 S_i + \alpha_3 \ln(y_i) + \delta_2(V2)_i + \beta_1[\ln(p_{0i}) \cdot (V2)_i] + \beta_2[(Si)(V2)_i] + \beta_3[\ln(y_i) \cdot (V2)_i] + \delta_3(V3)_i + \gamma_1[\ln(p_{0i}) \cdot (V3)_i] + \gamma_2[(S_i)(V3)_i] + \gamma_3[\ln(y_i) \cdot (V3)_i] + \eta X_i\},$$

where *V2* takes the value of unity if the observation is drawn from *verip2* and the value of zero otherwise. *V3* takes the value of unity if the observation is drawn from *verip3* and the value of zero otherwise. Equation 4 allows for differences across the three verips in the impact of the monetary severance incentives. In addition, it asks whether differences in severance rates exist among the verips *after accounting for the monetary incentives to quit.* (These effects are indicated by the estimates associated with the coefficients δ_2 and δ_3.)

The estimated differences in severance probabilities are reported in Column 5 of Table 6. The estimates attached to *V2* and *V3* indicate that, even after allowing for different impacts on severance rates of the monetary incentives, the probability of *verip2* being accepted was 19.4 percent below that of *verip1* while the probability of *verip3* being accepted was 8.3 percent below that of *verip1*. That is, the coefficient estimates of δ_2 and δ_3 imply that, holding constant the effect of the particular severance incentives, faculty in *verip2* and *verip3* were less quit prone than those in *verip1*. In Column 5, the estimates attached to the term *S.V3* imply that the responsiveness of the quit rate to differences in severance incentives (contained in *S*) in *verip3* was considerably below that in *verip1* and *verip2*. In *verip1*, a 10 percent increase in the severance incentive *S* is associated with a 14 percent higher severance rate in *verip1* and in *verip2* (in *verip2*, this is the sum of 1.415 and 0.023), but with only a 7 percent higher severance rate in *verip3* (the sum of 1.415 and −0.723). In other words, both the estimates attached to the dummy variables *V2* and *V3* and the estimates attached to the term *S.V3* indicate that *verip1*'s eligible population responded to the monetary incentives differently from the eligible population in *verip2* and *verip3*.[28]

28 The estimates reported in Column 6 of Table 6 are those that result from restricting the effects of the monetary variables, $\ln(p_0)$, *S*, and $\ln(y)$, to be the same in the three verips, but which allow for intercept-type differences among the verips. In Column 6, *verip2*'s severance probability is 7.2 percent below *verip1*'s (holding the monetary incentives fixed), but there is little difference between the severance probability of *verip1* and *verip3*. On conventional chi-square tests, the restrictions embodied in the estimates in Column 6 are not upheld. However, a less restrictive specification than that in Column 6 does not represent an inferior characterization of severance behavior (on the basis of chi-square tests) and this is one that allows for merely one interaction, namely, that represented by the term *S.V3*. Provided this term is included in the severance equation (together with the *V2* and *V3* variables and the age, department, and campus dummies), then the specification embodied in the estimates in Column 5 does not provide a superior fit.

C. Distinguishing "Repeaters" from "Nonrepeaters"

The previous paragraphs have presented evidence to suggest that the severance probabilities were different across the three verips even after adjusting for differences in the monetary incentives to quit. They were different, it is argued, because the eligible population in each verip consisted of people who were unlike in their quit propensities and because severance decisions were made in the context of contrasting expectations regarding future severance options. Further evidence compatible with this interpretation is provided by a comparison of the quit behavior of people who had rejected previous severance opportunities and that of people newly eligible for a verip. Thus, almost two-thirds of the faculty eligible for *verip2* had rejected the severance opportunities provided by *verip1*. These "repeaters" were much older and had a substantially higher pension income (p_0), two factors encouraging quitting, so perhaps it is, not surprising that their *verip2* severance rate was more than twice that of those newly eligible for the severance incentives. In results not reported here, however, it was determined that, even after adjusting for the age, pension income, and other differences between the two types of faculty, the "repeaters" had a 6.5 percent *lower* probability of quitting than those newly eligible to *verip2*. This lower severance rate of those who had rejected *verip1* supports the notion that the distribution of severance probabilities in *verip2* was different from that in *verip1* and, in particular, that *verip2*'s eligible population consists more of those faculty with a greater attachment to work at UC.

