THE SURVEY OF INCOME AND PROGRAM PARTICIPATION

SPELLS WITHOUT HEALTH INSURANCE: WHAT AFFECTS SPELL DURATIONS AND WHO ARE THE CHRONICALLY UNINSURED

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Table of Contents

List of Tables and Figures

I. INTRODUCTION

As earlier analyses of the population without health insurance have shown, the uninsured are comprised of many sub-groups of people with different characteristics and different reasons for being without health insurance. To be able to design effective policies for providing health insurance to the different groups of uninsured people, policy makers need to know more than just the characteristics of the uninsured at a point in time. In particular, analyses of the durations of uninsured spells and transitions between insurance states are needed to provide a multi-dimensional picture of the population that lacks health insurance. Such dynamic analyses can provide policy makers with the distribution of how many people experience long versus short spells without health insurance. Further, such analyses can reveal which factors are significant in distinguishing between people who have long uninsured spells and people who have short uninsured spells.

It is important to know who the people are with long uninsured spells-- and short uninsured spells--because such information has a direct bearing on the effectiveness of proposed policies for providing health insurance to the uninsured. For example, if the vast majority of people with long spells do not have strong attachments to the labor force, then mandating employer provided health insurance is not likely to provide health insurance to great numbers of the uninsured. Similarly, if most of the people with long uninsured spells are poor and live in states with low Medicaid income eligibility ceilings, then an expansion of Medicaid income eligibility might be a more effective policy for providing financial access to medical care for the uninsured. Finally, if many people with short spells have the spells because they are changing jobs, then a policy that provides for continuation of coverage for at least three months past the termination of employment might be effective.

In this paper we provide a first approximation of the types of people who are most likely to have long spells without health insurance and the types of people who are most likely to have short uninsured spells. This paper builds on our earlier analyses of the distributions of uninsured spell lengths (Swartz and McBride, May 1990). Our earlier findings indicate that:

- o Half of all uninsured spells end within four months while only 15 percent last longer than 24 months.

- o People in the age cohorts between 18 and 24 years of age and 55 years of age and older account for more of the people who experience spells without health insurance than is indicated by the age distributions of the uninsured at a point in time.

- o People with higher incomes in the first month of an uninsured spell are more likely to have shorter uninsured spells than are people with lower incomes.

- o People who are unemployed or are out of the labor force in the first month of an uninsured spell are more likely to have long uninsured spells; people who are employed (either full-time or part-time) are more likely to have short uninsured spells.

While our earlier findings provide the first analysis of the distribution of the duration of uninsured spells, multivariate models of spell durations are needed to estimate the relative impacts of personal characteristics and factors such as change in employment status on the duration of a spell without health insurance. In this paper, we present our initial estimates of models of uninsured spell durations using hazard functions.

Our principal findings from the multivariate duration analyses reported in this paper are:

- o Although the probability is high that an uninsured spell will end within four months, the length of time a person has already been in an uninsured spell has a strong and negative effect on the probability that the spell will end in any given month. That is, the longer an uninsured spell goes on, the lower the likelihood is that the spell will end.

- o The first finding (above) is consistent with two alternative possibilities about potential differences in the characteristics of people who have long uninsured spells versus short uninsured spells. The first possibility is that we cannot observe differences between the two groups of people but there are unobservable differences that explain why one group has long spells and the other group has short spells. The second possibility is that time spent in an uninsured spell in and of itself causes a person to change in some way that increases the probability that the person will remain uninsured as time in the spell increases.[1] Our findings indicate that the

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1. The analogy in unemployment dynamics is that time spent in a spell without employment causes the person's skills to decrease. Thus, the longer a person continues to be unemployed, the more his or her skill level declines, and the likelihood that an employer will want to hire him or her decreases as well. In
(Footnote continued on next page)

observable characteristics of the people with long uninsured spells (i.e., that last 9 months or more) are in some respects not different from the characteristics of people who have uninsured spells that end within 4 months. However, people who have longer uninsured spells are more likely to be unemployed or out of the labor force, have low monthly family incomes, and work in a service occupation than people with short uninsured spells.

- A person who is employed has a higher probability of ending an uninsured spell than an unemployed person, and a person who became employed within the previous four months has an even higher probability of ending an uninsured spell. Contrary to our expectations, a person who is employed part-time has a higher probability of ending an uninsured spell than an individual employed full-time.

- Monthly family income has a positive effect on the probability that an uninsured spell will end. As income increases, the effect of income on the probability that an uninsured spell will end also increases.

- The probability that an uninsured spell will end is higher for adults 18 to 24 years of age or 55 years of age and older than for adults 25 to 54 years of age. Married adults also have a higher probability of an uninsured spell ending than do people who are not married.

- People who live in the Northeast or Midwest regions of the U.S. have higher probabilities of uninsured spells ending than do people who live in the South or West.

- People who work in either manufacturing or the public sector have the highest probabilities of an uninsured spell ending.

- Finally, people who list their occupation as "service workers" (e.g., food service, health service, protective service, cleaning and building service, private household service) have lower probabilities than people in other occupations for an uninsured spell ending.

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the case of spells without health insurance, it may be that someone who has not been insured for some time may be looked upon with suspicion by an insurance company and therefore time in an uninsured spell may be a factor in and of itself. However, remaining uninsured may be indicative of being medically uninsurable or of some other unobservable characteristic--at which point we are back to the second possibility that unobservable characteristics differentiate people with long uninsured spells from people with short spells.

The plan of the paper is as follows. The Survey of Income and Program Participation (SIPP), the source of the data used to estimate our model of uninsured spell durations, is described in Section II. In Section III we briefly explain the duration models used to estimate the relative impacts of various socio-demographic characteristics and labor force status factors that affect the length of a spell without health insurance. We also discuss how we handled the problem posed by attrition from the SIPP. (A longer description of the methodology used in the paper is contained in the Appendix.) In Section IV we present the results from the estimation of the model and illustrate how various factors affect the probability that an uninsured spell will continue. In Section V, we discuss differences and similarities in the characteristics of people with uninsured spells that end within 4 months and people who have uninsured spells that last 9 months or more. Finally, in the concluding section, we discuss the implications of the model's results for proposed policies such as employer mandated health insurance and Medicaid expansion.

II. DATA

Our study is based on data from the 1984 Panel of the Survey of Income and Program Participation (SIPP). The SIPP is a multi-panel, longitudinal survey conducted by the Bureau of the Census. The first panel was initially interviewed in the fall of 1983 and is known as the 1984 Panel. Originally, the 1984 Panel had a sample of about 53,000 people, but due to sample attrition and intentional sample reduction caused by budget reductions, the sample fell to about 32,000 people. Subsequent SIPP panel samples have been smaller and therefore we elected to use the 1984 Panel.

The SIPP is a nationally representative sample of adults that provides detailed socio-demographic information as well as information on month by month fluctuations in household and individual income, labor force status, participation in government sponsored programs such as AFDC, Food Stamps, and Medicaid, and health insurance coverage and the like. The information is collected for the individual and the individual's household (including children under the age of 15) for the four months preceding each interview. The full 1984 Panel had eight interviews, covering a period of 32 months.[2] Thus, we have data on the health insurance coverage and other socio-economic characteristics of individuals for as long as 32 months.

People who were in the midst of a spell without health insurance when either the SIPP survey began or ended present censoring problems, i.e., we do not observe the true duration of their uninsured spells. In this paper we have chosen to measure only those uninsured spells for which we can observe a beginning. Thus, we are not including uninsured spells that are left censored in our model. Right censoring occurs when the end of a spell cannot be observed. The spell's conclusion will not be observed if either the survey ends before the spell ends or the person leaves the survey and the spell appears to be still in progress.

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2. A ninth wave of interviews was conducted for only half of the 1984 Panel sample because of budget cuts, and therefore longitudinal research with the SIPP is generally confined to the 32 month period covered for the full sample.

We have also chosen to model the duration of uninsured spells for adults at least 18 years of age at the beginning of the SIPP. We chose to omit children because children do not choose their health insurance coverage and because we believe factors that affect the duration of a child's uninsured spell are likely to be different than those that affect the duration of adults' spells. In particular, variables describing family formation and household transitions are likely to be associated with durations of children's spells without health insurance.

III. METHODOLOGY

The process studied here is the transition from uninsured to insured status. A common function used to describe this transition probability is the hazard function; the estimation of this function is called duration or survival analysis.[3] The hazard function measures the tendency of a given event (e.g., the transition from being uninsured to being insured) to occur at a given point in time. The Appendix contains a detailed discussion of the estimation methods and some important estimation issues. Here, we briefly describe the estimation procedures.

In observing health insurance coverage, the vast majority of health insurance policies are in force for calendar months--i.e., people begin (or end) coverage on the first (or last) day of a month. When the dynamic process being studied is measured in discrete intervals such as months, a "discrete" hazard model is the appropriate specification for the analysis and the hazard function can be estimated using a logistic regression function (Allison, 1982).

When the SIPP sample is used in the estimation of a hazard model, sample "attrition" becomes an important problem. Sample attrition occurs when a sample persons leaves the sample before acquiring health insurance. Table 1 presents counts of the number of uninsured spells, and the total uninsured "spell months" of individuals included in our sample. The end of a spell is not observed for roughly 40 percent of the uninsured spells and these spells account for just over half of the total spell months (where total spell months is defined as the length of observed spells summed across sample persons). Sample attrition accounts for 17 percent of the spells and two-thirds of these spells ended with voluntary attrition from the sample. However, the voluntary attrition cases account for only nine percent of the total spell months in the sample.

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3. There is extensive literature dealing with survival analysis and hazard functions. See, for example, Allison (1982), Kiefer (1988), Cox and Oakes (1984), or Kalbfleisch and Prentice (1980).

