Utilization of Health Care Services Related to Cancer Prevention for Women in the Medicaid Program

Final Analytic Study Design

Prepared by:

Elizabeth Kulas, Ph.D.
Walter Adamache, Ph.D.
Janet B. Mitchell, Ph.D.

Health Economics Research, Inc.

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Janet B. Mitchell, Ph.D.	**Gregory C. Pope, M.S.**
Project Director	**Scientific Reviewer**

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1 Introduction

Two of the goals of *Healthy People 2010*, published by the U.S. Department of Health and Human Services (DHHS), are to: "(1) increase quality and years of healthy life and (2) eliminate health disparities." As a component of DHHS, the Health Care Financing Administration (HCFA) supports these goals.

Several of the highlighted cancers in *Healthy People 2010* have their death rate reduction goals expressed in percentage terms in *Healthy People 2010*; among them are 21 percent for breast cancer and 34 percent for colorectal cancer. The *Healthy People 2010* goal to reduce the death rate from cervical cancer is from 3.0 to 2.0 per 100,000 females.

As one of the means of reducing the death rates from these three cancers, *Healthy People 2010* recommends increased screening (early detection). Accordingly, *Healthy People 2010* has goals to increase screening rates. For cervical cancer, *Healthy People 2010's* goals are to increase the proportion of women who have ever received a Pap test from 92 percent in 1998 to 97 percent and to increase the proportion in the preceding three years from 79 percent in 1998 to 90 percent. For breast cancer, *Healthy People 2010's* goal is to increase the proportion of women who have a mammogram during the preceding two years from 68 percent in 1999 to 70 percent. For colorectal cancer, *Healthy People 2010's* goals are to increase the proportion of adults who have a fecal occult blood test (FOBT) during the preceding two years from 34 percent in 1998 to 50

percent and to increase the proportion of adults who have ever had a sigmoidoscopy from 38 percent in 1998 to 50 percent.

Society's challenge is how to increase the proportion of women receiving screening tests for the above three cancers and to reduce racial/ethnic and other disparities in receipt of the screening tests. This is a difficult task since, for the nation at large, there are few levers that can be applied to all subgroups of women. This is especially so with regard to insurance coverage and income, two of the factors that generally influence medical care utilization.

The federal government, however, has a better prospect to "narrow" racial/ethnic disparities for women covered by public programs. One pro-active way the federal government could reduce disparities is to eliminate all copayments (including waiving the deductible) associated with screening tests under Medicare. Other, more passive, ways racial/ethnic disparities might be narrower in public programs than in the general female population is due to the criteria by which women become eligible for public insurance. Women enrolled in Medicaid, for instance, are more homogenous than women in society at large. That is, as a result of national policy, all Medicaid women have low income. Further, within Medicaid there are three relatively homogenous subgroups of women: women of child-bearing age, women with disabilities, and elderly women residing in households receiving federal (and/or state) supplemental security income (SSI).

In principle, given the relatively homogenous subgroups of women in Medicaid, racial/ethnic disparities *within* each of these subgroups in screening rates should be small compared to those in the general female population. Despite the diminution in the

insurance and income barriers to utilization, two of the most important confounding factors associated with racial/ethnic disparities, it is possible that racial/ethnic disparities exist in the utilization of screening tests. Some of the possible reasons for the persistence of racial/ethnic disparities include differences in state Medicaid coverage of screening tests, local provider supply, and differences in attitudes towards acceptance of public benefits.

One purpose of the proposed research is to document the existence and magnitude of racial/ethnic disparities, among Medicaid-covered women, in cancer screening tests. To do this, we will produce age-adjusted screening rates for Medicaid-covered women by race and ethnicity status and by eligibility status (e.g., disabled). This will be done by combining the data from all of the study states together and then, to ascertain the influence of confounding state-specific factors, for each of the study states. Both tabular and multivariate analyses will be performed. To the extent that the data allow, we will also examine the association between screening tests and outcomes. Finally, on the basis the literature review and our empirical work, we will make suggestions for improving cancer-related health outcomes for Medicaid-covered women.

This report is divided into seven chapters. Where apropos, the discussion reflects decisions made during the kickoff meeting. Chapter 2 describes the analytical requirements for the study. This includes the cancer selection criteria, data requirements and state selection strategy, and specifying the analytical classes of Medicaid women. Chapter 3 describes measurement and analytical file construction issues. This includes the specification of screening rates measures, how to account for turnover and breaks in Medicaid eligibility, and the rationale for the age standardization of screening rates. Also

included is a discussion of the structure of the analytical files and the types of analyses they will support. Chapter 4 discusses the tabular and multivariate analyses. It describes how we plan to determine the magnitude, if any, of racial disparities in screening tests and possible causes thereof.

Given the scope of the project, it is not possible to employ every analytical technique or variation of screening rate measures. Nonetheless, depending on HCFA's interest and the availability of resources, we propose in Chapter 5 several types of sensitivity analyses. These include the specification of alternative target populations and alternative criteria for the identification of screening tests. Because the analyses of screening rates might be affected by the choice of weighting factors for women that are not continuously eligible for Medicaid, several alternative methods for constructing weighting factors will be examined. We also propose alternative multivariate analyses.

Chapter 6 describes how we plan to synthesize the literature review and our empirical results in order to make suggestions to reduce any racial and other disparities in the provision of cancer screening tests. Chapter 7 describes the strengths and weaknesses of our proposed analyses and submits suggestions for further research.

2 Analytical Requirements

This chapter describes selected analytical requirements issues for the study. This includes the cancer selection criteria, data requirements and state selection strategy, and specifying the analytical classes of Medicaid women. The discussion reflects the kickoff meeting's decisions and discussions.

2.1 Cancer Selection

The selection of study cancers are guided by three criteria: (1) cancers which have established and reliable screening tests, (2) cancers which have high prevalence in women, and (3) cancers for which test rates can be calculated using common, if not consensus, definitions of numerators (screening tests) and denominators (target populations).

To a large extent, *Healthy People 2010* (Chapter 3) identifies those cancers that meet the first two criteria. Of the many types of cancers, *Healthy People 2010* specifies numerical goals for the death rates from the following cancers: lung, breast, cervical, colorectal, oropharyngeal, prostate, and melanoma. Of these cancers that affect women, *Healthy People 2010* specifies numerical screening and testing goals for breast, cervical, and colorectal cancer. Unlike these three cancers, *Healthy People 2010* recommends counseling for smoking cessation to reduce lung and oropharyngeal cancers and provides several guidelines to reduce the risk of skin cancer.

During the kickoff meeting, HER recommended that breast, cervical, and colorectal cancer be the study cancers – the HCFA Project Officers concurred.

2.2 Data Requirements and State Selection Strategy

This study requires states with SMRF data as well as adequate population size and racial diversity. In selecting states, we also consider characteristics of the Medicaid programs such as managed care enrollment that will influence the size of the actual sample we will be able to use. Finally, we consider the coverage policies by state Medicaid programs for the tests of interest. The process of elimination is described in the subsections below.

Our goal is to select 4 or 5 states to use for analysis. Because Medicaid programs vary state to state in eligibility criteria, populations in managed care and coverage of services, state results may not be directly comparable. We prefer a small subset of states to allow for some regional variation, but for this study probably prefer states that are comparable in their coverage and eligibility standards for ease of interpretation.

2.2.1 Medicaid Claims Data

HCFA collects Medicaid claims data for many states through the Medicaid Statistical Information System (MSIS). These files are converted to standardized files called the State Medicaid Research Files (SMRFs). The most recent year of data available is 1995 and there are 27 states that submit claims data and report racial information, a key

aspect of this study. Our strategy for choosing which states to analyze will be based on several factors.

The RFP suggests that a single year of data is adequate for the study. We propose to use 3 years of data because the screening tests are not necessarily recommended or received on an annual basis. There is controversy on the gold standard of care for these tests and there may be variation in coverage in the intervals for the screening tests, so 1-year rates are unlikely to provide the full range of outcomes of interest. We will compare 1-year screening rates with 2-year and 3-year rates where appropriate, depending on the guidelines for the given tests.

Because we feel it is important to use more than a single year of data, we will be further limited to states that have SMRF data for 1993-1995. Table 2-1 shows that most of the SMRF states do in fact have this data. We eliminated Colorado, Florida and Rhode Island due to lack of data for the whole time period of interest.

Using more years of data does create a problem for the analysis. Eligibility turnover is high in the Medicaid population generally and welfare reform has increased that volatility in the AFDC population. Many states had passed their own welfare reform and will not be representative of Medicaid as a whole, we will have to make corrections to our estimates for cases where we lack full information. Section 3.2 discusses these issues and possible solutions more completely.