D. Can Behavior in One Verip Reliably Forecast Quit Rates in the Next?

The previous paragraphs have documented differences among the verips in their acceptance probabilities (Table 6) even holding constant the monetary incentives to quit. Some of these differences arise because the eligible faculty changed with each verip: eligibility conditions eased with each verip and almost all those who rejected one verip were presented with new severance incentives in the following verip. These features made the quit propensities in each verip's eligible population systematically different.

Because of these differences across the verips in quit propensities, the accuracy of a severance probability equation fitted to one verip in forecasting severance rates in subsequent verips is quite unremarkable. Thus, suppose one fits the severance Equation 3 to *verip1* observations and then uses it to predict severance rates for *verip2*. Then the severance rates by age would be those listed in Column 5 of Table 7.[29] These predictions consistently overpredict *verip2*'s actual quit rates given in Column 4 of Table 7. Most of the observations describe faculty aged 59 to 64 years and for these ages the predictions are not too out of line, but the overprediction at many of the other ages is quite marked. Although the fitted *verip1* equation consistently overpredicts *verip2*'s quits, the correlation between the predicted quit rates and the actual quit rates is 0.82 (as given in the last row of Table 7).

29 The severance equation fitted to *verip1* includes age, campus, and department dummy variables. When using this equation to predict *verip2*'s quits, each individual's *verip2* quit probability is forecasted and then the quit probabilities are aggregated for faculty at each age The resulting predicted quit rates by age are those given in Column 5 of Table 7.

Table 7
Actual and Predicted Verip Acceptance Percentages by Age

	verip1	*verip2*			*verip3*			
	Actual	Actual		Predicted Quit Percent from. . .	Actual		Predicted Quit Percent from . . .	
Age in Years	Percent Quitting	Number Eligible	Percent Quitting	*Verip1*'s Quit Equation	Number Eligible	Percent Quitting	*verip1*'s Quit Equation	*verip2*'s Quit Equation
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
≤52	0	22	0	6.5	222	5.0	37.2	56.2
53	0	51	2.0	7.7	152	9.9	46.5	77.9
54	9.7	83	1.2	9.3	204	7.8	50.2	84.8
55	6.9	138	2.2	8.3	179	10.6	43.2	83.2
56	3.9	145	2.8	5.2	209	5.7	32.8	80.1
57	4.3	147	2.0	4.0	230	24.8	58.2	93.7
58	7.4	151	4.6	8.1	206	40.8	74.1	99.9
59	7.0	191	7.3	8.4	167	37.7	65.7	99.6
60	14.3	152	19.7	17.8	204	46.6	45.6	83.6
61	16.9	178	23.0	21.4	166	53.0	39.9	75.1
62	29.7	142	32.4	33.4	143	53.2	55.0	80.9
63	31.1	131	27.5	31.6	129	51.2	51.8	75.9
64	38.8	111	36.9	38.0	112	54.5	59.3	80.8
65	49.2	104	36.5	45.6	95	53.7	67.1	83.7
66	46.6	63	28.6	44.8	76	52.6	65.1	77.8
67	47.4	61	41.0	46.8	60	50.0	67.5	84.1
68	64.6	76	35.5	60.4	50	68.0	77.8	78.4
69	82.1	39	25.6	78.1	41	65.9	91.2	72.8
≥70	89.8	39	38.5	87.7	83	67.5	93.8	77.3
Total	30.8		17.8	23.6		33.0	54.1	82.2
Correlation				0.82			0.72	0.03

Would I have done better to ignore the estimates of the verip acceptance Equation 3 fitted to *verip1*'s data and instead naively predicted *verip2*'s severance rates by age simply from *verip1*'s severance rates by age? *Verip1*'s severance rates are listed in Column 2 of Table 7, while *verip2*'s severance rates by age are listed in Column 4 of Table 7. *Verip2*'s actual severance rates are 13 percent below those of *verip1* and for some ages the difference between actual behavior in the two verips is wide (such as ages 54, 66, and 69). Therefore, although I overpredict *verip2*'s severance behavior using the estimates of Equation 3 fitted to *verip1* data, I do better using these estimates than naively projecting *verip1*'s severance rates to *verip2* behavior. I overpredict severance in *verip2* by both methods, but I overpredict more severely if I naively forecast *verip2*'s behavior using *verip1*'s severance rates.