Table 1.
Distribution of sample persons and spell months,
by observed ending of spell during the survey period

	Sample persons		Spell months	
Type of spell ending	Number	Percent	Number	Percent
End of spell observed	3,191	61%	17,855	48%
End of spell not observed	2,042	39%	19,416	52%
Because of end of survey	1,159	22%	14,144	38%
Because of sample attrition	883	17%	5,272	14%
Deliberate sample reduction	283	5%	1,843	5%
Voluntary attrition	600	12%	3,429	9%
TOTAL	5,233	100%	37,271	100%

SOURCE: 1984 SIPP panel (see text).

If voluntary attrition is not random across the sample respondents, then it is likely that attrition would lead to biased estimation results if the attrition cases were excluded from the analysis. For this reason, we have included the attritors in the estimation sample and we treat attrition cases like spells that were still in progress when the survey ended. This is the approach suggested by Allison (1982). (See the Appendix for a longer discussion of this issue.) The advantage to this approach is that important information is not being "thrown away" for people who left the sample. For example, if a person is observed without insurance for 24 months and then leaves the sample in the 25th month, the model uses the information that the person's spell lasted at least 24 months. Nothing is known about the person's insurance coverage in the months following the 24th month, but this case is very similar to a person who is observed with an uninsured spell for 24 months and was still uninsured at the end of the survey period.

Although it is possible to specify a hazard function which does not depend on the characteristics of an individual, the purpose of this paper is to identify the characteristics that increase or decrease the probability that an uninsured spell will end for an individual. Thus, we estimate a hazard model which includes the characteristics of an individual, such as age and marital status, income, and variables that describe a person's job and labor force status. The Appendix contains a detailed description of these explanatory variables.

IV. RESULTS

In this section we present the results from the estimation of the hazard model described in the previous section. As part of the presentation of the results, we also provide several ways of viewing the implications of the model's estimated coefficients. The model was estimated using maximum likelihood techniques and the statistical package LIMDEP (Greene, 1988).

The hazard function does not provide direct estimates of the duration of uninsured spells. Instead, the hazard function is the basis for deriving the probability (or hazard rate) that a spell will end in the month under surveillance. Thus, the model is estimated with units of observation that are spell months and a hazard rate is calculated for each month of an uninsured spell for each person who has an uninsured spell. This model allows us to determine the effects of various socio-demographic and job-employment characteristics, as well as characteristics of the spell itself, on the probability that a spell will end in the current month.

Table 2 presents the results from the estimation of the hazard model. The signs of the coefficients indicate the effects of the variables on the hazard rate. Thus, a positive and significant estimated coefficient indicates that the variable causes the hazard rate to be higher, which in turn indicates that the uninsured spell is more likely to end in the month under surveillance. Similarly, a negative and significant coefficient indicates that the variable causes the hazard rate to be lower and the uninsured spell is less likely to end in the month under surveillance.

The nonlinearity of the logistic specification of the hazard model prevents the direct interpretation of the effects of the variables on the hazard rate. There are several methods for determining the effect of each of the variables on hazard rate. We present two such methods in turn. Each method involves estimating the hazard rate from the estimated model and simply varying one variable at a time.

One method for determining the effect of each variable involves calculating a hazard rate for a hypothetical person who has the mean value of each of the variables in the model. Then, the effect of each significant variable can be determined by altering one characteristic at a time and recalculating the hazard rate. Table 3 contains estimates of the hazard rate for an "average" respondent along with the recalculated hazard rates as each of the succeeding variables are altered.

Table 2.
Regression results

Variable	Coefficient	Standard Error	Mean
Socioeconomic characteristics:			
AGE2534	-.0959*	.0547	.319
AGE3554	-.1087*	.0640	.253
AGE55P	-.0728	.0847	.098
MARR	.1262**	.0539	.441
PREVMAR	.0475	.0680	.194
SOUTH	-.1930***	.0591	.374
MIDWEST	-.0963	.0635	.238
WEST	-.1777***	.0643	.227
INCLT12	.0162**	.0078	16.966
INC12T24	.0046	.0118	7.889
INC24P	-.0183***	.0062	3.728
RATLP5	.4480***	.0805	.093
RATG1P5	.0522	.0867	.061
Labor force and job characteristics:			
EMPLOYED	-.0901	.0746	.552
UNEMP	-.2325***	.0691	.181
TEMPE	.1454**	.0635	.114
TEMPU	.1290*	.0696	.136
PART	.2795***	.0543	.267
ICONST	-.1564	.1291	.042
IMAN	.3843***	.0834	.070
ISERV	.2693***	.0700	.193
IPUB	.7851***	.1523	.013
IRET	.1443*	.0756	.146
OPREC	-.0896	.0978	.058
OSERV	-.3137***	.0658	.154
Spell characteristics:			
SPL5T8	-.4639***	.0515	.218
SPL9T12	-.8969***	.0745	.120
SPL13T16	-.9784***	.0983	.070
SPL17T20	-1.3628***	.1467	.041
SPLG21	-1.8942***	.2165	.030
SEAM	2.4857***	.0434	.250
CONSTANT	-3.4710***	.0990	1.000
Log Likelihood			8,628
Log Likelihood (Slopes=0)			10,893
Observations			37,271

***Significant at 99 percent level.
**Significant at 95 percent level.
*Significant at 90 percent level.

Table 3.
Effects of significant variables on the estimated hazard rate

Characteristics	Hazard rate[a]
Average respondent	.0490
Age:	
Age<25 or Age>54	.0521
Age 25-34	.0476
Age 35-54	.0470
Marital status:	
Married	.0519
Not married	.0461
Region of U.S.:	
Northeast or Midwest	.0557
South	.0464
West	.0471
Monthly family income:	
$400	.0392
$800	.0417
$1,200	.0444
$1,800	.0500
$2,400	.0563
$3,600	.0580
Income ratio:	
Income ratio less than 0.5	.0716
Income ratio ≥ 0.5	.0470
Employment status	
Employed	.0535
Employed part-time	.0648
Employed full-time	.0498
Recently employed	.0594
Unemployed	.0428
Recently unemployed	.0469
Out of labor force	.0535
Recently unemployed	.0585
Industry:	
Manufacturing	.0639
Services	.0573
Public sector	.0924
Retail trade	.0509
Other	.0444
Occupation:	
Service worker	.0382
Other	.0515
Length of spell:	
Less than 5 months	.0708
5-8 months	.0457
9-12 months	.0301
13-16 months	.0278
17-20 months	.0191
21 or more months	.0113

a. Hazard rate calculated with all variables set equal to mean value, except for the variable noted.

An alternative method for illustrating the effect of each variable involves calculating how the survival probability changes over time as each variable is changed. Recall that the survival probability is a dynamic counterpart to that hazard rate, indicating the probability that a spell will last to a given month. Although the survival probability is calculated directly from the hazard rate (see Appendix A), the former measure is useful because it indicates how long an individual's spell would be expected to last given a set of characteristics. High estimated hazard rates are associated with lower survival probabilities because the hazard rate is the probability that a spell will end in a given month.

We present in Figures 1 through 8 the uninsured spell survival probabilities for people with different characteristics. The Figures start with a prototypical person (called the base case) who has the following characteristics: he/she is 25 to 34 years of age, married, resides in the South, has a monthly income of $1,700 (in 1983 dollars), is employed full-time in the service sector, but does not have a service occupation.[4] Each of these characteristics are varied in the Figures to illustrate the impact of the variables on the survival probabilities.

The two methods of interpreting the results from the estimated hazard model complement each other. We discuss the model's implications by referring to both Table 3 and the Figures. We discuss the effects of the variables in descending order of their effect on the probability that an uninsured spell will end.

Spell characteristics. The results provide strong evidence of negative "duration dependence" in spells without health insurance. Negative duration dependence occurs when the probability of a spell ending decreases as the length of time of a spell increases. Although the results indicate that the probability is high that an uninsured spell will end quickly (i.e., within four months), the results also indicate that if a spell does not end in the first few months, the spell is increasingly less likely to end as time goes on. The estimated hazard rates in Table 3 illustrate the effects of the different durations of spells. The hazard rate is quite high for a spell that has been in progress

4. These "base case" characteristics are the modal characteristics found in the sample (see Table 3).

for less than five months but as the duration of the spell increases, the hazard rates fall dramatically.

The "seam" effect is also in evidence in the Figures. As we noted in Section III, seam effects occur when transitions in characteristics appear to occur primarily in the month when the respondent is interviewed. SIPP is known to have seam effects (Young, 1988), and the results presented here confirm that the end of a spell without health insurance is much more likely to occur during a seam-interview month. The Figures illustrate nicely the way in which the probability that a spell will end declines more precipitously at seam months. Although we expected the seam effect to be significant, Young's investigation of seam effects indicates that they only affect the timing of a transition to insurance coverage during a four month period--and not the relationship between the other explanatory variables and the probability of a spell ending.