Table 2-1

SMRF State Characteristics

State	Continuous Years of Data (1)	Total Medicaid Enrollees	% Managed Care (2)	Racial Distribution (3) Percents					Coverage of (4)	
				White	Black	Asian	Indian	Hispanic Origin	Pap Smear	Mammogram
AL	1992-1995	498,006	6	73.2	25.8	0.7	0.4	0.8	Prenatal	No
AK	1992-1995	87,550	0	76.2	3.8	4.3	15.7	3.7	Phys. Order	Phys. Order
AR	1992-1995	371,047	37	82.7	16.1	0.7	0.5	1.6	Yes	Yes
CA	1992-1995	5,415,207	17	80	7.4	11.6	1	30.2	Yes	Yes
CO	1994-1995	259,949	91	92.5	4.3	2.3	0.9	14	Prenatal	Phys. Order
DE	1992-1995	73,798	8	79	18.8	1.9	0.3	3.1	Phys. Order	Phys. Order
FL	1994-1995	1,538,007	30	82.9	15.1	1.7	0.4	14	Phys. Order	Phys. Order
GA	1989-1995	968,008	11	69.8	28.2	1.8	0.2	2.5	No	No
IA	1992-1995	226,701	79	96.6	1.9	1.2	0.3	1.7	Yes	Yes
IN	1992-1995	432,558	16	90.7	8.2	0.9	0.2	2.2	Yes	Yes
KS	1992-1995	192,188	37	91.6	5.9	1.6	0.9	4.9	Phys. Order	Phys. Order
KY	1992-1995	531,728	41	92	7.2	0.6	0.2	0.7	Yes	Yes
MI	1989-1995	1,148,115	53	83.6	14.3	1.5	0.6	2.5	Yes	No
MN	1993-1995	47,700	26	93.6	2.7	2.4	1.2	1.6	Yes	Yes
MO	1992-1995	637,897	5	87.4	11.2	1	0.4	1.4	Lab only	Yes
MS	1993-1995	510,226	5	62.7	36.3	0.6	0.4	0.7	Lab only	Phys. Order
MT	1992-1995	79,000	42	92.9	0.4	0.6	6.2	1.7	Yes	Yes
ND	1992-1995	46,566	41	94	0.6	0.8	4.6	1	Yes	Yes
NH	1992-1995	72,158	10	98	0.7	1.1	0.2	1.4	Phys. Order	Phys. Order
NJ	1992-1995	706,812	11	80.3	14.5	4.9	0.3	11.5	Phys. Order	Phys. Order
PA	1992-1995	1,612,905	46	88.7	9.6	1.5	0.1	2.4	Prenatal	Yes
RI	1994-1995	113,891	40	92.6	4.8	2.2	0.5	6	Yes	Yes
UT	1992-1995	113,000	80	95.4	0.8	2.4	1.4	6.1	Yes	Phys. Order
VT	1992-1995	82,650	0	98.2	0.6	0.9	0.3	1	Yes	Phys. Order
WA	1992-1995	696,658	100	89.4	3.4	5.4	1.8	5.8	Prenatal	Yes
WI	1992-1995	463,142	22	92.2	5.5	1.4	0.9	2.4	Yes	Yes
WY	1992-1995	38,956	0	96.2	0.8	0.8	2.2	5.7	Yes	Phys. Order

NOTES: States without all necessary 1994-1995 data are not included in this list

SOURCES: (1) HCFA table provided in the RFP. Start at 1995 and work backwards for continuity; (2) HCFA Website, managed care enrollment by state as of 6/30/95; (3) Racial distribution: 1997-1998 State and County Data Book, Data from 1996; (4) Boss and Gluckes, AJPH 1992. Yes, means test is covered for all eligibles, No means the test is not covered at all. Phys. Order means the test is covered only with a physician's order. For pap smears, some states only cover them as part of prenatal care and some cover lab fees only.
Data are as of 1990.

2.2.2 Size of State

We will only be able to select a few states to analyze, therefore we prefer states with large Medicaid populations (not in managed care) and that are racially and ethnically diverse such that the total sample size will support the cross-tabular analyses we propose. Table 2-1 shows the racial and ethnic diversity of states and the total Medicaid populations.[1] Because racial and ethnic groups may vary by state, it is important to have within-state estimates of racial differences as well as an idea of overall Medicaid racial differences from pooling the states.

Ordering by size of Medicaid population alone, the largest states with appropriate data are:

1. California
2. Pennsylvania
3. Michigan
4. Georgia
5. New Jersey
6. Washington
7. Missouri
8. Kentucky
9. Mississippi
10. Alabama

Further considerations will be limited to these states.

2.2.3 Managed Care Programs

Table 2-1 shows that several of the large states have significant portions of the Medicaid population enrolled in managed care. State Medicaid managed care programs pose a potential problem for a few reasons. First, claims for managed care enrollees are

[1] Table 2-1 shows racial and ethnic diversity as two separate variables. The SMRF data code Hispanic as a category separate from white and African-American.

not available in the SMRF data. Large numbers of eligibles will not be in the data for states with high managed care penetration. Second, managed care programs lead to selection bias and worse health on average for those who remain in the fee-for-service system. State fixed effects as well as measures of managed care penetration in a multivariate model would help alleviate this problem, but it would be difficult to control for this problem in simple rate comparisons between states. For these reasons, we prefer states with lower managed care penetration. Managed care penetration is noted in Table 2-1 with other state characteristics.

Of the list of the 10 largest states, we note that at the time, Pennsylvania, Michigan, Washington and Kentucky had large numbers of eligibles in managed care. Washington was heavily reliant on capitated managed care and will be dropped from consideration. Kentucky used a PCCM program but is not as large or racially diverse as other states we are considering, so it will also be dropped. We have had some difficulty ascertaining how much of the Pennsylvania and Michigan populations are enrolled in Primary Care Case Management (PCCM) versus capitated HMOs. The issue is that if people in managed care are only enrolled in a PCCM program, they will still have claims and still be observable in our data.

We investigate Michigan, Pennsylvania and Missouri with the SMRF data. First we identify a preliminary sample of women ages 18 and over who do not have Medicare or private coverage and who are not Medically Needy. Tables 2-2 and 2-3 show the results of these preliminary investigations. Table 2-2 summarizes the percent of the

Table 2-2

Women in HMOs in Michigan, Pennsylvania, or Missouri

State	1993 Sample of Women	1993 Women in HMOs	1993 Percent of Women in HMOs	1994 Sample of Women	1994 Women in HMOs	1994 Percent of Women in HMOs	1995 Sample of Women	1995 Women in HMOs	1995 Percent of Women in HMOs
Michigan	333,979	83,461	25	305,027	90,468	30	259,852	94,986	37
Pennsylvania	336,745	85,534	25	351,461	120,964	34	353,987	145,575	41
Missouri	168,354	12,038	7	173,036	12,484	7	172,840	12,218	7

Programs: F10108A, F10110A

sample in managed care. In Table 2-3, we present the sample size in the first row and racial distribution by percent in the rows beneath for each state. We then describe the racial distribution of women who are in managed care during the year. Finally, we show the resulting sample once women in managed care are removed. This is repeated for all three years we plan to analyze.

Table 2-2 shows that the sample of women in managed care in Michigan and Pennsylvania are a substantial portion of women in the state, especially by 1995. In 1993, only 25 percent of women in Pennsylvania are in managed care, but by 1995, 41 percent are in managed care, with similar growth for Michigan. In contrast, Table 2-1 shows Georgia, California and New Jersey all have under 20 percent of beneficiaries in managed care. In Table 2-2, Missouri is a smaller state than Michigan or Pennsylvania, but has very little managed care (7 percent across all three years). In Table 2-3 we see that by 1995, Missouri has about the same sample size as Michigan once women in managed care are removed.

Table 2-3

Racial Distribution of Women in Michigan, Pennsylvania, or Missouri

State/Race	1993 Sample Women	1993 Any HMO	1993 Sample w/o HMO	1994 Sample Women	1994 Any HMO	1994 Sample w/o HMO	1995 Sample Women	1995 Any HMO	1995 Sample w/o HMO
Michigan (N)	**333,979**	**83,461**	**250,443**	**305,027**	**90,468**	**214,559**	**259,852**	**94,986**	**164,866**
White (%)	53	22	63	51	25	62	49	28	61
African-American	39	75	28	42	71	29	43	67	29
Native American	1	0	1	0	0	1	0	0	0
Asian	0	0	0	1	1	1	1	1	1
Hispanic	3	1	3	3	2	4	3	2	4
Unknown/Other	4	2	5	3	1	3	3	2	3
Pennsylvania	**336,745**	**85,534**	**251,211**	**351,461**	**120,964**	**230,497**	**353,987**	**145,575**	**208,412**
White	52	21	63	52	24	67	52	28	69
African-American	36	67	25	36	62	22	36	58	20
Native American	0	0	0	0	0	0	0	0	0
Asian	2	3	2	2	2	2	2	2	2
Hispanic	9	8	9	9	10	8	9	10	8
Other Race	1	1	1	1	1	1	1	1	1
Missouri	**168,354**	**12,038**	**156,316**	**173,036**	**12,484**	**160,552**	**172,840**	**12,218**	**160,622**
White	67	34	69	66	32	68	67	34	69
African-American	33	65	31	33	65	30	33	65	31
Native American	0	0	0	1	2	1	0	1	0
Asian	0	0	0	0	0	0	0	0	0
Hispanic	0	0	0	1	1	1	0	0	0

NOTES: percents may not add up due to rounding
Programs: F10108A, F10110A

Table 2-3 shows clearly that women in managed care constitute a substantial portion of the diversity in the state. For example, the overall sample of women in Michigan in 1993 shows 39 percent are African-American, but the HMO sample is 75 percent African-American, resulting in a reduced concentration in the sample we would analyze to 28 percent African-American. This results in a highly selected sample for analysis. Each state and year follows this pattern, though the problem is less significant in Missouri because of the small percent of women in HMOs.