Now consider predicting *verip3*'s severance rates. Suppose I fit Equation 3 separately to *verip1*'s data and to *verip2*'s data and then use each equation to predict severance rates by age in *verip3*. The resulting predictions are given by Columns 8 and 9 of Table 7. Again, these equations overpredict *verip3*'s actual quit rates especially in Column 9 where the weighted average of the *verip3*'s predicted severance rates is 82.2 percent compared with an actual severance rate (Column 7) of 33 percent. Moreover, even the correlation across ages between the forecasts from *verip2*'s equation and the actual quit rates is very weak (at 0.03).

Again we may ask whether we would have predicted *verip3*'s behavior better if Equation 3 were ignored and if *verip2*'s unadjusted behavior were naively applied to verip3. Actual severance rates by age in *verip2* and *verip3* are listed in Columns 4 and 7 of Table 7. The overall severance rate of 33 percent is almost double that of *verip2* and for some ages (especially for faculty in their late fifties) the difference between *verip3*'s and *verip2*'s severance rates is large. *Verip1*'s overall severance rate is 30.8 percent which is much closer to *verip3*'s. However, there are some sharp differences within certain age groups: whereas *verip1*'s severance rate among people in their late fifties is 4–7 percent, for *verip3* it is six times these figures.

In short, if I used Equation 3 estimates to forecast *verip3*'s behavior, severance rates in *verip3* would have been sharply overestimated. If I simply applied severance rates in *verip1* and *verip2* to *verip3* without any adjustment for differences among the verips in their terms, I would have underestimated severance rates. The underestimation would have been marked if I had used the immediately preceding verip, *verip2*, to forecast *verip3*. This suggests that accurate prediction requires some recognition of differences in the terms of the verips, but the manner in which these terms are reflected in the estimates of Equation 3 does not produce accurate predictions.[30]

30. Another way of illustrating the sharp differences across the three verips in the sensitivity of the faculty to the severance terms is to infer severance rates in *verip1* if *verip1*'s eligible faculty had been presented with *verip3*'s opportunities to quit. That is, suppose *verip1* faculty had been offered those severance terms that were designed for *verip3*. This means assigning to each individual in *verip1* the value of *S* that (given his age and service) is implied by the terms of *verip3* Assume that faculty in *verip1* behave in the manner described by the estimated parameters of Equation 3 when fitted to *verip1* data When this behavior in *verip1* is applied to *verip3*'s severance terms, the resulting severance rates are extremely high. Instead of a severance rate of almost 31 percent in *verip1*, the severance rate would have been double this at 60 percent. Indeed, at the younger ages where *verip3*'s severance terms were especially generous, severance rates would have been over ten times their actual rates This simulation demonstrates the combined effect of *verip3*'s more generous severance terms and the elasticity of *verip1*'s eligible faculty's responses to severance incentives

E. Heterogeneity

To account for the presence of unobserved quit propensities and for the changing composition of the population of such preferences across the verips, suppose each faculty member's unobserved quit propensity can be represented by a fixed effect, q_i. Going back at least to the research on "movers" and "stayers," there has been a recognition that, when faced with the same opportunities, some people appear to prefer to remain with their current employer while others prefer to leave. The unobserved quit propensity, q_i represents these individual-specific preferences. In conventional fixed effect models where individuals are observed in more than one period, a standard method to accommodate factors such as q_i is to estimate equations in first differences. I follow this procedure here, too, only in this case I do not observe all the faculty in each verip and need to account for the truncation that results.

In *verip1*, I do not observe those faculty eligible for *verip2* but not eligible for *verip1*. In *verip2*, I do not observe those faculty who accepted *verip1*'s severance offers and quit. Therefore I first estimate a probit equation to describe the probability that an individual is observed both in *verip1* and in *verip2*.[31] From this, I form the inverse of Mills' ratio (the ratio of the density to the cumulative function) and estimate a first difference equation relating the probability of accepting *verip2* to first differences in $\ln(p_0)$, S, and $\ln(y)$ controlling for the selection.[32] The linear probability estimates (with standard errors adjusted for arbitrary heteroskedasticity) are given in Line 1 of Table 8.[33] If the effects of age, department, and campus are different in *verip1* from their effects in *verip2*, then we should control for these variables. Therefore, in Line 1, age, campus, and department dummies are included in the severance probability equation.