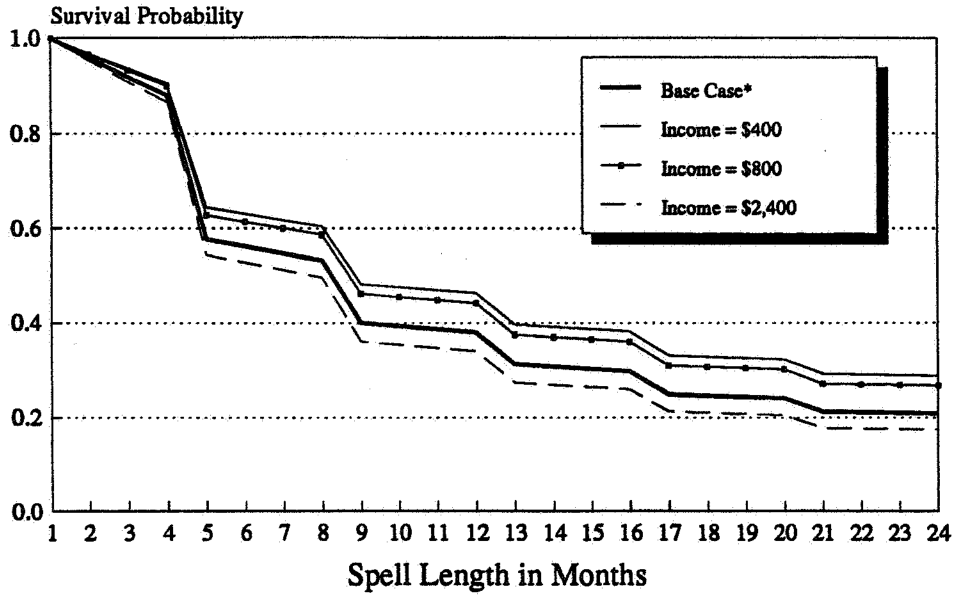
Family income. Monthly income has a strong impact on the probability that an uninsured spell will end. The results in Table 3 show that the hazard rate increases as income increases, although the increase is not monotonic. In particular, if a person's family income is above $2,400 per month (in 1983 dollars), the additional dollars of income above $2,400 have a very small impact on the hazard rate. Figure 1 illustrates the effect of monthly income on the survival distributions. The probability that an uninsured spell will continue is clearly lowest for someone with a monthly income of $2,400 and highest for someone with an income of $400 per month.

The effect of a change in monthly income is also quite strong. Table 3 shows that the hazard rate rises considerably when the person's income drops at least 50 percent, all else remaining the same. We suspect that one explanation for this is that people who experience such a sharp drop in monthly income are more likely to become eligible for Medicaid.

Employment status. Since health insurance is often offered as a benefit with employment, one would suspect that spells without health insurance would last longer for unemployed persons than for employed persons. The results confirm this hypothesis, since the estimated hazard rate is lower for persons who are unemployed than it is for persons who are employed (Figure 2 and Table 3). However, the hazard rate for employed persons is not significantly different than the hazard rate for persons who are out of the labor force (Table 2). The result may be explained by

Figure 1

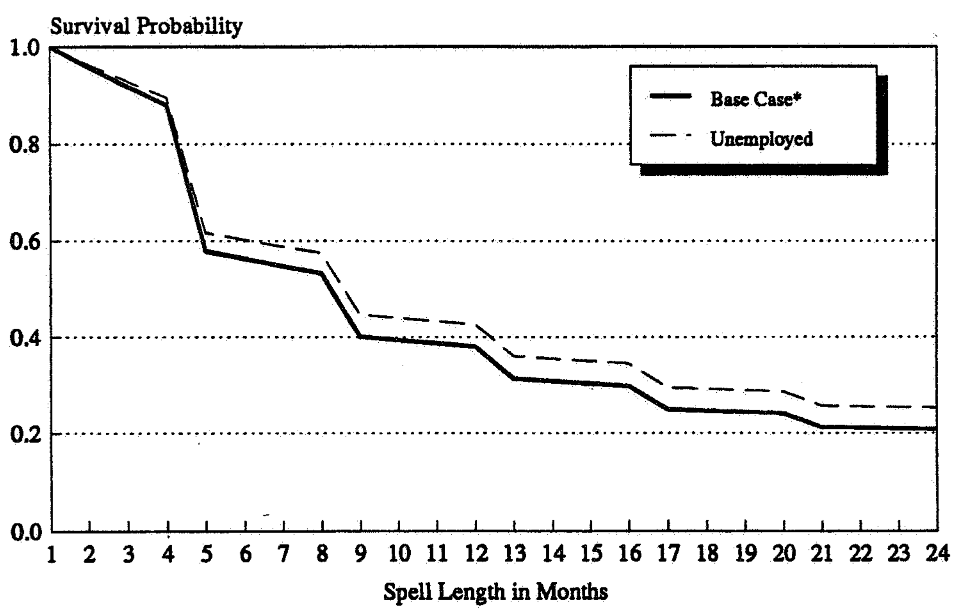
Survival Distribution: By Income



*Base Case: age 25-34, lives in the South, income = $1,700, married, and employed in the service sector (not in service or precision occupation).

Figure 2

Survival Distribution: Employment Status



*Base Case: Age 25-34, lives in the South, income=$1,700, married, and employed in the service sector (not in service or precision occupation)

the composition of these two subpopulations, because persons who are out of the labor force are more likely to have lost coverage from another person (e.g., a spouse) and analysis suggests that these types of spells are relatively short. Another explanation is that the difference in hazard rates between persons who are employed and persons who are out of the labor force is explained by the characteristics of a person's job (e.g., industry and occupation). In fact, results not shown here demonstrate that employment became significant when the industry variables were dropped.

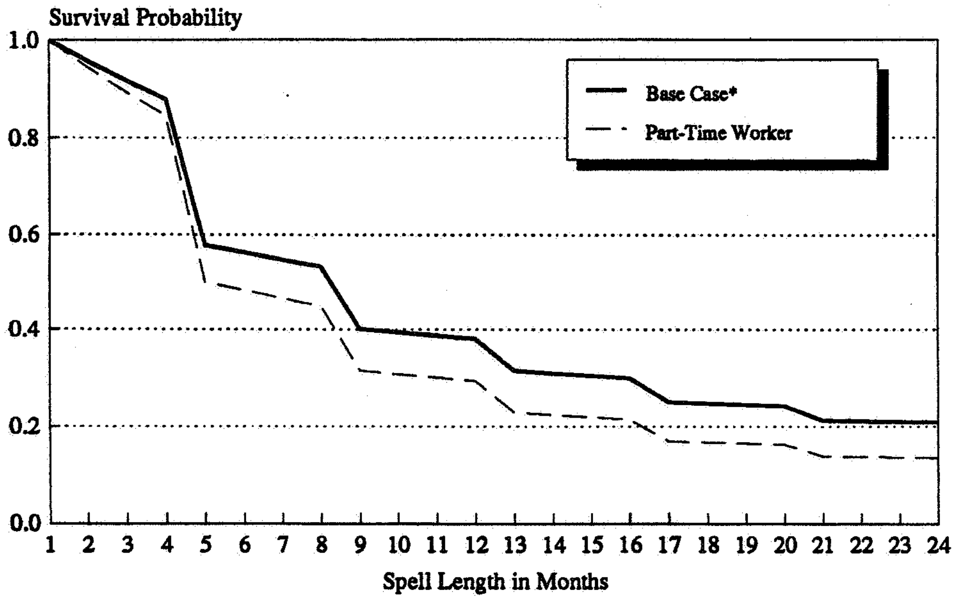
A recent change in employment status is likely to lead an increase in the hazard rate (Table 2). This is true even if a person was recently unemployed, as well as recently employed, although the latter coefficient is only significant at the 90 percent level. Recalling that these variables denote a change in employment status in the last four months, the implication of this result is that any recent change in employment status seems to indicate a person whose spell without health insurance will be brief. It is likely that this result captures persons who change jobs often and who lose and gain insurance coverage with each job change. This type of person may be important for policy purposes because they are likely to have multiple spells without health insurance. However, the analysis of multiple spells without health insurance is beyond the scope of this paper.

The one result from the model that we find puzzling is that the probability that an uninsured spell will end is higher if the person is employed part-time, all other factors being equal. (See Figure 3.) This result is quite significant and has a large effect on the hazard rate. This finding may confirm a fact that is well known: there are people with full-time jobs without health insurance and such people have long uninsured spells. In contrast, there are people who have part-time jobs in which the person either receives health insurance or the opportunity to purchase group insurance on a pro rata basis. The full-time, part-time distinction may also indicate something about a spouse's health insurance opportunities, but some of this should be controlled for by the marital status variable. As can be seen in Figure 4, being married has a small positive effect on the probability that an uninsured spell will end.

<u>Job characteristics</u>. The industry and occupation of a person's main job have large impacts on the probability that an uninsured spell will end. In particular, if a person's main job is in either

Figure 3

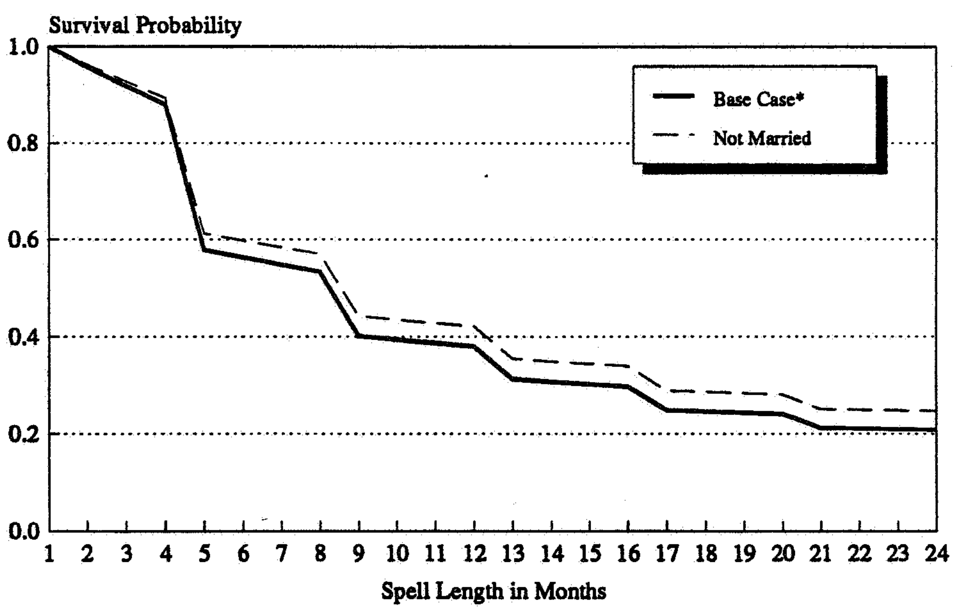
Survival Distribution: Part-Time Status



*Base Case: Age 25-34, lives in the South, income = $1,700, married, and employed in the service sector (not in service or precision occupation)

Figure 4

Survival Distribution: By Marital Status



*Base Case: Age 25-34, lives in the South, income=$1,700, married, and employed in the service sector (not in service or precision occupation)

manufacturing or the public sector, the probability is higher that the uninsured spell will end (Table 3). This is no doubt due to the fact that the prevalence of employer-group health insurance in these sectors is high. Figure 5 illustrates the effects of the various industries on the survival probabilities: having a job in the public sector is obviously a positive factor in ending an uninsured spell.

