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Social Interactions In Breast Cancer Prevention Among Women In The United States

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Social Interactions In Breast Cancer Prevention Among Women In The United States

by

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Dedication

I would like to dedicate this dissertation to my family.

To my dear daughters, Julia and Olivia: I hope that, in the years to come, this work will be a kind reminder that you, my darlings, are capable of achieving anything, once you put your minds to it.

To my husband, Clifton, whom I met during an economics class: you made me interested in economics, and encouraged me to pursue a graduate degree. I thank you for being patient, understanding, and supportive during my dissertation writing. You have always believed in me and helped me see things in myself that I didn't.

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Abstract

This dissertation contributes to the field of health economics, which, in the past couple of decades, has substantially increased our understanding of the determinants of human health, health-related behavior, and health care choices.

A large body of literature has documented the influence of peer group behavior on individual choices. The purpose of my research is to examine the extent of such a phenomenon in breast cancer preventive behavior. Using Behavioral Risk Factors Surveillance System (BRFSS) surveys from 1993-2008, I measured the effect of other female screening behavior on an individual's decision to have a routine breast cancer screening by calculating the size of a so called social multiplier in mammography.

I estimated a vector of social multipliers in the use of annual mammograms by taking the ratio of group-level effects of exogenous explanatory variables to individual-level effects of the same variables. Peer groups are defined as same-aged women living in the same geographical area: county or state. Several econometric methods were used to analyze the effect of social interactions on decision to undergo mammography, including ordinary least squares, fixed effects, the split sample instrumental variable approach, and a falsification test.

My results supported the hypothesis that social interactions have an impact on the decision to have a mammogram. For all women over age 40, I found strong evidence of social interactions being associated with individual's education and ethnicity. In addition, the decision for women ages 40-49 to have a screening was subject to peer influence

through their place of employment and ownership of health insurance. Finally, for women age 75 and older, being married and aging were the most important channels through which peer group influenced the decision to have a mammogram.

This research has important policy implications in the presence of current health care reform that reimburses breast cancer screening at 100%, while rates of mammography receipt remain below the policy goal.

Furthermore, I examined the effect of the 2009 United States Preventive Services Task Force change in screening recommendations on screening behavior. I demonstrated an immediate reduction in the receipt of mammography among women of all age groups following the revision of screening guidelines. I found that in 2010, the twelve month mammography receipt decreased by 1.97 (women ages 40-49), 2.20 (ages 50-74), and 3.61 (age 75 and older) percentage points, and the twenty-four months mammography receipt decreased by 1.47 (women ages 40-49), 1.05 (ages 50-74), and 1.92 (age 75 and older) percentage points. Analysis using a two-year follow up period after the revision of screening recommendations provided further support to this conclusion.

Chapter 1: Social Interactions in Breast Cancer Prevention

1.1: Introduction

Breast cancer is one of the most feared diseases among women in the U.S: a woman born today has approximately a 1 in 8 chance of having the disease at some point during her life. It is the most commonly diagnosed cancer among women in the U.S. and the second leading cause of cancer deaths, with more than 40,000 deaths annually as of 2012 (American Cancer Society, 2012).

Getting a screening mammogram on a regular basis is recognized as the most effective way of early detection of breast cancer. Currently, the majority of the health organizations in the U.S. recommend that women ages 50-74 undergo routine annual mammography (Table 1.1), as annual screenings increase the likelihood of successful treatment and reduce breast cancer mortality by 30% in this age group (Nyström et al., 1993). In spite of the benefits of early detection and a low or no out-of-pocket cost, only 59.1% of women 50-74 years old follow the recommendation (Pace, He, & Keating, 2013). A key public health policy objective of the U.S. Department of Health and Human Services is to increase the rate of adherence to mammography recommendations in this age group to 81.1% by the year 2020 (Healthy People, 2013). Traditionally, economists have encouraged action by lowering the price of participation. However, since annual screening mammography is already 100% covered under the Patient Protection and Affordable Care Act (2010), less conventional methods may be needed to reach the current policy goal.

Recent research shows that breast cancer prevention, particularly annual screening mammography, is seen as a socially desirable behavior in the United States (Cahalan, 1968; Presser & Stinson, 1998). Additionally, beliefs about the proportion of same-age peers who regularly undergo screening have been shown to have a significant impact on an individual's decision to pursue a screening mammogram (Allen, Stoddard, & Sorensen, 2008). In recent years, the American public has seen an increase in mammography promotion efforts, which have relied heavily on the social desirability of mammography in an attempt to increase screening participation rates.