A similar procedure can be employed to pool individuals from *verip2* and *verip3*. The relevant faculty are those eligible for *verip2* and *verip3* (so they must have rejected *verip2*). First, I estimate a probit equation describing the probability that an individual is observed in both *verip2* and *verip3*. From this I construct a selection term that is entered into a linear probability equation where the severance incentives are expressed as first-difference variables, their *verip2* values subtracted from their *verip3* values. These estimates are provided in Line 2 of Table 8. Again, the estimates are those that result after including *ag*, campus, and department dummies in the equation.

This procedure should be much more effective when pooling *verip2* and *verip3* observations than when pooling *verip1* and *verip2* observations. The reason is that the severance program parameters of *verip1* and *verip2* were the same so the first

31. In this probit equation describing a person's inclusion in both verips, the variables affecting this probability are $\ln(p_0)$, $\ln(y)$, age dummies, campus dummies, department dummies, years of seniority, gender, and a race variable

32. Let A_k take the value of unity if *verip k* is accepted Then, the dependent variable in this first difference specification is $\text{Prob}(A_2 = 1) - \text{Prob}(A_1 = 1)$ However, given that those for whom $A_1 = 1$ are not observed in *verip2* (and this fact is taken into account with Mills' ratio), the dependent variable is simply dichotomous, being unity if $A_2 = 1$ and zero if $A_2 = 0$

33 Linear probability equations were fitted to all the equations described so far in this paper and the inferences about marginal probabilities from these equations were close to the probit estimates reported. Fixed effect estimators in probit models are inconsistent whenever there are a relatively small number of observations on each individual

Table 8

Fixed Effect Estimates of the Severance Probability (heteroskedastic-consistent standard errors are in parentheses)

	Which Verips?	Δ ln(p_0)	Δ S	Δ ln(y)	Selection Term
1	1 and 2	0.367	0.784	−1.113	−0.117
		(0.278)	(1.781)	(0.551)	(0.045)
2	2 and 3	0.270	0.798	−0.661	−0.168
		(0.389)	(0.194)	(0.502)	(0.051)
3	1 and 2	0.563	1.958	−1.331	Excluded
		(0.263)	(1.718)	(0.541)	
4	2 and 3	0.051	0.662	−0.455	Excluded
		(0.383)	(0.198)	(0.497)	

There are 1,315 observations underlying the estimates in Lines 1 and 3 and the fraction of these accepting *verip2* was 0.227. There are 1,632 observations underlying the estimates in Lines 2 and 4 and the fraction accepting *verip3* was 0.439 Δ denotes the difference between the value of the indicated variable in one verip and its value in the previous verip.

differences across faculty in S should be close to zero and should display little variation. Indeed, this is the case: among those eligible for both *verip1* and *verip2*, the mean value of ΔS is -0.012 with a standard deviation of 0.007. By contrast, the parameters of *verip3* were different and more generous than those of *verip2* so ΔS should be positive and display more variance. This is so: between *verip3* and *verip2*, the mean of ΔS is 0.200 with a standard deviation of 0.142.

The results in Table 8 support this reasoning. The effects of differences in S on the quit probability are much more precisely estimated in Line 2 (where I use *verip2* and *verip3* data) than in Line 1 (where I use *verip1* and *verip2* data). However, the point estimates of the effect of S on the severance probability are now identical in *verip1* and *verip2* to those in *verip2* and *verip3*. In Line 1, the effect of a 10 percent higher S is to raise the severance probability by 7.8 percent while in Line 2 the corresponding effect is 8.0 percent. In fact, these estimates are close to those in the probit equations fitted to all three verips pooled as given in Column 1 of Table 6.

The results in Lines 3 and 4 of Table 8 indicate that, for *verip1* and *verip2*, the inclusion of the selection term, the inverse Mills' ratio, is important for this result. When this term is omitted, the estimated effect of S rises toward its value reported in Table 10. This is not true for the first difference model applied to *verip2* and *verip3*: in Line 4 where the selection term is excluded, the effects of differences in S on the severance probability are around 7 percent and, as such, these effects are only a little below the 8 percent estimated in Line 2 when the inverse of Mills' ratio is included.