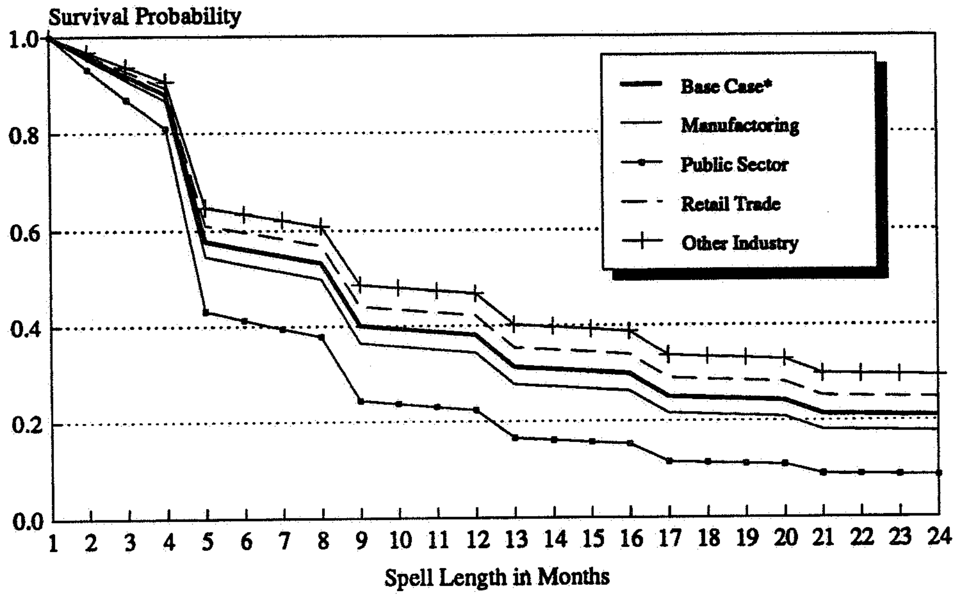
If a person has a service occupation (e.g., food service, protective service, janitorial and building cleaning service), the probability that an uninsured spell will end quickly is particularly low (Figure 6). Analysis suggests that none of the other possible occupational categories were significant in their effect on the probability that an uninsured spell would end.

Age and Region of Residence. The effect of age on the hazard rate is negative for persons who are between age 25 and 54, although the results are significant only at the 90 percent level. The estimated hazard rate for a person between age 25 and 54 is lower than the estimated hazard rate for younger and older adults, all else equal (Table 3). Put another way, these results imply that spells without health insurance are more likely to be long if a person is between age 25 and 54, than if the person is younger or older. An explanation for this result may be that old persons are more likely to reacquire insurance because they are more likely to acquire government insurance through Medicare and Medicaid. On the other hand, the spells without health insurance for young persons may be the temporary result of a transition from coverage under another person's policy (e.g., a parent's policy) to their own coverage. Being between 25 and 34 years of age or between 35 and 54 years of age have a small negative impact on the probability that an uninsured spell will end but the effect for both of these groups is for all intents and purposes the same (Figure 7).

Being a resident of either the South or the West, relative to being a resident of the Northeast, has a negative impact on the probability that an uninsured spell will end (Table 3). Residing in the South has a particularly large negative effect, as can be seen in Figure 8. One explanation for the negative impact of residing in the South or West is that most states in these two regions have relatively low income eligibility ceilings for Aid to Families with Dependent Children and Medicaid. Also, many industries in these regions do not offer health insurance benefits to

Figure 5

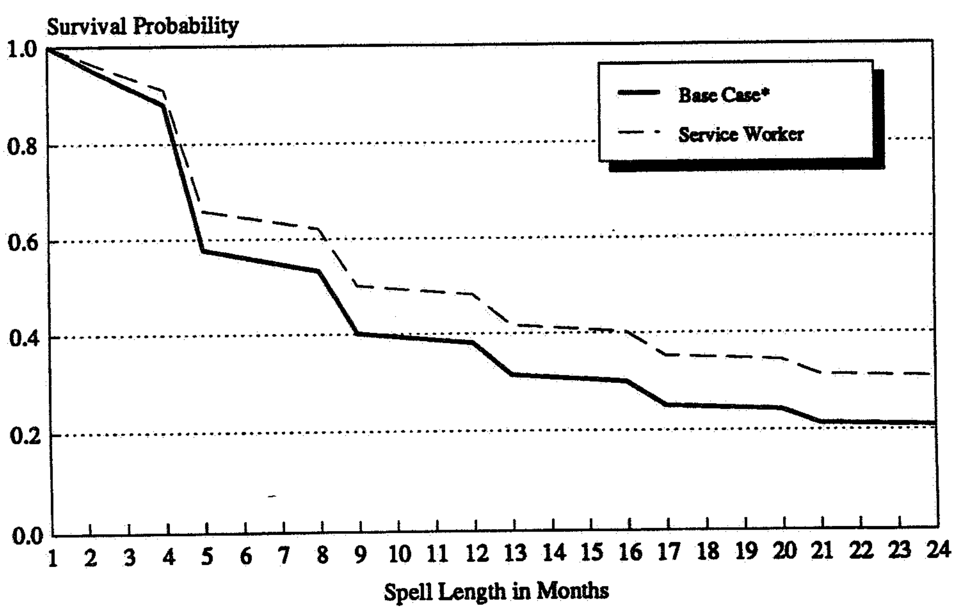
Survival Distribution: By Industry



*Base Case: Age 25-34, lives in the South, Income=$1,700, married, and employed in the service sector (not in service or precision occupation)

Figure 6

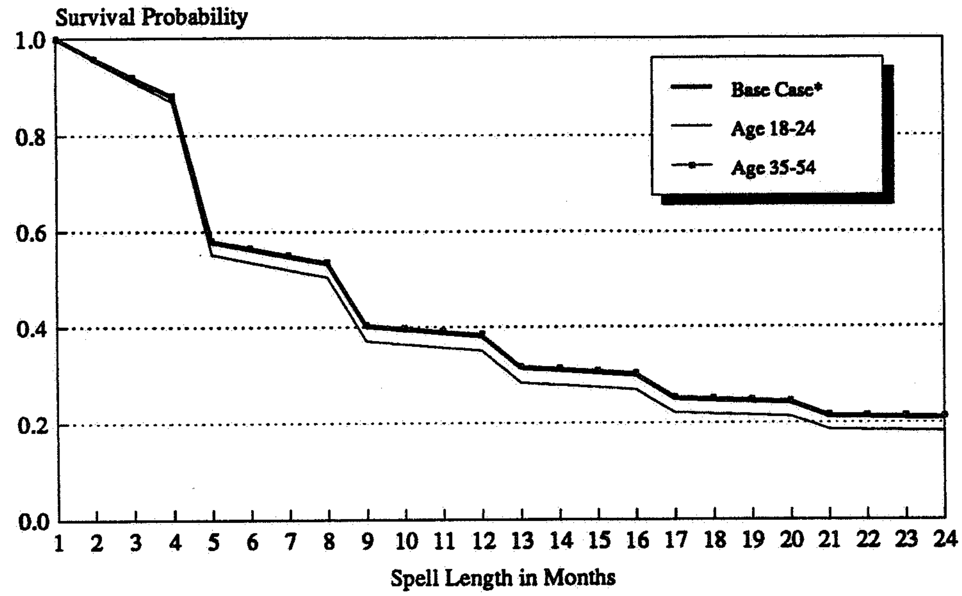
Survival Distribution: By Occupation



*Base Case: Age 25-34, lives in the South, income=$1,700, married, and employed in the service sector (not in service or precision occupation)

Figure 7

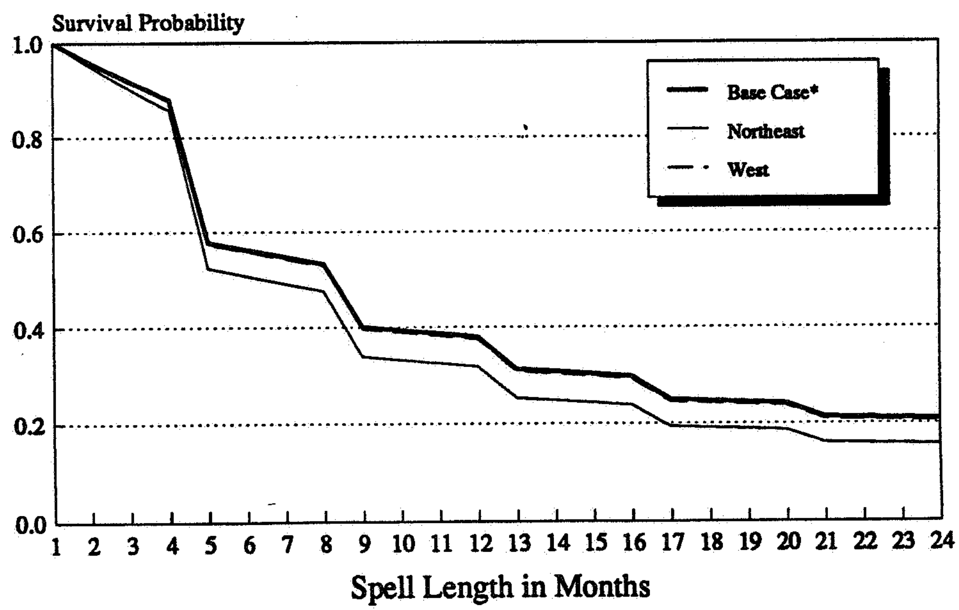
Survival Distribution: By Age



*Base Case: Age 25-34, lives in the South, income=$1,700, married, and employed in the service sector (not in service or precision occupation)

Figure 8

Survival Distribution: By Region



*Base Case: Age 25-34, lives in the South, income = $1,700, married, and employed in the service sector (not in service or precision occupation).