We find this result because managed care is highly concentrated in certain urban areas of the states and those areas also have a high concentration of African-American women. For example, Wayne county in Michigan is the main county in Detroit and is heavily penetrated in all three years (around 70 percent managed care). Even if we were to include Michigan as an analysis state, we would probably seek to delete the entire county, further reducing the sample size.

Given these results, we will be unable to analyze Michigan and Pennsylvania as part of this project. Missouri, while a smaller state, has less managed care and will be a better state to analyze. Only one county in Kansas City has significant penetration (Jackson) and St. Louis is generally free of managed care.

2.2.4 Screening Test Coverage

Medicaid covers preventative services, but covering screening tests is at the discretion of the states. A 1992 study by Boss and Guckes shows a range of coverage between states for Pap smears and mammograms (last two columns in Table 2-1). The study did not ask about coverage for colorectal screening. They surveyed states in 1990, so the information is slightly out of date for our 1993-1995 time frame. Of the states we

are considering, only California covers both tests with no conditions. New Jersey covers the tests with a physician's order. Since most screening tests are done at the recommendation of a physician, we do not consider this to be a significant barrier to coverage.

Only Georgia did not offer any coverage for Pap smears or mammograms. Upon further investigation, we found that Georgia passed a general law in 1992 requiring coverage of these tests, but it is unclear if Georgia Medicaid adopted such a policy. The SpData Medicaid book does not list anything about test coverage in Georgia Medicaid in 1992 or 1993. Again, we propose a quick analysis that compares Georgia to Mississippi, which had reasonable coverage in the Boss and Guckes study. We will pick one of these states over Alabama because both are larger and Alabama also has limited coverage for pap smears and no coverage for mammograms in 1990. Both Georgia and Mississippi are racially diverse and either would provide a southern state to the study.

We did a quick search for claims for Mammograms and Pap Smears in the outpatient claims data. The goal was to see if similar numbers of claims and implied rates were found in Georgia and Mississippi. These samples and rates are first pass estimates and will be re-estimated systematically for the project. Table 2-4 shows the appropriate sample of women, the number of women who had at least one claim for the given procedure and the implied rate for the two states over three years. Sample sizes inGeorgia are larger than Mississippi and the implied screening rates are similar, so we suggest using Georgia as a state.

Table 2-4

Preliminary Pap and Mammogram Rates for Georgia and Mississippi

	Mississippi						Georgia					
	Mammogram			Pap			Mammogram			Pap		
Year	Count	Eligibles	Rate	Count	Eligibles	Rate	Count	Eligibles	Rate	Count	Eligibles	Rate
1993	1,495	16,430	9%	30,439	103,244	29%	6,209	39,954	16%	76,694	244,184	31%
1994	1,655	15,872	10%	28,036	95,761	29%	6,510	41,514	16%	88,005	258,022	34%
1995	2,061	17,190	12%	27,209	94,900	29%	6,425	43,608	15%	87,650	266,247	33%

NOTES: Estimates are pre-cleaning for state selection purposes only
Count is the number of women that had at least 1 procedure in the year
Eligibles are women aged 18 and over for paps and aged 40 and over for mammograms
Eligibles do not include those with race missing, dual eligibility, any private insurance, any HMO, medically needy status.
Rate is count divided by eligibles

2.2.5 Summary of State Recommendation

We have selected the following states to analyze for this project:

California
Georgia
Missouri
New Jersey

These states represent racially diverse states with large Medicaid populations. These states also have appropriate data and do not suffer from extreme selection due to managed care. The states represent different geographic areas as well. Comparisons from state to state may be difficult because the states are not homogeneous, but should provide an overview of how cancer screening rates for women vary by race in different Medicaid programs across the country.

2.3 Medicaid Women – Analytical Classes

Medicaid is a health insurance program for the poor, but not all people who are poor can qualify for Medicaid. The three major eligibility categories for poor women under 65 are through the AFDC program, SSI, and pregnancy. Poor women over age 65 can also qualify for Medicaid via the SSI program. Many women who qualify via SSI will also have Medicare coverage. Most of the elderly women will have this dual coverage. As discussed below, we plan to eliminate duals from our sample.

2.3.1 Pregnant Women

In order to improve access to appropriate prenatal care, states have extended Medicaid coverage to women who are poor and expecting a baby. In most states, the income eligibility standard for pregnant women to receive Medicaid is more generous

(i.e. one qualifies at higher incomes) for pregnant women than for women who qualify via AFDC or SSI. Most of these women are under the age of 40, so are not relevant on the basis of age to receive mammograms and CRC screening. However, Pap smears are administered as part of appropriate prenatal care for any pregnant women. Pregnant women may be eligible for less than a year, and yet still should receive a Pap smear. There will be no weighting to correct for lack of data. It is also important to note that women who qualify on the basis of AFDC or SSI may also be pregnant and will be analyzed with women who only qualify by being pregnant. We will identify pregnant women with procedure codes related to pregnancies or deliveries and investigate the reliability of the pregnancy code included on the person summary file. We may also extend the lower limit on age to include pregnant teens to determine if they are getting Pap tests as well.

2.3.2 AFDC Women

AFDC women span a range of ages, but must have at least one child under the age of 18 to qualify, so the distribution is skewed to younger women. Pap tests for cervical cancer screening are recommended for all women over age 18, so the sample will be reasonably representative of the eligibility groups of Medicaid women. The earliest guidelines for regular mammograms begin at age 40. Many women on AFDC will fall out of this sample and even more will be removed for colorectal screening, which is recommended for those over age 50.

States vary in the required intervals for re-certifying AFDC and Medicaid eligibility. Generally a one-year or six-month period is standard. These women are likely to experience changes that affect their eligibility. A new job, wealth from family, getting married, aging children are all reasons a woman may lose eligibility. Turnover and incomplete data is likely to be a larger problem for these women than for those who qualify via SSI. We will identify pregnant women with procedure codes related to pregnancies or deliveries and investigate the reliability of the pregnancy code included on the person summary file.

2.3.3 SSI Women

Women who qualify by virtue of SSI are disabled or elderly. The disabled are by definition under age 65 – once a disabled person reaches age 65 and still meets the income and wealth restrictions, the person qualifies on the basis of age. Those who qualify on the basis of age are obviously older than the other eligibility categories. Women can become disabled at any point in their life, but again, will tend to be older than the groups that qualify because of pregnancy or AFDC.

While women on SSI have more stability in their eligibility spells, there is still reasonable turnover in the population for all the same reasons as for women on AFDC. Re-certification periods vary by state. SSI benefits are intended for at people with a long-term disability that will keep them out of work for at least a year. Some people are chronically ill and their health will never improve nor will they be as likely to have a change in income or wealth that would change their qualification for Medicaid. Others

may experience a long-term health problem that does improve so that the person can return to work. SSI women may also have other developments such as gaining Medicare eligibility, which will cause disruption in our sample.

2.3.4 Omission of Duals

Because Medicaid eligibility is tied to the Social Security system via SSI, many of these women also qualify for SSDI and Medicare (dually eligible or duals). We will not examine Medicare claims, but Medicare will be the primary payer for duals, so it is unlikely screening tests will be found in the Medicaid data for this group. For this reason we plan to omit women with dual coverage. Women who are NOT dual either did not work enough in the United States to qualify for SSDI benefits before becoming disabled or are in the interim period where they receive SSDI but must wait two years for Medicare coverage.

Given the nature of the Medicaid sample, we may wish to find benchmarks for other disabled people for mammograms and CRC screening. Others (Iezzoni *et al*, 2000) have shown that the disabled are less likely than others to undergo preventative care and screening tests.

3 Measurement and Analytical File Construction Issues

This chapter describes measurement and analytical file construction issues. This includes the specification of screening rates measures (the specification of target populations reflects the kickoff meeting's decision), how to account for turnover and breaks in Medicaid eligibility, and the rationale for the age standardization of screening rates. Also included is a discussion of the structure of the analytical files and the types of analyses they will support.