Hence I infer that, because the composition of the eligible population changed across the three verips, it is difficult to use the information on each verip to estimate with confidence the effects of the severance incentives on quit probabilities in subsequent verips. When I estimate to the verip-specific data selection-adjusted severance probability equations that allow for variations in unobserved quit propensities, I derive estimates of the effects of the severance incentives that are close to those estimated when the data from all three verips are pooled. Presumably this is because the equations fitted to each verip separately have more serious selection problems than the equations fitted to the pooled data.[34]

Can the estimates in Table 8 help forecast severance rates more accurately? To address this question, I took the estimates of the first difference specification fitted to *verip1* and *verip2* observations (those corresponding to Line 1 of Table 8) and forecast severance rates in *verip3* for those faculty who were eligible for both *verip2* and *verip3* (the "repeaters").[35] The resulting implied severance rates by age underpredict quits by about 14 percent. As a result, although the impact of S on quits is estimated to be similar in *verip2* and *verip3* by the methods whose results are reported in Table 8, the estimates of the impact of the other variables is sufficiently different to lead to forecasts that are erratic across ages and that, in general, underpredict the severance of repeaters in *verip3*. Once again, confidence in our forecasting ability is unwarranted.

F. The Impact of the Verips on Severance

The form of the severance probability equation, Equation 3, lends itself to determining the impact of the program on quits. A natural measure of the impact of the incentive program on quits is to fit this equation to each verip and, with the values of the α and η parameters thus determined, set S to zero and impute the implied quit probabilities. The predicted impacts on the quit rates at each age are given in Table 9.[36] For each verip, there are two sets of predictions. There are those implied by the fitted equation at the given values of S; these are in the columns headed $S \neq 0$. Then there are the predictions corresponding to setting the severance incentives to zero; these are in the columns headed $S = 0$. The difference between the entries in the two columns may be interpreted as estimates of the impact of the employee buyout programs. The table also lists actual severance rates in each verip and, except for a few people at the very young ages in *verip1*, the actual and predicted (with $S \neq 0$) severance rates are very close.[37]

Thus, in *verip1*, the actual severance rate was 30.8 percent. According to our

34. The reasons offered for consistently overpredicting *verip3*'s quit rates using estimates of Equation 3 fitted to *verip1*'s and *verip2*'s data have to do with the changing composition of the eligible population accompanying changing expectations. A different potential explanation questions whether Equation 3 is the best available specification for use in forecasting. In particular, the effects of differences in S may depend on the level of S possibly, the effects of a 1 percent higher S when S is 19 (its mean value in *verip1* and *verip2*) are greater than a one percent higher S when S is .45 (its mean value in *verip3*) In fact, equations were estimated allowing for this, but there is no persuasive evidence of a decreasing impact of S at higher values of S.

35. In so doing, we need to predict not only the probability of quitting employment, but also the probability of being a repeater so that each observation has a value for the inverse Mills ratio

36. Each individual's quit probability is predicted and then the individual probabilities are aggregated at each age level to derive the age-specific quit rates.

37 The line "correlation" in Table 9 presents the value of the correlation coefficient between the actual severance rates by age and those predicted when $S \neq 0$.