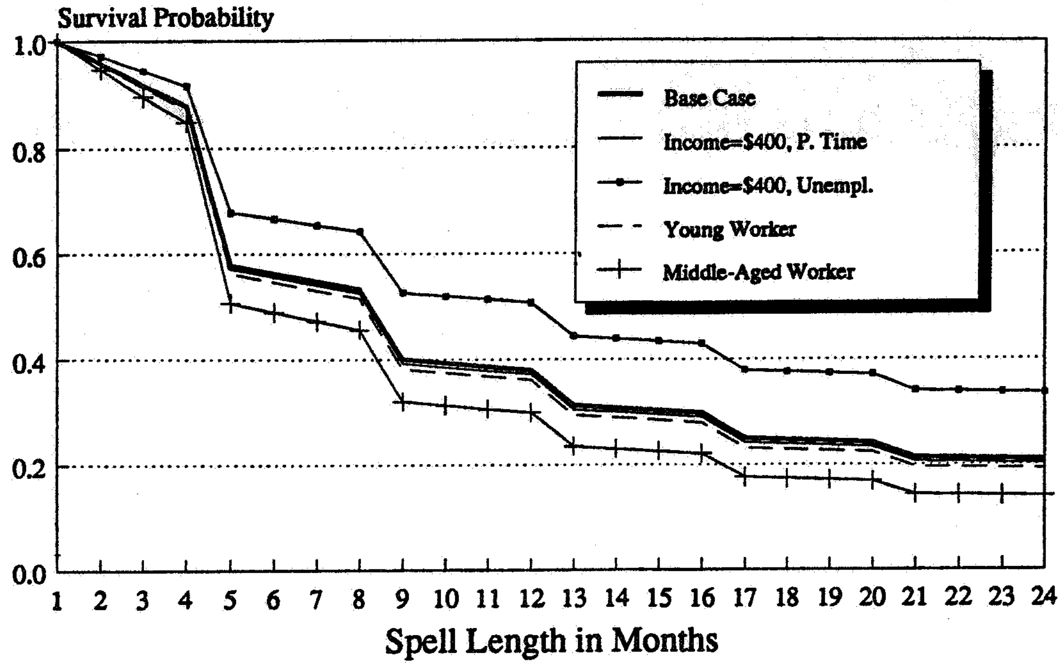
employees so workers are less likely to have health insurance in these regions than are their counterparts in the Northeast and Midwest. Thus, all other things equal, a resident of the South or West has less access to public or private health insurance coverage compared with a resident of the Northeast or Midwest.

In sum, the factor that has the largest effect on the probability that an uninsured spell will end in a given month is the length of time that the spell has been in progress. Most spells end within the first four months, but if an uninsured spell does not end in that time then the probability that a spell ends declines quickly. The characteristics that have the largest impact on the probability of an uninsured spell ending are income, gaining employment within the previous four months, being unemployed or being employed part-time, and industry of employment.

Figure 9 provides a summary of survival probabilities for five typical people with various characteristics who might a priori be thought to be among the uninsured population. Figure 9 enables us to see how the survival probabilities of "whole" people differ rather than just observing how survival probabilities vary as one characteristic changes while all other characteristics remain constant. Our "base case" person is represented in Figure 9: he/she is 25 to 34 years of age, is married, lives in the South, has a monthly income of $1,700 (in 1983 dollars), is employed full-time in the service sector and has a non-service occupation. A second person, labeled "young worker" on Figure 9, is between 18 and 24 years of age, is not married, is employed part-time, has a monthly income of $800, but like the base case person lives in the South and has a non-service occupation in the service sector. The fact that the survival probability distributions of the young worker and the base case person are not really different illustrates the interactive effects of the various characteristics. Being employed part-time contributes a large positive effect to the survival probability and counteracts the small negative effect of the drop in income to $800, while the effects of being between 18 and 24 years of age and not married counter-balance each other. The third "typical" person shown in Figure 9 has all the same characteristics as the base case except that he/she is employed part-time and has a monthly income of $400. This person's survival probability distribution is almost indistinguishable from those of the first two examples.

Figure 9

Survival Distribution: Example Cases



*Base Case: Age 25-34, lives in the South, income = $1,700, married, and employed in the service sector (not in service or precision occupation).

The reason for this is that the effect of the drop in income to $400 is effectively counteracted by the effect of the part-time employment.

In contrast, the fourth and fifth "typical" people shown in Figure 9 do have different survival probability distributions than those of the first three examples. The person with the lowest survival probability distribution--indicating the lowest probability that the spell will continue and therefore the highest probability that the spell will end--is the "middle-aged worker". The middle aged worker is between 35 and 54 years of age, is married, lives in the West, has a monthly income of $2,400, is employed full-time in the manufacturing sector and has a non-service occupation. The positive effects of the higher income and working in the manufacturing sector are clearly evident in the middle-aged worker's relatively low survival probability distribution. By implication, the middle aged worker also has the highest probability of experiencing a short uninsured spell compared with the other four examples.

The fifth "typical" person has the highest survival probability distribution among the five examples. This person differs from the third example only in terms of being unemployed--i.e., he/she shares the characteristics of the base person except that the monthly income is $400 (as with the third example) and is unemployed. Clearly, the large negative effects of having a low monthly income and being unemployed are evident in this example. A person with all of these characteristics is much more likely to continue in an uninsured spell than any of the other examples, and by implication to have a higher probability of experiencing a long uninsured spell.

We next turn to describing the characteristics of the people who have long spells without health insurance and contrast them with the people who have short uninsured spells.

V. CHARACTERISTICS OF THE SHORT-TERM VERSUS LONG-TERM UNINSURED

As described in Section III, one of the uses of the regression results presented above is the ability to differentiate people who are likely to have long spells without health insurance from those whose uninsured spells end quickly. Table 4 presents a number of observable characteristics of uninsured people, differentiated by the length of the person's uninsured spell: those with uninsured spells that end within four months, and those with spells that last 9 or more months.[5] The latter group might be thought of as the chronically uninsured. Recall that the characteristics of these people are their characteristics as observed in the last observed month of the spell (i.e., an individual's characteristics in the last month of the spell for individuals with completed spells and an individual's characteristics in the last observed month for people with right censored spells).

The results in Table 4 demonstrate that the observable characteristics of the long-term uninsured are different in many respects from the observable characteristics of the short-term uninsured. The most striking result from Table 4 concerns the income distributions of the two groups. Sixty percent of the people with short uninsured spells have monthly incomes in excess of $1,200 (in 1983 dollars), while only 45 percent of the people with longer uninsured spells have similar incomes. At the lower end of the income distribution, 37 percent of the people with longer uninsured spells have monthly incomes below $800 per month--a figure roughly equivalent to the poverty line in 1983--while just 26 percent of the people with short uninsured spells have a monthly income below $800. These numbers strongly suggest that people below the poverty line are very likely to be found among the chronically uninsured and that people with more economic resources are more likely to quickly acquire health insurance if they lose it.

The employment status distributions of the short-term and longer-term uninsured reflect the uneven impact of employment status as a predictor of the length of an uninsured spell. On the one

5. An important caveat to all these results is that our sample does not include left censored spells, i.e., spells that were in progress at the start of the SIPP panel. Although it is possible that some of these people are in the midst of short uninsured spells that started right before the first SIPP interview, it is most likely that these people are in the midst of long uninsured spells. Thus the results presented here, calculated from analysis of just the spells for which we observe a beginning, will be biased by the exclusion of the left censored spells. Efforts to rectify this problem were beyond the scope of this project, but will be addressed in future work.

hand, a slightly higher proportion of the people with short spells are employed than are the people with longer spells (62 percent versus 55 percent). But, in a comparison of the proportions working part-time versus full-time, we observe again what we found in the regression results presented earlier: part-time workers are more likely than full-time workers to experience short spells without health insurance. This result might be explained by the high incidence of part-time work among young workers and people who are covered by someone else's (e.g., a spouse) health insurance plan. Clearly more research in this area needs to be done if we are to fully understand how employment status affects the duration of an uninsured spell.

Differences in the occupational distributions of the short-term and longer-term uninsured appear mainly in the technical and service occupations. A third of the short-term uninsured who are employed have technical occupations as compared with just under a quarter of the longer-term uninsured. Conversely, 22 percent of the short-term uninsured who are employed are in service occupations while 30 percent of the longer-term uninsured are in service occupations. The distributions of the two groups of uninsured among the other occupational categories are quite similar.