3.1 Measuring Screening Rates

Screening rates for three types of cancers are proposed: (1) mammography rates for breast cancer, (2) Pap smear rates for cervical cancer, and (3) fecal occult blood test (FOBT) rates, rigid or flexible sigmoidoscopy rates, screening colonoscopy rates, and barium enema rates for colorectal cancer. For colorectal cancer, we propose that rates be calculated for the four screens collectively as well as individually.

Any screening rate has two components, a denominator (target population) and a numerator (number of screening tests). These are discussed in turn.

3.1.1 Target Populations

A number of different groups have specified target populations for screening tests. Among them are the *Healthy People 2010* consultants and NCQA's HEDIS® standards. Because of HCFA's commitment to *Healthy People 2010* standards, it was decided during the kickoff meeting that its target populations will be used in the basic analyses (cf., Chapter 4). The *Healthy People 2010* target populations for the three study cancers are:

- breast cancer screening: women age 40 and older;
- cervical cancer screening: women age 18 and older; and
- colorectal cancer screening (other than digital rectal exams): persons age 50 and older.

One of the problems of the target populations for breast and colorectal cancer screening tests is that, in some states, the number of Medicaid eligibles might not be sufficiently large to support extensive stratification. This issue will be further discussed in Chapter 4 and Section 5.1. In particular, we will ask our physician consultant for her opinion on the specification of target populations.

3.1.2 Identification of Screening Tests

In specifying numerators for the screening rate measures, the basic issue is how to identify screening tests. NHIS, the source of many of the historical cancer testing rates cited in *Healthy People 2010*, is based on respondent recall rather than on

claims/encounter data. To identify screening tests in claims data requires a set of specifications.

NCQA has developed HEDIS® specifications for identifying mammograms and Pap smears (Exhibit 3-1), but not for FOBT or other colorectal cancer screening. For colorectal cancer, Joan Warren at the *National Cancer Institute* kindly shared with us the set of codes that she has used in SEER-Medicare analyses where screening and diagnostic tests had to be identified. During the literature review, we also noted codes that other researchers have used to identify screening and diagnostic tests. We have also sent these codes our physician consultant, Ann Nattinger, for her review and comment. Dr. Nattinger also reviewed codebooks for additional codes that we should consider using.

Exhibit 3-1
HEDIS® 3.0 Screening Test Identification Standards

Cancer	Codes
Breast	CPT-4 codes: 76090, 76091, or 76092 OR ICD-9-CM procedure codes: 87.37 or 87.36 OR Revenue (UB-92) code: 401 or 403 OR UB-92 codes 320 or 400 in conjunction with ICD-9-CM diagnosis codes 174.xx, 198.81, 217, 233.0, 611.72, 793.8, V10.3, V76.1
Cervical	CPT-4 codes: 88150, 88151, 88155, 88156, or 88157 OR ICD-9-CM procedure code: 91.46 OR UB-92 code: 923 OR UB-92 codes 300 or 310 in conjunction with ICD-9-CM diagnosis codes 180.x, 233.1, 622.x, 795.1, V72.3, V76.2

There are several problems and issues with regard to developing the test identification specifications. An important problem is whether Medicaid covers the screening test. In those states where screening tests are not covered, physicians might bill Medicaid for screening but using diagnostic procedure codes. Physicians or their billing clerks also might inadvertently bill a screening test using a diagnostic procedure code. Because widespread acceptance of screening standards for breast and colorectal cancer has occurred only in the past 10-15 years, some physicians, out of habit, might

always bill using a diagnostic procedure code rather than screening code. For some CPT codes (e.g., barium enemas), it is not clear whether the test is performed as a screening or diagnostic test – it may be context sensitive. Finally, even in states that cover screening tests as well as diagnostic tests, the presence of a diagnostic procedure code in the absence of a screening code could be taken to indicate that the woman might have received a screening test prior to getting (back) on Medicaid or that she might have received it as part of some free program. Consequently, our recommended strategy for ascertaining whether a woman received a screening test includes checking for diagnostic procedure codes as well screening codes. Since we are not counting the number of screening tests, for a specific type of cancer, received by a woman during a year, this strategy will not double count the number of screening tests in those states which cover screening tests in addition to diagnostic tests.

The study years cover 1993 through 1995. Since codes are continually be added, dropped, or otherwise being changed, we will use the applicable annual CPT and ICD-9 codebooks for 1993 through 1995. We will also use the 1992 codebooks since some physicians might not have adopted any new 1993 codes until well after their introduction. We will also use the 1996 codebooks since some physicians might have submitted some of their 1995 claims late and, thus, the codes on claims were recoded to the 1996 standard. Also, since new codebooks are issued in the previous fall, some physicians might start using the newer codes right away rather than wait until the payment year changes. More generally, as we search for screening tests, we will mark any claim that has an applicable code from 1992 through 1996, regardless of the year of the claims data.

This will allow us to pick up all coding vagaries as well as any mid-year introduction of codes.

Another issue is that states often do not use standard HCPCS codes – that is, they develop their own *local* codes for payment purposes. We plan to obtain state-specific local codes from the HCFA Project Officers. Once we have received the local codes, in conjunction with HCFA, we will review them to determine whether it is advisable to contact the states directly to supplement HCFA's list.

3.1.3 Cancer-Specific Screening Codes

Exhibits 3-2 through 3-4 show the recommended codes for identifying screening tests for each cancer we study. Each cancer is discussed in the subsections below.

Breast Cancer

For the 1992-1995 mammography rates posted by HCFA on its website during the mid-1990s, mammograms were identified by CPT-4 codes 76090, 76091, and 76092 and ICD-9-CM procedure codes 87.36 and 87.37. HEDIS® has a much more extensive specification for identifying mammograms (Exhibit 3-1). HEDIS® includes the above CPT-4 and ICD-9-CM procedure codes. HEDIS® also includes revenue or Uniform Billing (UB-92) codes, either separately or in conjunction with ICD-9-CM diagnosis codes. We plan to include all of these codes in our search for tests and add a new code for magnetic resonance imaging of the breast HCPCS 76093 and 76094. These codes can be used for screening or diagnostic purposes.

Exhibit 3-2
Breast Cancer Screening Tests

Code Source	Procedure Codes		
	Screening	Diagnostic	Other
Mammograms			
HCPCS - CPT	76092	76090, 76091	
ICD-9	87.37, 87.36		
UB-92	401 or 403		320 or 400 in conjunction with ICD-9 diagnosis codes 174.xx, 198.81, 217, 233.0, 611.72, 793.8, V10.3, V76.1
Other Breast Radiological Services			
HCPCS - CPT	76093, 76094	76093, 76094	
ICD-9			
UB-92			

Exhibit 3-3
Cervical Cancer Screening Tests

Code Source	Procedure Codes		
	Screening	Diagnostic	Other
Pap Smears			
HCPCS - CPT	88150, 88151, 88155, 88156, or 88157	88150, 88151, 88155, 88156, or 88157	
HCPCS - Level II	P3000, P3001		
ICD-9	91.46		
UB-92	923		
Other			UB-92 codes 300 or 310 in conjunction with ICD-9-CM diagnosis codes 180.x, 233.1, 622.x, 795.0, V72.3, V76.2

Exhibit 3-4

Colorectal Cancer Screening Tests

Code Source	Procedure Codes		
	Screening	Diagnostic	Other
Fecal Occult Blood Tests			
HCPCS - CPT	82270		
ICD-9			
UB-92			
Proctosigmoidoscopy (Rigid Sigmoidoscopy)			
HCPCS - CPT		45300, 45302, 45303, 45305, 45307, 45308, 45309, 45310, 45315, 45317, 45320, 45321	
ICD-9		48.22, 48.23	
UB-92			
Flexible Sigmoidoscopy			
HCPCS - CPT		45330, 45331, 45332, 45333, 45334, 45336, 45337, 45338, 45339	
ICD-9		45.24	
UB-92			
Colonoscopy			
HCPCS - CPT		44388, 44389, 44391, 44392, 44393, 44394, 45335, 45378, 45379, 45380, 45382, 45383, 45384, 45385	
ICD-9		45.23, 45.25, 45.42, 45.43	
UB-92			
Barium Enemas			
HCPCS - CPT	74270, 74280		
ICD-9	87.64		
UB-92			

Cervical Cancer

For cervical cancer, we plan to use similar codes to those specified by HEDIS®. We note that the CPT codes can be used for screening as well as diagnostic purposes. The only addition we have are two HCPCS level two codes. While these are stated in the manual as screening codes, there are no corresponding diagnostic codes, so they may be used for diagnostic purposes as well. We identify codes by purpose as much as possible, but we plan to use all codes in identifying tests.

Colorectal Cancer

For fecal occult blood test, we have only identified a HCPC code for the relevant time period; there are no ICD-9 codes. We will not be able to estimate FOBTs as a separate group if there are states that use ICD-9 codes exclusively.

We separate codes for rigid and flexible sigmoidoscopies in Table 3-4 as there are many for each procedure. We plan to include codes for either procedure. We accept all codes that imply the procedure, even as part of some other procedure.