Among some recent screening promotional efforts are social events at hospitals and clinics, such as "Ladies Night Out," "Mammogram Parties," and "Mamm and Glam," which offer a relaxed setting where a woman and her friends can also consent to a screening mammogram. Another campaign, the so-called "Pinky Pledge," was administered via Facebook and Twitter, and challenged women to schedule a mammogram and post a proof of the screening visit on the website at a later time. The success of these methods depends on women to encourage one another to have a screening during their interactions, as well as to hold each other accountable (as in the case of "Pinky Pledge") for a timely test.

This chapter empirically examines whether social interactions are an important factor in increasing mammography participation among women in the United States. *Social interactions* in this context are defined as the influences of a group's average mammography rate on an individual woman's likelihood of having a mammogram (*endogenous* social interactions), as well as the influence of a group's average exogenous characteristics on the probability of screening (*exogenous* social interactions). Manski

(1993) and Blume at al. (2010) emphasized that disentangling the endogenous social interactions from exogenous effects is difficult without detailed information on both the individual and his/her peer behavior within a narrowly defined friendship group. Since I will not be able to distinguish between the endogenous and exogenous effects in this study, my goal is to establish whether social effects are present in breast cancer screening decisions and to measure their magnitude by calculating the so-called “social multiplier”. In regards to breast cancer screening, social interactions among women may create a social multiplier, where an individual’s choice to have a mammogram can influence the choices of others and lead to an increase in screening rates at the group level.

To estimate the size of the social multiplier, I employed a strategy developed by Glaeser and Scheinkman (2000), Glaeser et al., (2003), and Graham and Hahn (2005), which elucidates the presence of social interactions from differences in the impact of exogenous characteristics on the dependent variable (mammography screening in this case) at the group and individual levels in repeated cross-sectional data. This method is built on the intuition of the social multiplier, which suggests that in the presence of social spillovers, individual exogenous characteristics will have both a direct effect on an individual woman’s breast cancer preventive behavior, and an indirect effect on her peers’ behavior. Thus, in the presence of social influences, the regression coefficient at the group level should be much larger than at the individual level. In the absence of the social multiplier in mammography, the characteristics should have the same impact on both individual- and group-level behavior.

To investigate this problem, I used the Behavioral Risk Surveillance System (BRFSS) from 1993 through 2008, which is a data set containing information about individual health related behavior, including breast cancer screening. I considered a woman's reference group to be defined by same-aged women who live in the same geographical area. Given the nature of the data, my units of geographic aggregation were county and state. To this end, I assumed that women are more likely to be influenced by women with whom they come in frequent contact in everyday life, such as co-workers, neighbors, and perhaps people who belong to local clubs and associations.

If social interactions, also known as "peer effects", are an important factor in promoting preventive health behaviors, such as mammography participation, then small changes in individual incentives to take a screening test can result in large changes in group screening rates due to social spillovers. Knowledge of the magnitude of these effects is important from a health policy perspective, as it may imply that the cost of achieving the current goal for breast cancer screening rates is much smaller than predicted by the standard estimates computed at the individual level. On the other hand, the policy makers should be aware that, in the presence of social multiplier, the value of any type of screening intervention is higher than the one that would be measured at the individual-level. In addition, if mammography participation is subject to peer influence, then interventions that parlay social influence can be designed to increase the screening rates.

1.2: Mammography and Breast Cancer Background

1.2.1: Breast Cancer Background

1.2.1.1: Breast Cancer Incidence and Mortality in the U.S and Worldwide. In 2014, it was estimated that more than 230,000 American women will develop breast cancer, which accounts for 29.9% of all new cancer cases among females (Ferlay J, 2012). Cancer is the second leading cause of deaths for U.S. females of all races (22.1% versus 23.5% of deaths caused by heart disease) (World Health Organization, 2010). Breast cancer accounts for 15% of all cancer deaths (more than 40,000 deaths annually), which makes it the second most common cause of cancer deaths for females, after lung cancer (Ferlay J, 2012).