Table 4 shows that there are only small differences in the distributions of industry of employment, age, marital status, and region of residence for the two groups of uninsured people. Thus, by themselves, these characteristics are not good indicators of who will have short uninsured spells and who will have longer uninsured spells.

In conclusion, the results in Table 4 indicate that the short-term and longer-term uninsured are different in terms of monthly family income, employment status, and occupation (if they are employed). However, the two groups of uninsured people are not significantly different in terms of the other observable characteristics shown in Table 4.

Characteristics of persons with long and short spells: estimates from the 1984 SIPP panel[1]

Characteristic	Characteristics of persons with spells lasting: <4 months	9+ months
Income		
Less than $800	26%	37%
$800-$1,199	15%	18%
$1,200 or more	60%	45%
$1,200-$2,399	33%	28%
$2,400 or more	27%	17%
Employment status		
Employed	62%	55%
Employed full-time	33%	41%
Employed part-time	29%	14%
Not employed	37%	45%
Unemployed	14%	18%
Out of labor force	23%	27%
Occupation (Percentage of employed persons)		
Technical	34%	24%
Service	22%	30%
Laborer	18%	20%
Professional	12%	10%
Precision	11%	10%
Other	3%	5%
Industry (percentage of employed persons)		
Service	36%	34%
Retail	25%	27%
Manufacturing	16%	13%
Other	22%	27%
Age		
Age 18-24	34%	30%
Age 25-54	56%	60%
Age 55 or older	10%	10%
Marital status		
Married	46%	43%
Not married	55%	57%
Previously married	18%	22%
Never married	37%	35%
Region		
East	19%	14%
Midwest	23%	24%
South	36%	39%
West	22%	23%
TOTAL	100%	100%
Percentage of all spells	50%	31%

NOTE: 1. The characteristics are defined as the characteristics of a person in the last observed month of the uninsured spell (see the text).

VI. CONCLUSIONS AND POLICY IMPLICATIONS

As we noted in the Introduction, analyses of the durations of uninsured spells are needed to provide a multi-dimensional picture of the population that lacks health insurance. In this paper, we have provided further details on the distribution of how many people have long versus short uninsured spells, and the characteristics that are significant in distinguishing between the types of people who have long uninsured spells and the types of people who have short uninsured spells. As part of the latter analyses, we also determined the relative importance of socio-economic characteristics and other factors that are associated with increasing the probability that an uninsured spell will end.

Our principal findings are:

- Although the probability is high that an uninsured spell will end within four months, the length of time a person has already been in an uninsured spell has a strong and negative effect on the probability that the spell will end in any given month. That is, the longer an uninsured spell goes on, the lower the likelihood that the spell will end.

- The observable characteristics of the people with long uninsured spells (i.e., that last 9 months or more) are in some respects not different from the characteristics of people who have uninsured spells that end within 4 months. However, people who have longer uninsured spells are more likely to be unemployed or out of the labor force, have low monthly family incomes, and work in a service occupation than people with short uninsured spells.

- A person who is employed has a higher probability of ending an uninsured spell than an unemployed person, and a person who became employed within the previous four months has an even higher probability of ending an uninsured spell. A person who is employed part-time has a higher probability of ending an uninsured spell than an individual who is employed full-time.

- Monthly family income has a positive but non-linear effect on the probability that an uninsured spell will end. As income increases, the effect of income on the probability that an uninsured spell will end appears to shift at several points. Our functional form for monthly income has two "shift" points, one at $1,200 and the other at $2,400 (in 1983 dollars).

- Adults 18 to 24 years of age or 55 years of age and older have higher probabilities of an uninsured spell ending than do adults 25 to 54 years of age.

- People who live in the Northeast or Midwest regions of the U.S. have higher probabilities of uninsured spells ending than do people who live in the South or the West.
- People who work in either manufacturing or the public sector have the highest probabilities of an uninsured spell ending.
- Finally, people who list their occupation as "service worker" have lower probabilities than people in other occupations for an uninsured spell ending.

There are several implications from these findings for policy makers concerned with developing policies for providing financial access to health insurance coverage for the uninsured. First, our analyses provide evidence that people who are poor (e.g., with incomes below the poverty level) are more likely to have long spells without health insurance than people with higher incomes. Given this, it is unlikely that chronically uninsured people can be expected to pay very much towards the cost of health insurance. This suggests that policy proposals such as Medicaid buy-ins that are based on voluntary participation by the uninsured are unlikely to garner a high participation rate among the uninsured.

Second, our analyses provide evidence that people with long spells without health insurance are more likely to be unemployed or out of the labor force than are people with short uninsured spells. While it is true that just over half of the uninsured with spells that last 9 months or more are employed, these analyses cast some doubt on the effectiveness of mandating employers to provide health insurance as a fringe benefit. In particular, the fact that people employed in service occupations are particularly likely to experience long uninsured spells implies that an employer mandate that exempts people in such occupations is not going to "capture" very many of the uninsured workers who would be likely to experience long uninsured spells.

Even though about half of the people with long uninsured spells are employed, the total family monthly income figures suggest that many of the employed earn low wages. This casts further doubt on the effectiveness of a mandate requiring employers to provide health insurance as a fringe benefit. At a time when employers in general are struggling with the costs of health insurance, a mandate may cause many employers of low wage workers to consider ingenious ways of avoiding the mandate.

Our analyses of the durations of spells without health insurance and the characteristics of people who have long versus short uninsured spells provide a new look at the dynamics of health insurance coverage. Further analyses of the factors affecting the durations of uninsured spells, particularly analyses that include more job characteristics, would be useful in evaluating the effectiveness of employer mandates for providing health insurance to the uninsured.

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APPENDIX

This appendix describes the methods used to estimate the hazard model described in the paper and reviews a number of issues involved in the specification of the estimation model. The hazard function estimated here measures the tendency of a given event (e.g., the transition from being uninsured to being insured) to occur at a given point in time. The hazard function can be written as follows:

$$\lambda(t;Z_{it}) = P(\, LOS_i=t \mid LOS_i \geq t, Z_{it}\,) \tag{A-1}$$

The function $\lambda(t;Z_{it})$ represents for person i the hazard rate at time t, given the matrix of explanatory variables Z_{it}. The length of a person's spell without health insurance, LOS_i, is typically measured as $LOS_i=T_i^e-T_i^b$, where T_i^b is the beginning of the spell and T_i^e is the end of the spell.

As described in the paper, the individuals in the SIPP sample are observed in discrete intervals, i.e., people begin (or end) coverage on the first (or last) day of a month. When the dynamic process being studied is measured in discrete intervals such as months, a "discrete" hazard model is the appropriate specification for the analysis (Allison, 1982). An additional benefit of the discrete model is that it is easy to incorporate time-varying variables into a discrete hazard model. This is an important benefit for models of spells without health insurance because it is likely that a person's characteristics will change while they are in the midst of a spell without health insurance (e.g., a person becomes employed) and these changes may be associated with changes in health insurance status (e.g., a person acquires insurance because he/she becomes employed).

<u>Right censoring and attrition</u>. There are three possible reasons for observing the end of a spell without health insurance: (1) the person acquired health insurance coverage, (2) the survey period ended before the person acquired health insurance coverage (right-censoring), and (3) the person left the sample before acquiring health insurance (described as sample "attrition").

Right censoring is a common problem in the analysis of the hazard function. Formally, the end of a person's spell is not observed because of right-censoring when $T_i^e > T_i^s$, where T_i^s is the last month in which a person is included in the sample. Various methods have been developed to deal with the right-censoring problem. In brief, the methods generally allow the individual whose spell ending is not observed to contribute to the analysis rather than omitting such individuals. Including such people in the analysis takes advantage of the fact that they were "at risk" for acquiring insurance throughout the time they were observed, even though health insurance was never acquired (i.e., the spell began in month T_i^b and had not ended by month T_i^s).

Sample attrition is a somewhat more difficult problem. The SIPP, like any longitudinal survey, suffers from sample attrition. The extent of attrition in the 1984 Panel is over 40 percent. This includes involuntary attrition, the result of an intentional 16 percent cut in the 1984 panel for budget reasons. However, it also includes 25 percent of the sample that left the sample voluntarily (McArthur, 1987; Kasprzyk and McMillen, 1987). Approximately two-thirds of this latter group left the sample entirely, while the others missed some interviews but eventually returned to the sample. Analysis of the attrition from the SIPP shows that most of the voluntary attrition occurs early in the sample -- roughly 20 percent of the sample had missed at least one interview by the fifth interview (McArthur, 1987). Table 1 in the text presents estimates of the number of uninsured spells affected by sample attrition. Recall that 17 percent of the spells in the estimation sample ended with sample attrition and two-thirds of these spells ended with voluntary attrition from the sample. However, the voluntary attrition cases account for only nine percent of the total spell months in the sample.

If voluntary attrition is not random across the sample respondents, then it is likely that attrition would lead to biased estimation results if the attrition cases were excluded from the analysis. The problem is especially serious if the characteristics of people who are more likely to leave the sample are also characteristics of people who are more likely to become insured after a spell without health insurance. For example, exploratory analysis suggests that people who left the 1984 panel were more likely to be young, to work full-time, and to have recently experienced a change in employment status. Since these are also characteristics that are likely to influence the probability that a person will acquire insurance coverage, the potential bias from excluding attrition cases from the sample is a serious problem. For this reason, we have included the attritors in the estimation sample.

Although it seems clear that the attrition cases should not be dropped from the sample, there is no consensus in the econometrics literature about how to deal with attrition. Instead, there are two possible approaches to dealing with the attrition problem in the estimation. One approach is to treat attrition as another form of right-censoring, similar to the right-censoring caused by the inability to observe the end of spells that are still in progress at the end of the survey period. A second approach is to treat attrition as another type of exit from a spell without health insurance (called a "competing risk") and explicitly estimate the process of attrition.