For colonoscopy procedures, again we use a broad definition which will include patients who have presumably had previous colon surgery. Such patients should still be treated and/or screened, so we feel it is appropriate to include those codes (44388, 44389, 44391, 44392, 44393 and 44394). Barium enemas only have a few codes, but there are codes in each of the main systems (HCPCS and ICD-9). As is noted or the other cancers, it is difficult to distinguish between screening and diagnostic procedures. We categorize most the procedures as diagnostic, but plan to estimate rates using all procedures listed.

3.2 Continuity of Medicaid Eligibility

The cleanest way to observe all screening tests during a year is to limit the analysis to women in fee-for-service Medicaid continuously through the year. We have no data for women enrolled in managed care organizations or who are not enrolled in Medicaid. The only reason *not* to require continuity of fee-for-service enrollment is the expected large loss of sample. Lucey and Kumar (1996) limited their study of breast cancer screening rates in Louisiana to women aged 50-65 who are continuously enrolled, leaving only 55 percent of the eligible sample. This is a significant drop in sample size. One of our concerns with following this lead without further analysis is that the remaining sample may not be representative of Medicaid women as a whole in ways that are important to the outcomes of this study. The first fear is that there are distinct demographic differences in the continuously enrolled and other Medicaid groups and the second is that the screening rates of the continuously enrolled may not be representative of Medicaid women as a whole. As mentioned in section 2.3, continuity and racial distribution in the sample will vary by basis of eligibility categories.

Implications for Screening Rates

The main problem with requiring continuous eligibility is that there may be some correlation between who stays continuously enrolled and who gets the screening tests, particularly for the AFDC population. For those that qualify for AFDC, women who are continuously enrolled may be more or less likely to get screening tests due to unobserved factors correlated both with getting tests and being continuously enrolled. For example,

if a woman places a higher value on medical care or have high use of medical care, she is more likely to maintain continuity in enrollment (if otherwise eligible) and more likely to have recommended screening tests. In this case, any estimate made solely on women who are continuously enrolled will over-estimate screening rates for all Medicaid women. On the other hand, women who qualify via AFDC and are continuously enrolled may be less employable. The factors that make one less employable (substance abuse, domestic abuse, chronic conditions that do not qualify as disabilities, attitudes) may also make one less likely to undergo screening tests. In this case, our sample would lead us to infer lower screening rates for Medicaid women than we would find if we were able to observe complete data on all of these women.

Analysis Plan

In order to determine how important continuous eligibility is to our results, we will evaluate differences in means and other relevant statistical tests to ascertain whether or not the continuously enrolled sample is representative of the Medicaid population as a whole. We will analyze spells of eligibility quickly to ascertain the extent of the problems with requiring continuous enrollment. We may wish to analyze multiple samples - one that is restricted to continuously eligible women and one that does not.

It is possible that the rates between groups are not significantly different. Women who are low income and 'churn' in and out of Medicaid are likely to be uninsured when not enrolled, so it is likely that they do not have screening tests during those periods. If these women have the same underlying propensity to get screened, simply weighting the

data by months of eligibility in fee-for-service Medicaid should correct the problem. The opposite may be true of women who are in managed care for part of the year and fee-for-service part of the year. Because managed care will assign them a primary care provider in many cases, they may be more likely to receive screening services if they are in managed care for long enough.

One way to expand the sample is to define 'continuously-enrolled' as 10 of 12 months allowing for some slack in re-determination. It might not be necessary to weight these women differently because, presumably their full year of medical services are in the claims because if they had needed to consume services during the gap, someone would have helped them re-qualify for Medicaid.

Another possibility would be to sample any person with 10 or 12 months of continuous eligibility during the three-year period. We would not have 3 single rates to compare for 1993, 1994 and 1995 this way, but if we find those rates are not changing much over time, we could expand the sample by allowing years to run between any months, not just January to December.

For a single year of data, the continuity problem may not be too limiting. Allowing some slack may capture a more representative sample of the Medicaid group as a whole. However, if three years of continuous enrollment are required, the more likely it is to be a non-representative sample. We will segment the sample into types of spells to test for differences with the continuously enrolled sample. Those who do not have statistically different estimates of screening rates can be combined for these purposes.

How we deal with sub-samples that appear to be drawn from different populations will depend on who these groups are and what specifically we find in the data.

3.3 Structure of the Analytic Files

In this section we discuss our basic file structure and some specific options we have for measuring the dependent variable. We would also like to note that our empirical findings in forming these samples may force us to drop or drastically change our multi-year analysis.

3.3.1 Type of File

We will construct a person level file (starting from the SMRF person file) for each state to allow for flexible construction of samples for the core analysis and any sensitivity or other descriptive analysis we plan to do. For each state, we will limit the person file to include only women who are aged 13 and older. This will include all adult women and would capture pregnant teens who we may wish to analyze. We do not plan to include women with additional coverage or who are medically needy in this file as these women will not be included in any analysis we do.

Other sections of the report discuss other file restrictions we may make to analyze each type of cancer screening. Having a base file that contains all these women with identifiers for characteristics such as HMO enrollment that we may choose to remove from the sample gives us the most flexibility over the course of the analysis.

Once we have identified unique persons over the course of the three years, we will include time sensitive person-level variables so we do not lose the detailed information available in the annual person file over the course of time. We will also use a finder file based on the person file to retrieve any claims we need to construct needed utilization measures.

3.3.2 Time Frame for the Dependent Variable

Having three years of data allows for some flexibility in defining the dependent variable of interest. We do not believe that the single year screening rates will change significantly between 1993 and 1995 if we measured separate rates for 1993, 1994 and 1995. However, some of the *Healthy People 2010* guidelines suggest that people should have a given test within a period longer than one year. We would like to be able to construct these measures as best we can with multiple years. Below we list several options for ways to construct the dependent measure rates. They are separated into 1-yr, 2-yr and 3-yr construction possibilities. We use quotations for 'continuous' eligibility because our sensitivity analysis may suggest that continuous eligibility is too restrictive. Section 3.2 discusses the alternatives to continuous eligibility that we may need to employ to maintain an unbiased sample.

One Year

To compare states, we could look at a one-year rate based on those 'continuously' eligible for each calendar year 1993, 1994 and 1995. This would allow for comparability

to findings from other studies that are often based on a 'year' of data. Calculating rates for all years will allow us to ascertain if there are any charges in screening behavior over this short time frame. We could analyze a year either by requiring 12 months of eligibility, 10 months and treating it as 12 months or any months of eligibility with weighting to be determined in the course of study.

Any one year period of 'continuous' eligibility from 1993-1995

This would increase the number of people with 'continuous' eligibility in the sample and not limit the analysis to calendar year events – so a person eligible from June 1993-June 1994 would be included in the sample as a full year of eligibility. We are not sure how much we would gain from such a definition and such a definition would be unusual in the literature.

Two Year

Base sample on eligible in 1994 and look forward and back one year

For this method, we would base the sample on who was eligible in 1994 and create two-year rates by running through the 1993/4 claims and then the 1994/5 claims with this sample of enrollees. This time period would be based on when in 1994 we first observe the individual in Medicaid. If the person is first eligible in March 1994, then we look forward to March 1995 and back to March 1993. We would weight observations based on total months of eligibility during the two-year period. Identifying the sample this way prevents double counting and allows us to make the best use of the three-year interval.

Three Year

'Continuous' eligibility during all three years.

We expect this sample to be small, but it is possibly interesting for particular cancers such as colorectal where the recommendation for screening is not every year or two. We also expect this sample will be skewed to include mostly women on SSI because they are less likely to experience turnover.

Dependent Variable Construction

We presume the dependent variable is to be measured as any screening versus no screening for the tests in question, not number of screening events found in the claims for each person. We presume it unlikely that there is more than one event in any given year other than for those having irregular findings from the test or other problems with the test and that we do not wish for these events to factor into our averages. For instance, if the sample is two people, one person had two pap tests and the other had zero pap tests, the average for the population is one. This is misleading for our purposes. Such events are more likely the longer the time frame we analyze. So using the two-person example from above, one person may have a pap test every year and the other person has none. Over a two-year time frame, we do not want to count the two tests for the population of two and determine that all are receiving screening tests.

3.4 Age Standardization

Both actual and age-adjusted screening rates will be calculated. Age-adjusted rates, such as those published in *Healthy People 2010*, eliminate differences in observed rates that result purely from differences in the age distribution of population subgroups. Following *Healthy People 2010*, age-adjusted rates will be calculated using the *direct* method (without use of multivariate models),

$$AADR = \sum_i w_{si} \cdot R_i .$$

R_i is the age-specific rate for age class i and w_{si} is the standard weight for age class i:

$$w_{si} = \frac{N_{si}}{\sum_{si} N_{si}}$$

where N_{si} is the population in age class i in the standard population. The sum of the weights are constrained to equal one so that the weights are proportion of the standard population in each age class. Other types of age-adjusted rates might be calculated to account for the possibility that some subgroups (e.g., African Americans) might be more likely than others to lose eligibility during the redetermination process – see Section 3.2.