Table 9
Actual and Predicted Verip Acceptance Rates (in Percent) by Age

	verip1			*verip2*			*verip3*		
	Actual	Predicted		Actual	Predicted		Actual	Predicted	
		$S \neq 0$	$S = 0$		$S \neq 0$	$S = 0$		$S \neq 0$	$S = 0$
Total	30.8	30.7	13.0	17.8	17.8	0.6	33.0	33.0	14.5
Age									
≤52 years	0	3.1	0.3	0	0.7	0	5.0	5.9	0.7
53	0	7.7	1.1	2.0	1.0	0	9.9	8.2	1.0
54	9.7	6.9	0.8	1 2	1.5	0	7.8	9.1	1.2
55	6.9	6.9	0.9	2.2	2.5	0	10.6	10.6	1.7
56	3.9	4.1	0.4	2.8	2.7	0	5.7	5.7	0.7
57	4.3	4.3	0.5	2.0	2 2	0	24 8	24.6	3.1
58	7.4	7.2	0.9	4 6	4.8	0	40.8	40.7	7.3
59	7.0	6.9	0.9	7.3	7.1	0	37.7	37.6	7.6
60	14.3	14.3	2.3	19.7	19.4	0.2	46.6	46.5	22.8
61	16.9	16.7	3.3	23.0	23.4	0.3	53.0	53.0	29.9
62	29.7	29.7	7.9	32.4	32.3	0.9	53.2	53.2	30.2
63	31.1	30.9	8.3	27.5	27.2	0.6	51.2	51.2	28.3
64	38.8	38.9	12.5	36.9	36.7	1.5	54.5	54.4	31.3
65	49.2	49.1	19.6	36.5	36.5	1.1	53.7	53.4	29.8
66	46.6	46.5	16.7	28.6	28.7	1.1	52.6	52.7	28.4
67	47.4	47.2	17.1	41.0	40.9	2.7	50.0	49.9	26.7
68	64.6	64.4	30.0	35.5	35.5	2.1	68.0	67.6	41.9
69	82.1	81.2	53.8	25.6	26.2	0.8	65.9	65.3	40.0
≥70	89.8	89.7	67.5	38.5	39.1	4.5	67.5	67.3	43.1
Correlation		.997			.999			.999	

estimates of Equation 3, if there had been no program (thus S would have been zero), the severance rate would have been 13 percent, almost 18 percentage points lower.[38] It is interesting that, in the absence of the program, the severance rates in the younger ages would have been very much lower. At ages younger than 60 years, in the absence of *verip1*, severance rates would have been all less than 1 percent; in fact, severance rates at these ages were as much as 7 percent. Or at age 62 years, the actual severance rate was 29.7 percent and yet the severance rate in the absence of

38. By way of comparison, in the year before *verip1*, the severance rate for faculty in these age groups (the fraction of those eligible to receive pension benefits who quit and drew upon their pension) from UC was 8.25 percent. This might suggest that the prediction of a severance rate of 13 percent in the absence of *verip1* appears high Perhaps The difficulty in comparing the 13 percent prediction with the severance rate in the previous year is that the eligible populations are different: the 1989–90 severance rate measures the number accepting pension benefits as a fraction of all those who were aged 50 with five or more years of UC service; the (actual and predicted) *verip1* severance rate has a much more stringent pool of eligibles (namely, those whose age plus years of service add up to 80 or more years) So the *verip1* eligible population is an older and more senior subset of all faculty eligible to quit and receive pension benefits.

the program is predicted to be 7.9 percent, more than 20 percentage points lower. Therefore, the overall average quit rate of 13 percent in the absence of the program is somewhat misleading; *verip1* had a particularly measurable impact on quits at younger ages and a much smaller impact on quits at older ages.

The impact of *verip2* on severance rates is even greater. The quit rate in the presence of the program was 17.8 percent; we infer the quit rate in the absence of the program would have been less than one percent. This is by no means implausible; *verip1* had induced many quits of people close to the margin of leaving employment so it is unlikely that, in the absence of the program, there would have been more than a handful of quits. Indeed in 1995, after *verip3* had passed, the severance rate among those eligible to receive a pension income was 0.7 percent—almost the same as that I predicted for *verip2* in the absence of the program.

Finally, I predict that the severance rate in 1994 in the absence of *verip3* would have been 14.5 percent. This seems a high figure in view of the generosity of *verip3*'s severance benefits. As in *verip1*, however, what is striking is the large measured impact of *verip3* on severance rates among younger faculty. For faculty aged 58, the severance rate was 40.7 percent; the severance rate in the absence of *verip3* is predicted to be 7.3 percent, almost one-sixth of the actual quit rate.

V. Conclusions

In the introduction I identified two principal questions regarding the acceptance rates of employee buyout programs. One concerned the composition of acceptances and the other concerned the sensitivity of the acceptance responses of employees to buyout opportunities. The composition of acceptances is the adverse selection problem: did the more valuable members of UC's faculty reveal a greater propensity to quit? Insofar as the value of the faculty to UC is measured by their salary (holding constant their age and department), there seems no evidence to support an adverse selection problem.[39] Consistently, quit probabilities fall with salary regardless of the particular set of controls included in the severance equation. A typical finding is that, holding constant other variables, a 10 percent higher salary is associated with a 5–6 percent lower probability of quitting.[40] This finding is consonant with a wide class of research describing a negative association between pay and quit propensities. (See, for instance, the studies cited by Farber 1999.)