If there is evidence to suggest that the voluntary decision to leave the sample is not random, then attrition differs from the right censoring that occurs because of the end of the survey or the involuntary sample reduction. Tuma, et al. (1979) argue that this type of situation should be estimated with a competing risks model, in which attrition is treated as a separate type of exit from a spell. However, this approach requires the assumption of statistical independence between the competing risks. If this assumption is violated, then the results from the competing risks model will also be misleading. Moreover, Allison (1982, pp. 42-45) argues for treating attrition as another form of right censoring because attrition does not remove the individual from the "risk" of acquiring insurance. On the contrary, it is likely that many of the people who left the 1984 SIPP sample eventually acquired insurance. This is in contrast to the competing risks model, where the occurrence of one type of event removes an individual from the risk that another type of event will occur (e.g., death removes an individual from the risk of exiting the hospital).

The lack of consensus in the literature over the two types of approaches leaves unresolved the proper estimation approach. Because of the questionable assumption of statistical independence between the choices in the competing risks model, we have chosen to use the first of the two approaches described above -- the single risk model with attrition treated as a form of right censoring, as suggested by Allison (1982).[1]

Specification of the estimation model. The starting point for the specification of the econometric model is the "hazard" function, described by equation (A-1) above. To estimate equation (A-1), it is necessary to specify how the hazard rate varies with time and explanatory variables. A common choice is the logistic regression function:

$$\lambda(t;Z_{it}) = \frac{\exp[\alpha_t + \beta Z_{it}]}{1 + \exp[\alpha_t + \beta Z_{it}]} \tag{A-2}$$

where α_t and β are vectors of parameters that need to be estimated. To form the likelihood function for estimation purposes, we introduce an indicator variable, HI_i, defined as:

$$HI_{it} \begin{array}{l} = 1 \text{ if person i becomes insured in month t,} \\ = 0 \text{ if person i remains uninsured in month t.} \end{array}$$

The estimation equation (A-2) can also be written in logit form, using the log of the odds ratio:

$$\ln\left[\frac{P(HI_{it}=1)}{P(HI_{it}=0)}\right] = \alpha_t + \beta Z_{it} \tag{A-3}$$

Using maximum likelihood estimation techniques, equation (A-3) can be estimated as a binomial logit model.[2] Note that the logit model proceeds by estimating a set of coefficients for the probability of exiting from a spell without health insurance. The choice of remaining uninsured is described as the "reference" choice and estimates from the model must be interpreted with this in mind.

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1. To test the effects of attrition on the estimation results, one could compare the results from the single risk model to results from a competing risks model. or to results estimated using a "restricted sample" which excludes people who left the sample during the survey period. If the attrition process is random, then the results from either of these two models should not differ substantially from the results using the single-risk model. A final model could be estimated with the restricted sample excluding the attritors, but using the sample weights constructed by the Census Bureau, adjusted to account for non-random attrition (U.S. Census Bureau, 1987). Although a comparison of the results from these three models provides a test of the effects of attrition on the model estimates, these comparisons are beyond the scope of this paper.

2. See Allison (1982, pp. 74-75) for the specification of the likelihood function for estimation.

The right censoring problem is handled easily within the discrete-time model by including what is known about individuals in the sample -- namely that they remained uninsured through time t, but were not observed in time t+1. In this context, this means including observations for this person through month t and always coding the dependent variable HI_{it} as equal to zero.

Explanatory variables in the model. Although it is possible to specify a hazard function which does not depend on the characteristics of an individual, the purpose of this paper is to identify the characteristics that increase or decrease the probability that an uninsured spell will end for an individual. For this reason, the hazard model estimated here will include as explanatory variables the characteristics of an individual, including: demographic characteristics, income, and variables that describe a person's job and labor force status. Table A-1 lists the sociodemographic and job-employment characteristics of individuals that we chose from the SIPP to use as explanatory variables in modeling the duration of uninsured spells. The sociodemographic characteristics are age, marital status, region of the U.S. in which the person resides, total monthly family income (in 1983 dollars), and whether or not the monthly family income changed by more than 50 percent this month (either increased or decreased by 50 percent or more). Each of these characteristics are measured in the current month of the uninsured spell.

In exploratory analysis, we found that age does not have a monotonic relationship with the duration of an uninsured spell. Instead, we have chosen to use a step function format for the age variable with "steps" of 18 to 24 years of age, 25 to 34 years of age, 35 to 54 years of age, and 55 years of age or older. (Recall that we are modeling the duration of uninsured spells only for adults). Marital status is differentiated into three categories: never married, married, or previously married (i.e., divorced, separated, or widowed).[3] There are four geographical regions in which an individual is identified as residing: Northeast, Midwest, South, or West.

Since we suspect that monthly family income also does not have a monotonic relationship with the duration of an uninsured spell, we tried a number of different specifications for the income variables. We finally settled on a functional form that allows for shifts in the slope coefficient as income increases. The monthly income groupings that we chose are: less than $1,200, $1,200 to $2,399, and $2,400 or greater. Thus, if someone has a monthly income of $1,500, the marginal effect of income on the hazard rate is equal to the sum of the first two coefficients for the income groups. Finally, because we believed that a change in monthly income might be a factor in explaining the duration of an uninsured spell, we include two dummy variables to capture such changes. One is a drop in monthly income of 50 percent or more, and the other is for an increase in monthly income of 50 percent or more in the current month. We chose 50 percent breaks because we wish to avoid monthly income fluctuations due to months with an extra pay period or overtime pay.

The job and employment characteristics that we included in the analysis are employment status, whether or not the person became employed or unemployed within the previous four

3. We also created dummy variables to indicate whether or not a person had had a change in marital status during the previous four months. We had anticipated that marital status changes might be an explanatory factor in the duration of an uninsured spell. However, such variables were not found to be significant because so few people had experienced changes in marital status during a spell without health insurance.

Table A-1
List of explanatory variables with definitions and sample statistics

Variable	Definition	Mean	Standard Deviation
Sociodemographic characteristics			
AGE2534	Respondent is between 25 and 34 years old (1=yes; 0=no)	.319	.466
AGE3554	Respondent is between 35 and 54 years old (1=yes; 0=no)	.253	.435
AGE55P	Respondent is age 55 or older (1=yes; 0=no)	.098	.297
MARR	Respondent is married (1=yes; 0=no)	.441	.496
PREVMAR	Respondent has been previously married (e.g., divorced, widowed or separated) (1=yes; 0=no)	.194	.395
MIDWEST	Respondent resides in the Midwest (1=yes, 0=no)	.238	.426
SOUTH	Respondent resides in the South (1=yes, 0=no)	.374	.484
WEST	Respondent resides in the West (1=yes, 0=no)	.227	.419
INCLT12	Total monthly family income (in hundreds of dollars)	16.97	17.51
INC12T24	Slope coefficient for income between $1,200 and $2,400 (INC12T24=INCLT4-12)	7.89	15.65
INC24P	Slope coefficient for income greater than $2,400 (INC24P=INCLT4-24)	3.73	12.69
RATLP5	Income dropped by 50 percent or more this month (1=yes; 0=no)	.093	.290
RATG1P5	Income increased by 50 percent or more this month (1=yes; 0=no)	.061	.239
Job/employment characteristics:			
EMPLOYED	Respondent is employed (1=yes; 0=no)	.552	.497
UNEMP	Respondent is unemployed (1=yes; 0=no)	.181	.385
T4EMPE	Respondent became employed in the previous four months (1=yes; 0=no)	.114	.318
T4EMPU	Respondent became unemployed in the last four months (1=yes; 0=no)	.136	.343
PART	Worker usually works part-time (1=respondent usually works less than 35 hours, 0=otherwise)	.267	.443
OSERV	Occupation of main job: service (1=yes; 0=no)	.154	.361
OPREC	Occupation of main job: precision production, craft and repair (1=yes; 0=no)	.058	.234
ICONST	Industry of main job: construction (1=yes; 0=no)	.042	.200
IMAN	Industry of main job: manufacturing (1=yes; 0=no)	.070	.256
IRET	Industry of main job: retail trade (1=yes; 0=no)	.154	.353
ISERV	Industry of main job: services (1=yes; 0=no)	.193	.394
IPUB	Industry of main job: public administration (1=yes; 0=no)	.013	.113
Spell characteristics:			
SPL5T8	Spell has lasted 5-8 months (1=yes; 0=no)	.218	.413
SPL9T12	Spell has lasted 9-12 months (1=yes; 0=no)	.120	.325
SPL13T16	Spell has lasted 13-16 months (1=yes; 0=no)	.070	.255
SPL17T20	Spell has lasted 17-20 months (1=yes; 0=no)	.041	.199
SPL21P	Spell has lasted 21 or more months (1=yes; 0=no)	.030	.171
SEAM	Dummy denoting that current month is a "wave seam" month (1=if current month is month 4,8,12,...32; 0=otherwise)	.250	.433

months, whether the person worked part-time or full-time, and the occupation and industry of the person's main job. Each of these characteristics are identified for the current month of the uninsured spell. Employment status is differentiated into three possible states: employed, unemployed, or out of the labor force. If the person became employed or unemployed some time within the previous four months, a dummy variable identifies this event. Note that it is possible for an individual to have experienced both recent transitions.

A dummy variable indicating that a person usually works part-time (less than 35 hours per week) is included to capture differences between part-time and full-time workers. We use three occupational categories for the occupation of the person at his or her main job: service (e.g., food service, protective service, health service, and cleaning and building service); precision production, craft, and repair; and all other occupational categories. For the industry of the person's main job, we use six categories: construction, manufacturing, public administration, and all others.