The standard population we plan to use is the Medicaid population in each state. We will calculate the age distribution with the SMRF data.

4 Primary Analyses

The subject of this chapter is how we plan to determine the magnitude, if any, of racial disparities in screening tests and possible causes thereof. Both tabular and multivariate analyses will be performed.

4.1 Tabular

Since SMRF data will not allow us to replicate *Health People 2010* screening rate tables, we propose to analyze and present cancer screening rates for women in a table format similar to that shown in Table Shell 4-1. Table Shell 4-1 allows for the comparison of screening rates by the SMRF race/ethnicity categories, Medicaid eligibility status, geographic location, and age. Instead of just an urban/rural distinction, *urban* can be broken down into *large urban* and *other urban*. Both actual (crude) and age-adjusted screening rates can be produced – statistical tests for proportions can be performed to ascertain whether screening rates differ by race/ethnicity, eligibility status, and geographic location.

To the extent that the claims data allow, we would also like to produce cancer screening rates conditioned on the receipt of prior primary care (Table Shell 4-2). The reason is that primary care utilization may be a critical pathway in receiving cancer screening tests. (A possible exception may be Pap tests for pregnant women.) One of the

TABLE SHELL 4-1

Pap Test Rates,
Medicaid-Covered Women Aged 18 Years and Older

	Actual Rates		Age-Adjusted	
	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years
Total				
Race and Ethnicity (SMRF classes)				
American Indian or Alaska Native				
Asian or Pacific Islander				
Black or African American*				
White*				
Hispanic or Latino				
Eligibility Status				
Pregnant Women				
AFDC"				
Disabled (not covered by Medicare)				
Geographic Location				
Urban				
Large				
Other				
Rural				
Age				
18-39				
40-49				
50-64				
65+				

*Not Hispanic
"Temporary Assistance to Needy Families (TANF) program, implemented 1996 to 1998.

TABLE SHELL 4-2

Pap Test Rates,
Medicaid-Covered Women Aged 18 Years and Older

	All				with Prior Primary Care**				without Prior Primary Care			
	Actual Rates		Age-Adjusted		Actual Rates		Age-Adjusted		Actual Rates		Age-Adjusted	
	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years	in Past Year	in Past 3 Years
Total												
Race and Ethnicity												
American Indian or Alaska Native												
Asian or Pacific Islander												
Black or African American*												
White*												
Hispanic or Latino												
Eligibility Status												
Pregnant Women												
AFDC/TANF												
Disabled (not covered by Medicare)												
Geographic Location												
Urban												
Large												
Other												
Rural												
Age												
18-39												
40-49												
50-64												
65+												

*Not Hispanic

Temporary Assistance to Needy Families (TANF) program, implemented 1996 to 1998.

**CPT-4 codes: 90918, 90919, 90920, 90921, 99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, 99215, 99301, 99302, 99303, 99311, 99312, 99313, 99321, 99322, 99323, 99331, 99332, 99333, 99341, 99342, 99343, 99351, 99352, 99353, 99375, and 99376.

reasons that prior primary care could be important is due to the uncoordinated nature of most fee-for-service care. That is, without primary care, a woman might not learn about or be directed to obtain a screening test. Additionally, in the case of Pap smears, a pregnant woman who has primary care prior to delivery might be more likely to have had a Pap smear than a woman who does not have any care until she actually goes to a hospital or birthing center for delivery. There are several ways to define primary care services. In HER's HEDIS project, primary care was defined by the presence of primarily CPT-4 evaluation and management (E&M) codes on claims (see notes to Table Shell 4-2). This definition of primary care or a variation that takes into consideration physician specialty can be used; we will confer with our physician consultant and the HCFA project officer.

Tables based on the table shells can be produced containing overall rates for all states in the study. However, because of differences in state Medicaid coverage of screening tests, the emphasis will be on state-specific tables. Further, as permitted by sample size, tables will be produced by controlling simultaneously for eligibility status and urban/rural residence. This will allow the confounding effects, if any, of eligibility status and geographic location to be removed from the racial/ethnic cancer screening rates. For instance, tables could be separately produced for pregnant women residing in large urban areas, pregnant women residing in other urban areas, and so forth. Similarly, tables could be separately produced for AFDC women residing in large urban areas and so forth. We also propose to produce age-specific screening rates within each of the eligibility categories, further reducing potential confounding effects.

An important issue to be resolved is whether screening rates should be calculated for "look-back" periods such as the 3-year period in the table shells. As indicated in

Section 3.3, there are several ways to define study populations. If a cohort approach is taken, then there is the possibility that the number of women meeting the criteria could be very low and, hence, unrepresentative of Medicaid women in their state as well as nationally. If look-back periods are not used, it might be difficult to compare our screening rates with *Healthy People 2010* rates and other rates in the literature.

4.2 Multivariate Analysis

If the data allow, we would like to perform multivariate analyses of screening behavior. Race is confounded by many other factors, some of which we observe with the SMRF data, and many of which we do not. We would like to simultaneously control for these factors as much as possible to help explain why we see differences by racial categories (presuming that we will see differences as other studies have.) There may also be interactions between race and other explanatory variables that we would try to detect.

4.2.1 Dependent Variables and Basic Model

The basic dependent variable of interest is whether or not a given woman received the specific cancer-screening test in a specified time frame. We anticipate analyzing each of the three tests separately with a one-year look-back for an individual. We would duplicate the analyses for multi-year look-back periods if the sample sizes are adequate. Construction of the three basic dependent variables would be:

- Does a woman have a claim for a Pap-smear in the past year?
- Does a woman have a claim for a mammogram in the past year?

- Does a woman have a claim for a fecal occult blood test in the past year?

These binary variables are estimable with a logistic regression using the series of independent variables discussed below. We will calculate odds ratios for ease of interpretation.

4.2.2 Independent Variables

The SMRF data are the primary source of information for this study. We also plan to merge the information from the Area Resource File (ARF) by zip code to the SMRF data. The most important variables for this analysis are the break down of race and ethnicity. The SMRF data combine these into one categorical variable. As sample size permits, we will use initially use indicator variables for each of the values of the race variable. We presume that whites, African-Americans and Hispanics can be identified while others may have to be in a 'other race' category for highly segmented analyses. Section 4.2.3, additional models, discusses this segmentation.

While the samples will control for age by only looking at certain ranges, we will use age as an independent variable as well. As women get older, they become more aware of the risks of cancer and the screening tests and should be more likely to have the tests. The risks of getting cancer also increase with age, making the screening test more valuable to older women. In some cases, tests may fall off at much older ages creating a non-linear affect. This could be because a woman has other conditions or the tests are not recommended as strongly by her physicians, or the quality adjusted life year benefit

shrinks such that the hassles of the test for older women (discomfort, transportation, etc) may outweigh any lasting benefits (Mandelblatt *et al*., 1992). There is some dissent of the value of the different tests as women age.

An indicator that may be useful is time since first eligible for Medicaid. This may be able to separate long term Medicaid users from those who are on Medicaid for some time, but do leave may have different preferences for preventative care and cancer screening.

An urban/rural indicator variable can be constructed with either the county or zip-code level information. The ARF provides county level information for several additional variables. Rough measures of access to care such as providers per 1,000 population and hospital beds per 1,000 population may be important indicators for why there are racial differences in screening rates. Also county level unemployment, education and income may be helpful since we do not have individual measures of employment, education or income in the claims data.

There are several ways to measure co-morbidities with claims data. We could calculate a risk score using risk adjustment software such as DPS to summarize how 'sick' a person is. These models are designed to predict expenditures, but do so based on diagnoses from claims data. A concurrent model of diagnoses may be a useful model to describe the number and severity of other illness from claims data. Others have used Charlson indices adapted for breast cancer (Wang *et. al.*, 2000). We may also wish to account for whether or not the person has a diagnosis code of cancer or procedure codes related to the cancer of interest for each test. The HEDIS® standards would remove

people with radical mastectomies from the analysis of who gets mammograms for instance. We do not have reason for disability for disabled women, but having some specific common estimates of disabling conditions using claims may be helpful in looking more specifically at who in the disabled population is getting or not getting screening tests. For example, Iezzoni *et al.* (2000) find that people with mobility impairments are not receiving screening and preventive services at the same rate as the rest of the population using data from the National Health Interview Survey.

An important co-condition to measure is pregnancy and as noted in Section 2.3, we plan to analyze pregnant women separately.

It will be important to control for the basis of eligibility among Medicaid women. The largest distinctions will be between women who qualify by virtue of pregnancy, AFDC, and disability. Initially we plan to include indicator variables for basis of eligibility other than pregnant women. We discussed the rationale for separating these regressions in Section 5.4, but other sample segmentations such as for racial groups takes precedence in our analysis. Too much segmentation (each state, each race and each basis of eligibility group) is unlikely to be possible. We will determine empirically the most appropriate analysis structure and expect that given the interests of the project, the racial characteristics will dominate.