The second major question related to the ability of employers to predict the overall response of employees to the severance incentives offered. Employers are more likely to adopt employee buyout programs if the severance (or takeup) rate can be predicted accurately so that the cost of the program can be calculated with some

39 One dimension of the value of a faculty member to a university is his research contributions measured imperfectly by his publications. Kim's (1995) survey of 233 verip-eligible faculty at UCLA included questions about the faculty's research and publications He found little difference in lifetime publications between those accepting and those not accepting *verip3* although those who published less during the four years immediately preceding *verip3* had a greater tendency to quit.

40 This particular estimate comes from Column 1 or Column 5 of Table 6 Of course, a simultaneous 10 percent increase in salary and 10 percent increase in pension income reduces severances by about 2 percent

reliability. Of course, what needs to be predicted is not the overall severance rate itself, but the response of severances to different alternative monetary incentives. These verip programs at the University of California provide an unusual opportunity to evaluate this issue as there were three such programs and it is natural to ask whether the behavior revealed in one verip may be used to forecast behavior accurately in subsequent verips. Surely, the opportunity for accurate prediction in this context is high: in each case, one is predicting from behavior revealed by one group of employees to subsequent behavior by the employees of the same company—in some cases, the very same employees—no more than eighteen months later.

I considered two methods of forecasting severance behavior. In one I naively apply the severance rates in one verip to those in a subsequent verip without any adjustment for differences in the terms of the verip. This method yields predictions that overpredict *verip2*'s takeup rates compared with *verip1* behavior and that underpredict *verip3*'s takeup rates compared with *verip2* behavior. The divergence between actual and predicted severance rates at the aggregate level is 13 and 15 percentage points respectively.

A second forecasting method is to use the estimates of Equation 3 that incorporate the terms of each verip to predict severance behavior. Using the estimates of Equation 3 in one verip to predict severance rates in the subsequent verip results in persistent overprediction of severance rates. At the aggregate level, the overpredictions are about six percentage points when using *verip1*'s estimates of Equation 3 to predict *verip2* behavior and 49 percentage points when using *verip2*'s estimates of Equation 3 to predict *verip3* behavior. This second discrepancy is especially disappointing because the severance terms offered by *verip3* were unlike those of *verip2* and so this comparison may be regarded as the more relevant test of the performance of Equation 3 as a forecasting device.[41]

There are two reasons for the poor forecasts. One concerns changing expectations: *verip1* had no precedent at the University of California and faculty had every reason to believe this was to be their only opportunity to benefit from the severance incentives; *verip2* demonstrated that an early retirement program need not be a singular event and this induced people to wonder whether other programs were going to be offered to help meet the UC's budgetary problems. Inevitably, forecasting is going to be frustrated in contexts in which expectations have changed and in which these changes are unobserved.

The other factor thwarting accurate forecasts is the changing population of faculty eligible for the severance programs. If each individual responds to monetary incentives differently and if these different propensities to accept the severance packages are unobserved by the researcher, then it will be difficult to predict behavior when the population eligible to receive the severance incentives changes. The problem is that the population eligible to receive severance payments is heterogeneous in its propensity to accept such payments and, furthermore, this population changes from one verip to the next in ways the researcher does not observe. When we adjust for

41. Many other variants of Equation 3 were used to predict severance behavior and these other specifications yielded forecasts that diverged about as much as those exhibited by the particular estimates reported The source for the discouraging forecasting performance of Equation 3 is not to be sought in respecifying this equation in obvious ways.

such heterogeneity, the impacts of the severance incentives in *verip2* and *verip3* (as indicated by the estimates attached to ΔS in Table 8) appear similar. However, the estimates of the impacts of the other variables are sufficiently different that forecasts for *verip3* remain discouraging.

As a device to bring about large reductions in an organization's work force, therefore, an employee buyout program has the serious defect that its takeup rate is difficult to predict with accuracy and, consequently, the costs of the program will be hard to project. Hence, notwithstanding the occasional representation by economists of buyouts as "refined" instruments that dominate indiscriminate layoffs, in fact the information required to make buyouts an attractive severance option for employers is so great that firms retain a preference for layoffs. However, at colleges and universities where layoffs of tenured academic staff are infeasible (except in conditions of dire institutional emergency), some form of buyout program is the only method of effecting substantial cuts in employment. Most programs at universities have cut payrolls by targetting older faculty and, for this reason, severance programs have become intertwined with issues about retirement behavior and the nature of retirement plans.