To test for the possibility of duration dependence, the model needs to include variables that measure the length of an uninsured spell. Duration dependence is the phenomenon where the likelihood that a spell ends depends in part on the length of time the spell has been in progress (Kiefer, 1988). For example, negative duration dependence occurs when a spell is increasingly likely to continue the longer the spell has been in progress. Here, the relationship between the duration of a spell and the hazard rate is represented by the parameter vector α_t in equation (A-3). Although it is possible to specify a parameterization of the relationship (Allison, 1982), a more general specification would include dummy variables for each time period and estimating a coefficient for each of these dummy variables. However, this specification requires the estimation of a large number of dummy variables which might not be supported by the data. Instead of specifying a model with over two dozen time-in-spell dummy variables, the model estimated here includes only dummy variables in four-month breaks:

$$\alpha_t = \alpha_0 + \alpha_1 \mathrm{SPL5T8} + \alpha_2 \mathrm{SPL9T12} + \alpha_3 \mathrm{SPL13T16} + \alpha_4 \mathrm{SPL17T20} + \alpha_5 \mathrm{SPL21P} \quad \text{(A-4)}$$

where α_0 is a constant and the spell length dummies are defined in Table A-1. While this specification imposes some restrictions on the relationship between spell duration and the hazard rate, it is less restrictive than a linear specification or the functional forms imposed under the family of proportional models (Kiefer, 1988).

A related issue to the time in the spell without health insurance is the treatment of the "seam effect," which occurs in the SIPP when a respondent's answers are affected by the timing of the interview. Since the SIPP questions are asked only once every four months, and respondents are asked to identify events that occurred over the last four months, several analysts have found that SIPP respondents tend to identify transitions as more likely to occur during the seam (or interview) month (see Young, 1988, for a complete review of the seam issue). If the estimation does not control for the seam effect, the estimated coefficients are likely to be biased -- especially the coefficients capturing the effects of time-in-spell. However, Young (1988) has noted that the seam bias is likely to affect the timing of events of interest, but not the relationship between independent variables and the timing of transitions. Thus, we have chosen to control for seam bias by including a dummy variable to denote months that are seam months.[4] This is the approach used here.

We chose to measure duration of an uninsured spell in months because when a person has health insurance it is almost always for a calendar month. That is, coverage generally begins on the first day of a month and continues through to the last day of the month. Thus, this measurement of duration conforms to what occurs in the health insurance market. As an alternative, we could have chosen to measure the duration in terms of interviews (SIPP "waves"), but we did not wish to discard information about changes in health insurance status or changes in other characteristics that might be changing during the months between waves.[5]

Finally, it is important to note that because we created variables to capture changes in employment status that might have occurred in the four months preceding the month of interest in an uninsured spell, we do not consider uninsured spells that begin prior to the fifth month of the SIPP. Thus, any spell for which we cannot observe the four months prior to the spell's beginning is not included in the sample of spells. This "rule" treats any spell that begins within the first four months of the SIPP as left-censored, just as any uninsured spell that began prior to the first SIPP interview is left censored. Our decision to create the variables indicating if the person became employed or unemployed in the four months prior to the spell month of interest also forces the maximum observed duration of an uninsured spell to be 28 months. We feel that the loss of observed uninsured spells that began in the first four months of the SIPP was more than compensated by the explanatory power to be gained from knowing if a person's employment status changed during the previous four months.

Identification of the chronically uninsured. One reason for modeling durations of uninsured spells is to be able to identify persons who are uninsured for short periods of time from those with long spells without health insurance. Here we define the first group as those with spells that last four or fewer months and the second group (which might be described as the "chronically uninsured") as people whose spells without health insurance last 9 or more months.[6]

Although the endings of many of the uninsured spells in the sample are not observed -- they are "right censored" -- it is possible to identify persons who will fall into the two groups defined above. Here, the first group will be comprised of three types of persons: (1) respondents who had a completed uninsured spell that lasted less than 5 months, and (2) respondents whose spell without health insurance was right-censored before reaching the 4th month of the spell but whose spell is likely to last less than four months. Similarly, the chronically uninsured will be comprised of three types of persons: (1) respondents who had a completed uninsured spell that lasted 9 or more months, (2) respondents whose spell without health insurance was right-censored, but the

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4. This has been an approach that has been used in other duration analysis using the SIPP (Sharon Long, 1990).

5. Short, Cantor and Monheit (1988) chose to measure the duration of Medicaid coverage in terms of interviews ("waves") because they felt that the seam effect on Medicaid coverage was very strong.

6. Defining the chronically uninsured is obviously a subjective process. Other definitions of the chronically uninsured were considered here, but in most cases the definitions did not change the results markedly, mostly because most uninusred spells end very quickly.

observed portion of the spell had already lasted 9 or more months, and (3) respondents whose spell without health insurance was right-censored before reaching the 9th month of the spell but whose spell is likely to last 9 or more months.

The survival probability, calculated from the hazard function, can be used to identify right-censored cases that are "likely" to be part of either of these two groups defined above. Starting with the chronically uninsured, define $P_{ic}(Z_{it})$ as the probability that a person will be among the chronically uninsured, and noting that it is true by definition that $\lambda(LOS_i;Z_{i,LOSi})=1$, this probability can be identified with certainty for three types of sample persons:

$$P_{ic}(Z_{it}) = \begin{cases} 1 \text{ if } LOS_i \geq 9 \text{ and } d_i=1, \\ 1 \text{ if } LOS_i \geq 9 \text{ and } d_i=0, \text{ and} \\ 0 \text{ if } LOS_i < 9 \text{ and } d_i=0. \end{cases} \tag{A-5}$$

where d_i is a dummy variable indicating that person i's spell was right-censored. Equation (A-5) uses the information that people in whose spells were observed to last nine months or more are known with certainty to be among the chronically uninsured. Similarly, people whose spells were observed to end before the 9th month are known with certainty to not be among the chronically uninsured.

Table A-2.
Distribution of observed spells without health insurance, by length of the observed spell and right-censoring status

Spell length	Spell ending observed	Right-censored spells	TOTAL
Spells observed for:			
1-4 months	2,112	858	2,970
5-8 months	636	418	1,054
9 or more months	443	766	1,209
TOTAL	3,191	2,042	5,233

SOURCE: 1984 SIPP panel (see text).

Table A-2 displays counts of the number of spells by observed length of the spell and right-censoring status. The identification of persons as either chronically uninsured or not (spells lasting nine or more months) can be made with certainty for 3,191 persons because the spell ending is observed. Of these, 443 (14 percent) had spells that lasted at least 9 months. An additional 2,042 spells are right censored. Of these, 766 spells lasted 9 or more months, thus reaching the length of a chronic spell with certainty under the alternative definitions outlined above. This leaves 1,276 sample cases, or roughly 24 percent of the sample, for which the probability that a spell will last 9 or more months has to be assigned. Also note from Table A-2 that we know for certainty that 2,112 spells are short spells lasting four or fewer months, while the probability that a right-censored spell will end in four or fewer months has to be assigned for 858 cases.

The difficulty in identifying the chronically uninsured among the right-censored cases occurs because the ultimate length of their spell without health insurance is not known. To bridge this gap in the data, the survivor function can be used to identify the chronically uninsured among those who have a right-censored spell that is observed to last for less than 9 months and the short-term uninsured from those right-censored spell lasted less than five months. The survivor function gives the probability that person i with characteristics Z_{it} is still uninsured at time t or, equivalently, the probability that a person's spell of uninsurance will last t or more months. The survivor function is written as a function of the estimated hazard function:

$$S(t;Z_{it}) = \prod_{k=1}^{t} [\, 1 - \lambda(k;Z_{ik})\,] \qquad \text{(A-6)}$$

Although equation (A-6) provides an estimate of the probability that a spell that is just beginning will last t or more months, note that the SIPP sample includes additional information about the right-censored cases, i.e., that their spell without health insurance lasted at least LOS_i months. Using this information, the probability that a person's completed spell (LOS_i^*) will last 9 or more months, given that it has already lasted LOS_i months can be estimated as:

$$P_i(LOS_i^* \geq 9;Z_{it}) = S(9|t \geq LOS_i,Z_{it}) = \prod_{k=LOS_i+1}^{9} [\, 1 - \lambda(k;Z_{ik})\,] \qquad \text{(A-7)}$$

Similarly, to estimate the probability that a spell will last four or fewer months:

$$P_i(LOS_i^* < 5;Z_{it}) = 1\text{-}S(5|t \geq LOS_i,Z_{it}) = \prod_{k=LOS_i+1}^{5} [\, 1 - \lambda(k;Z_{ik})\,] \qquad \text{(A-8)}$$

The probabilities $P(LOS_i^* \geq 12;Z_{it})$ and $P(LOS_i^* < 5;Z_{it})$, described by equations (A-7) and (A-8), are used here to identify people who are likely to have long and short spells, respectively.

However, a problem with the approach described here is that the hazard model cannot be used to derive the survivor probability without making some assumptions about the future paths of explanatory variables. To see this, recall that the model used to estimate the hazard rate is based on variables that change from month to month. Thus, the unobserved hazard rate in some future month is a function of the characteristics in that month, and not the characteristics in the current month. The assumption used here is that a person's characteristics in future months remain constant and equal to their characteristics in the last month they were observed. Although this is a very restrictive assumption, this seems to be the most reasonable and most straightforward assumption possible. Prior to the estimation of the hazard model, a hypothesis cannot be made about the error that will be introduced into the estimates because of this problem. However, the estimates in the text are accompanied by a discussion of the possible biases introduced by this assumption.