For multivariate analyses, we plan to estimate multivariate analyses for each state independently. We will also evaluate the appropriateness of pooling state data using indicator variables for the state and potentially for relevant policies such as having expanded eligibility standards or not.

4.2.3 Additional Core Models

Separate Logistic Estimations by Racial Category

There is a growing recognition in the health services research literature that the influence of factors that determine medical utilization patterns and outcomes may vary in fundamental ways across racial and ethnic groups (White-Means, 1995). For example, urban residence may not have the same impact on whether or not a person receives screening tests for African-Americans as for whites. Models that simply include a variable to control for race/ethnicity assume that this only has a direct effect on the dependent variable (shifting the mean up or down) and that the effect of all other explanatory variables is uniform across racial and ethnic populations. Even just including an interaction for age is inadequate if the effect of all the independent variables is different by race. Additionally, because of nonlinearities, interactions can be difficult to interpret, particularly for odds ratios.

We presume from the literature that there are significant interactions between the racial categories and the other independent variables described above. Mandelblatt et. al. (1999) find interactions between race and age. Sung et. al. (1997) find interactions between race and urban/rural dwelling. We have found (Kulas *et. al.*, 2000) that race interacts with basis of eligibility and we presume this also indicates a link with months and continuity of eligibility.

In order to allow for the possibility that the effects of explanatory variables in our model differ across racial and ethnic groups, we would like to estimate a separate regression for each of the six racial/ethnic groups that can be identified in SMRF data as

the sample sizes allow. We can test the appropriateness of this specification with a Chow test. Separate regressions are the equivalent of a 'fully interacted' model. We will compare the inference of this model to a direct model with just the racial identifiers and a partial model where race is only interacted with a few key variables.

Ideally, we would be able to run separate regressions for each of the key interactive groups – for instance, running regressions over urban/rural residence and race. That is, a separate regression for urban African-Americans, another regression for rural African-Americans, another regression for urban whites, and so forth. We presume that sample size will limit our ability to do this within state, but know other studies have found significant differences in cervical cancer rates for urban and rural African-Americans. Analyses such as these are considered to be alternative analysis and are discussed in Section 5.4.

Conditional Logistic Analysis Based on Use of Primary Care Services

Studies have found that physician referral is a key factor in determining whether a person receives cancer-screening tests or not. To account for this knowledge, we plan to condition the screening questions on receiving medical care in a physician office during the time period. Other literature has found there are many unobserved barriers among certain populations to receiving care. We cannot investigate these barriers because we have no data on them, but controlling for people who receive care at all may reduce any differences among races due to barriers in receiving any care at all.

There are different ways to define the conditioning dependent variable – did you receive any care at all, did you have a primary care visit, did you have any office visit are possibilities. We would lean toward having a physician office visit of any kind for a few reasons. Receiving any care may be too broad; it would include ER visits and other acute episodes that may not reflect access to care, willingness to visit a provider or having a visit where a physician should be concerned about your overall state of health. Primary care visits would greatly increase the chances of receiving screening tests since primary care specialists focus on the general health of the person and preventative care in general. Access to and willingness to use primary care may be important factors in why a person does not get screening tests. Primary care visits could be defined to include annual gynecological visits and prenatal visits since many women receive information about screening during these visits. We can separate visits for illness from 'well checkups' as a further refinement.

On a cautionary note, many states bundle fee-for-service pregnancy services so we may not be able to identify prenatal visits with claims. It might be misleading to code disabled women the same as those not having any visits because they are likely to have many office visits of some type during the course of a year. The disabled population in Medicaid will be a larger proportion of people than in the general population studies, so it is important to understand obstacles they may have to receiving screening services over and above the effect of race and income.

A model of receiving care and receiving tests would be a two-stage model where we first estimate the probability of having an office visit and then use that information to

condition the second regression on testing. This is akin to the Heckman sample selection correction technique. We presume identification will be difficult for this type of model because we do not observe independent variables that would affect the probability of receiving care that do NOT affect the probability of receiving a screening test.

Another possibility would be to estimate a simultaneous equation model which allow for different dependent variables with the same independent variables, correlated errors, and unobserved heterogeneity. These techniques are complex and may not produce useful, stable estimates. Once we have the data, we will have a better idea of what analyses will be supported.

4.2.4 Sample, Weighting, Corrections

The basic sample for each test will consist of Medicaid women of the proper ages for each state and year. We discuss options for the observational unit in Section 3.3. While we may be interested in overall Medicaid rates, it is likely there are several populations we will want to delete from the basic sample:

1. Women in managed care during the year and possibly counties with heavy managed care penetration;
2. Women who are medically needy and/or have private insurance coverage (i.e., Medicaid is a secondary payer); and
3. Women with Medicare coverage.

The reason to delete these women is that it is likely we would not observe screening tests for these women even if they had them. This is because either we do not observe enough months of data in a given time period or because another payer likely covered the test and Medicaid was not billed.

We can use weighting and partial observability models as appropriate and necessary to be able to do analyze women who are not continuously eligible. As noted in Section 3.3.2, we may broaden the definition of continuously eligible to mean 10 of 12 months. If we need to include women with any eligibility for the integrity of the sample, we need to think carefully about how we weight such women. We will create unweighted rates as well as rates weighted by months of eligibility. As previously noted, the choice to weight or not weight implies certain assumptions about unobserved behavior in the time outside of Medicaid.

5 Sensitivity Analyses

Given the scope of the project, it is not possible to employ every analytical technique or variation of a screening rate measures. Nonetheless, depending on HCFA's interest and the availability of resources, we propose in this chapter several types of sensitivity analyses. These include the specification of alternative target populations and alternative criteria for the identification of screening tests. Because the analyses of screening rates might be affected by the choice of weighting factors for women that are not continuously eligible for Medicaid, several alternative methods for constructing weighting factors will be examined. We also propose alternative multivariate analyses.

5.1 Alternative Target Populations

The specification of the *Healthy People 2010* target populations is limited to age criteria. Other groups, such as NCQA, have additional criteria. For instance, NCQA's HEDIS® mammography and Pap smear target populations have medical history criteria. HEDIS® excludes women who were identified as having had a radical bilateral mastectomy. HEDIS®, however, was developed for reporting by managed care organizations that, presumably, have complete medical histories on their members. Thus,

Exhibit 5-1

Identifying Radical Bilateral Mastectomies in Claims

Code	Description
CPT codes with modifier = 50	
19200	Mastectomy, radical
19220	Mastectomy, radical
19240	Mastectomy, modified radical
ICD-9-CM codes	
85.44	Bilateral extended simple mastectomy
85.46	Bilateral radical mastectomy
85.48	Bilateral extended radical mastectomy

criteria would have to be developed to identify radical bilateral mastectomies in claims data. HER, as part of its evaluation of the applicability of HEDIS® measures in Medicare FFS, developed such criteria. It involves examining claims for specific mastectomy procedures during the "current" or "previous" years (Exhibit 5-1). Given the turnover in the Medicaid population, we would have to explore the possibility of employing this standard. Further, it might not be necessary to exclude women on the basis of radical bilateral mastectomies since Medicaid women are relatively young and, hence, few would have had the procedure. HEDIS® also specifies a medical history criteria for Pap tests, namely the exclusion of women identified as having had a hysterectomy with no residual cervix (not an issue for pregnant women). (Pap tests were not included among the study measures in the aforementioned HER study because Medicare does not require managed care organizations to report such rates.)

HEDIS® also has different target population age criteria than *Healthy People 2010* for mammographies and Pap smears. If HEDIS® standards are followed for mammography rates, for example, then only women aged 52 years and older would be included. This standard, of course, would exclude many AFDC women of child-bearing age from the analysis. If HEDIS® mammography standards are followed, then the population would be further restricted to ages 52 through 69. For Pap smears, the HEDIS® age standards are women age 21 through 64. NCQA has yet to specify HEDIS® measure for colorectal cancer, but did mention the possibility of a target population consisting of adults age 55 and older (*HEDIS 3.0, Volume 1*, p. 40).

Other organizations and expert panels might have target population criteria that differ from *Healthy People 2010*. We recommend that both HEDIS® and these other criteria be considered in a sensitivity analysis.

5.2 Alternative Weights

For comparability purposes, in Section 3.4 we indicated that we planned to use the direct method for age standardization. We might want to consider using an indirect, regression-based, method for age standardization. Another problem is the potential racial bias in the continuity of eligibility (Section 3.3). We might want to devise a weighting scheme, for use in the tabular analyses, to account for such bias. This methodology might be regression-based as well – we are still investigating the handling of such biases.

The general discussion of continuity of eligibility in Section 3.3 suggests that several alternative methods for weighting observations could be used. If this indeed the case, then we might want to ascertain the sensitivity of the screening rates to different weighting methods.