The program studied in this paper concerned the modification of a defined benefit (DB) pension plan to induce separations. At the University of California, faculty were very responsive to the separation incentives: holding constant a number of other factors (such as age and salary), someone presented with a 10 percent higher severance incentive had an 8 percent higher severance probability although, in the first program, there was an even greater response.[42] I conjecture that, at universities where faculty participate in a defined contribution (DC) plan, the use of the retirement program to induce separations is likely to be less effective. That is, to an employee, a DB plan has the attraction of designating a distinct annual pension income (sometimes cost-of-living adjusted, too) so that a severance program that augmented the annual flow is presenting faculty with a precisely specified incentive almost free of income uncertainty in the future. By contrast, an individual's annual retirement income under a DC plan is not guaranteed into the future so that, in a environment of uncertainty regarding his future income, a risk-averse faculty member may well be less inclined to accept a separations bonus. To this effect of income uncertainty is added the fact that a DC plan embodies greater incentives to remain at work compared with a DB plan.[43] For these reasons, the sensitivity estimated in this paper for University of California faculty with respect to the separations incentives offered in the three verips is unlikely to be replicated at universities with DC plans. However, this sensitivity may well be exhibited by faculty at universities with DB plans. In due course, if buyout programs at Universities appear to be expensive mechanisms

42 This eight percent figure comes from Column 1 of Table 6 (on the row corresponding to S) or from Lines 1 and 2 of Table 8 (under the Column ΔS) while the statement about the greater responsiveness in the first verip may be inferred from Column 5 of Table 6 (in the line corresponding to S)

43. This is because, under a DC plan, with each year of work, the employee adds another year of contributions to his pension wealth, he earns returns on his prior pension wealth, and his monthly annuity will be larger at an older age to reflect the shorter life expectancy remaining. Under a DB plan, one more year of work adds one more year of service to the formula defining pension income, but this is unlikely to yield as large an increase in pension income as the three factors listed in the previous sentence that operate for a DC plan. For a clear statement of this, see Gillam and Shoven (1996)

to reduce employment, the entire tenure system will come into more serious question and long-term but limited-duration contracts will replace open-ended, indefinite, tenure contracts.

References

Ashenfelter, Orley, and David Card. 1996. "Faculty Retirement in the Post-Mandatory Era: Early Findings from the Princeton Retirement Survey" Paper prepared for the Princeton Conference on Higher Education, March.

Bowen, William G., and Julie Ann Sosa. 1989. *Prospects for Faculty in the Arts and Sciences: A Study of Factors Affecting Demand and Supply, 1987 to 2012.* Princeton: Princeton University Press.

Chronister, Jay L., and Thomas R. Kepple, Jr. 1987. *Incentive Early Retirement Programs for Faculty: Innovative Responses to a Changing Environment.* Washington, D. C.: ASHE-ERIC Higher Education Report, No. 1 Association for the Study of Higher Education.

Farber, Henry S. 1999. "Mobility and Stability: The Dynamics of Job Change in Labor Markets." In *Handbook of Labor Economics, Volume 3B*, ed. Orley Ashenfelter and David Card, 2439–83. Amsterdam: Elsevier Science.

Gillam, Kathryn M., and John B. Shoven. 1996. "Faculty Retirement Policies: the Stanford Experience." In *Education in a Research University*, ed. K.J. Arrow, R.W. Cottle, B.C. Eaves, and I. Olkin, 37–63. Stanford: Stanford University Press.

Hogarth, Jeanne M. 1988. "Accepting an Early Retirement Bonus: An Empirical Study." *Journal of Human Resources* 23(1):21–33.

Kim, Seongsu. 1995. "Early Retirement Incentives in a Restructuring Organization: The Case of University Professors." Ph.D. dissertation: U.C.L.A.

Lazear, Edward P. 1995. *Personnel Economics.* Cambridge: MIT Press.

National Education Association 1994. *Early Retirement Incentive Programs.* NEA Research Division.

Rees, Albert, and Sharon Smith. 1991. *Faculty Retirement in the Arts and Sciences.* Princeton: Princeton University Press.