5.3 Alternative Multivariate Models

5.3.1 Other Sample Segmentations

We may wish to estimate separate regressions for basis of eligibility categories because each group may not have the same underlying rate of propensity to seek care. These eligibility groups are also correlated with race and we may wish to interact with race in any regressions that pool the groups.

5.3.2 Correlations Between Types of Screening Tests

Other studies (Kirkman-Liff and Kronenfeld, 1992) found that receiving a Pap-smear and a mammogram were correlated in their analyses – if a woman received one test, it was likely she had received the other in the proper age ranges. In their study, they simply used having one test as an independent variable in the regression for the other test. They were able to independently control for having a usual source of care and other features that might explain the correlation, allowing them to calculate a simple odds ratio. Many of the factors that would lead one to both types of screening are unobserved in claims data, so a more appropriate specification might be a conditional logit or a joint estimation of receiving the two tests. Breast and cervical cancer are primarily or exclusively problems for women and the screening tests may be suggested or performed in an annual gynecological exam, so it is not surprising that these are correlated.

5.3.3 Correlations Between Screening Tests and Other Utilization

Our primary analysis will condition receiving screening tests on having had a physician visit during the relevant time frame. In addition, we could consider the number of physician visits, primary care visits or ER visits as predicting screening behavior. Burns *et al*. (1996) found differential effects by race of the effect of seeing a physician on screening behavior. Depending on our initial findings, we may wish to specify this analysis in alternate ways for sensitivity and a more complete understanding of the relationship between having a 'usual source of care' and receiving screening tests may be.

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6 Improving Health Outcomes

Lower rates of cancer screening among poor women and women from racial/ethnic minorities have been well-documented. There are far fewer studies of differences in screening rates by race/ethnicity for women with similar insurance coverage. This proposed study will shed important light on this issue. If Medicaid cancer screening rates vary by race/ethnicity *within the same state*, this suggests that health insurance alone is not sufficient to assure access. Policymakers may need to consider innovative outreach programs to improve health outcomes for those groups with lower than desired rates. Such approaches might include, among other things, educational materials written in the primary language(s) spoken by women from these racial/ethnic groups, culturally-sensitive educational activities targeted to their communities, etc.

Low rates of cancer screening for certain racial/ethnic groups may also suggest that some women are encountering barriers to *primary care.* Women who do not visit their primary care provider, or can not find a Medicaid-participating provider, are unlikely to undergo cancer screening of any sort. Higher Medicaid payment rates are one obvious solution to low provider participation in state Medicaid programs. However, cultural and language barriers may also be important reasons why some women do not seek primary care; state policymakers might want to consider special recruitment efforts aimed at enlisting providers who come from these same racial/ethnic groups.

7 Strengths and Weaknesses of the Study

This chapter describes the strengths and weaknesses of our proposed analyses and submits suggestions for further research.

7.1 Design

The strengths of this study are that it will answer the basic question of whether or not Medicaid women receive cancer screening tests and if the test rates vary by race. No previous work uses the range of Medicaid claims data proposed here. We will look at rates over multiple years accounting for special features of the Medicaid population. The study will provide a benchmark for the Medicaid population which can be used to help judge specific programs aimed at increasing the awareness and receipt of screening tests.

Healthy People 2010 proposes a single standard of screening rates among all people and to eliminate racial disparities. Understanding differences in screening rates for a population such as Medicaid that has been found in other studies to have low screening rates will be important to reaching the 2010 goals.

While we propose several large states of analysis, we are not able to analyze all states for a representative national picture. Medicaid is a state driven program, but national results would be of interest to inform our progress on national goals.

Interpreting an overall screening rate for Medicaid should be done cautiously. The Medicaid population is not a representative sample of all poor Americans, but rather

those categories of people who qualify for benefits. Also, some of the factors that may influence the rate of screening among Medicaid women could be confounded with race. We will control as best we can for basis of eligibility, months eligible, and co-conditions such as pregnancy that may affect the rates. Understanding the differences in the Medicaid population will help clarify findings and how the results compare to national standards and other studies.

7.2 Data

Administrative data have the advantage of accurately recording covered events. Provider payment depends on such records. Other standard sources of data such as surveys and chart reviews have drawbacks not found in administrative data. Surveys rely on patient recall, are often based on convenience samples of a given provider and are difficult to administer to low-income populations. Chart reviews require physician interpretation, are labor-intensive and therefore often have small samples, and also tend to be based on provider-based samples.

Administrative data cover large sample sizes and are very complete for services covered by insurance, in this case Medicaid. The limitation is that any screening that is performed and not covered by Medicaid will not be detected in the claims. It is unlikely that low-income women with many barriers to screening will be screened elsewhere, particularly when we plan to eliminate women with significant other insurance coverage from the study. We do note that during the time period, many states had additional programs funded by the CDC's National Breast and Cervical Cancer Early Detection

Program (NBCCEDP). The National Breast and Cervical Cancer Early Detection Program began in 1991 with 8 states (including California) and by 1995 included all the states we plan to study. By 1996, all 50 states had programs. Women screened through outreach efforts coordinated by this program will not have Medicaid claims for these services. One study of NBCCEDP data from the Bronx, New York showed that only 8.5 percent of those screened had Medicaid coverage. We presume that this means we are not missing screening tests for a significant sample of women in our sample.

While large sample size is an advantage of our analysis strategy, once we restrict and subdivide the sample for analysis, there may be problems. One problem is that the restrictions of the sample could bias the results. As described in section 3.2, we prefer continuously enrolled women to ensure we detect all screening. However, continuous enrollment may be correlated with factors that influence screening behavior and may also be correlated with race. Another problem may come from restricted sample sizes. Ideally, we would like to analyze each racial category as a sub-sample, but controlling for all other features, we could have some small cell problems. For example, can we identify a separate rate for women over age 50 (the age-group recommended for regular CRC cancer screening), who are Hispanic, who qualify via AFDC and have no other insurance and continuous enrollment? Our analysis plan will address these issues as best we can.

If we determine in the course of the study that it is better to be inclusive in our sample definitions, we trade the small sample problems for less complete data. If we include women who are not continuously enrolled we will have to determine how to

appropriately weight those observations because we will not observe complete data for those women.

Another short-coming of the SMRF data is that it is somewhat dated. The files are carefully analyzed to provide conformable, accurate data across states, but the process of creating these files delays their release so that the most current data is 1995. However, for the population of interest, we feel these files are the most efficient to analyze and will provide useful information about the progress toward *Healthy People 2010* goals. CRC screening gained more public attention through the course of the 1990s, but increasing screening rates for CRC cancer was a *Healthy People 2000* goal as well as a 2010 goal. One benefit of the older data is that welfare reform introduced more churning and eligibility turnover problems among Medicaid recipients. Federal welfare reform was passed in 1996, prior to the time period we will analyze.

7.3 Multivariate Analysis

The multivariate analysis proposed allows us to simultaneously control for several subdivisions in the data that may affect screening rates. Ideally, we would estimate screening behavior in separate estimations for each racial category. Sample sizes and lack of variation in some independent variables may limit our ability to do this, particularly if we estimate state by state. We presume we will be able to pool the states to estimate these regressions, but will check to ensure such pooling is appropriate.

Another strength of the study is the idea of using conditional analysis based on primary care utilization to estimate screening behavior. Other literature has shown that

screening is positively correlated with use of primary care and negatively correlated with heavy use of emergency rooms. However, this finding may not hold as strongly across all racial categories.

Weaknesses of the multivariate analysis include the limited availability of independent variables such as income and education as well as factors that are generally unobservable such as fear of radiation. The sample of Medicaid eligible women will all be low-income, though there is still variation between women that may be of interest that we will be unable to detect.

7.4 Issues for Further Study

One possible follow-up to this study would simply be to include more states in the analysis. As data become available one could also extend the years studied to analyze trends over time to see if any racial disparities are declining over time. Another possible follow-up would be to focus on the relation between types of co-conditions and disabilities with the likelihood of getting screened. It is possible that people with chronic disabilities receive less primary care and preventative care for other conditions such as cancer and heart disease. While we will separate the disabled from other eligibility groups and be able to make some statements about their likelihood for being screened, it is possible that type of primary disability influences such behavior.

While screening tests can be well detected with claims data, outcomes measures are more difficult to monitor. Traditional outcomes such as stage of diagnosis are not available in claims data. While it may be possible to link a few areas with SEER data

which contain these statistics, the volatility of Medicaid enrollment would hinder any panel efforts to link screening efforts with outcomes directly. Medicare and SEER data have been linked and analyzed.

Another future study could be to analyze follow-up behavior after tests. While claims data do not report test results, there are published norms for how often one might expect an abnormal Pap or mammogram and further guidelines for care.

One could also look at basic mortality rates of people who have a diagnosis of cancer within a 3-5 year period, but without additional linking to death certificates, a researcher would not know if the death was attributable to cancer or not.

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