Figure 1.1 compares the estimates of breast cancer incidence and mortality across the World Health Organization (WHO)-defined regions of the world for 2014. Breast cancer incidence varies more than ten-fold between different regions: the highest incidence is predicted for Western and Northern Europe (166.9 and 153.6 cases per 100,000 respectively) and Northern America (144.5 per 100,000); the smallest incidence is estimated for Middle Africa (16.3 cases per 100,000), Eastern Asia (18.9 per 100,000), and Western Africa (25 per 100,000). Higher incidence of breast cancer in developed countries is generally attributed to dietary effects, a later first childbirth, lower parity, and shorter breastfeeding time (Peto, 2001). However, the range for breast cancer mortality between different regions is smaller than that for incidence, with 38.5 per 100,000 in Western Europe and 8.9 per 100,000 in Middle Africa (Ferlay J, 2012). The mortality rate among women with breast cancer is higher in Middle Africa than in Western Europe or the U.S. (54.60% vs 23.07%). While the discrepancy between the mortality rates among women with breast cancer can be partially explained by the better medical treatment in developed countries, it is plausible that early detection may also play a role. Early detection in countries with limited resources may not be feasible: currently, only about 25 countries have an established or pilot-based national breast cancer screening program

(Anderson et al., 2003; National Cancer Institute, 2013b). Absence of early detection programs results in breast cancer being diagnosed at later stages, which may be harder or impossible to treat.

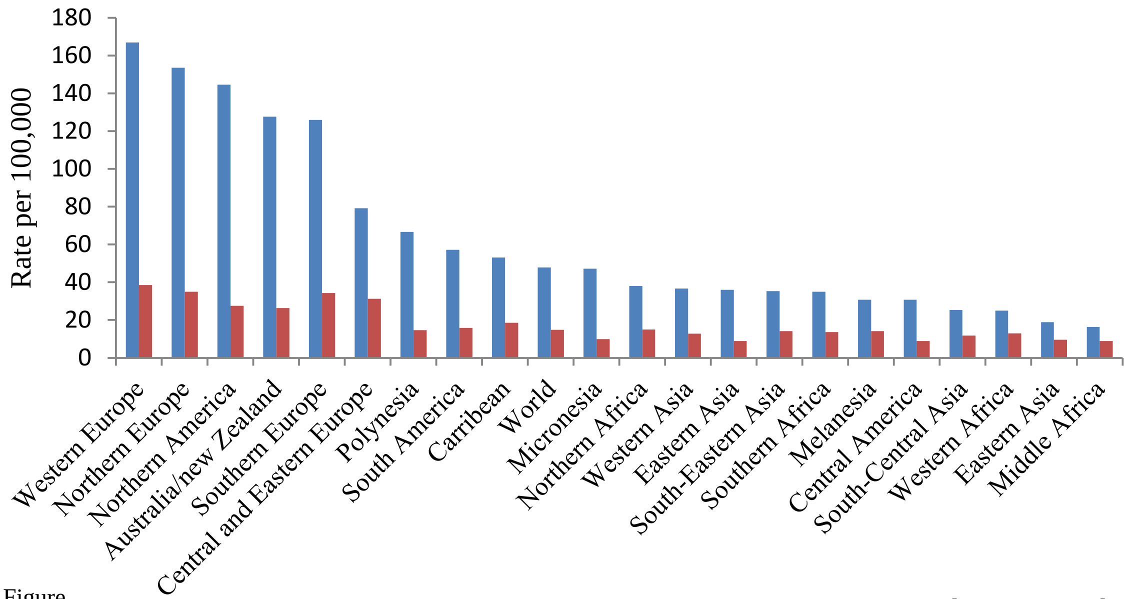

Figure 1.1: Breast Cancer Mortality and Incidence, World, 2014. Adapted from "Breast, all ages" by Ferlay J., 2012. Updated estimates can be found at the International Agency for Research on Cancer Website: http://globocan.iarc.fr/Pages/online.aspx

1.2.1.2: Breast Cancer Risk Factors. Although it is not possible to identify a specific risk factor in the majority of breast cancer cases (Peters et al., 2009), the strongest factor associated with the disease is old age: as a woman gets older, the probability of developing breast cancer increases (Howlader, 2012). Figure 1.3 shows that the risk that a woman will be diagnosed with breast cancer during the next 10 years of her life increases from 0.44 percent when she is 30 years old (or 1 in 227) to 3.82 percent at age 70 (1 in 26), almost a nine-fold increase (Howlader, 2012).

Other factors that can increase the risk of developing breast cancer include inheriting changes in certain genes (BRCA1, BRCA2: present in less than 10% of cases), having a personal or family history of breast cancer, having dense breasts, experiencing menarche before age 12, starting menopause after age 55, having your first pregnancy after age 30, never having been pregnant, being obese after menopause, and using alcohol (Howlader, 2012).

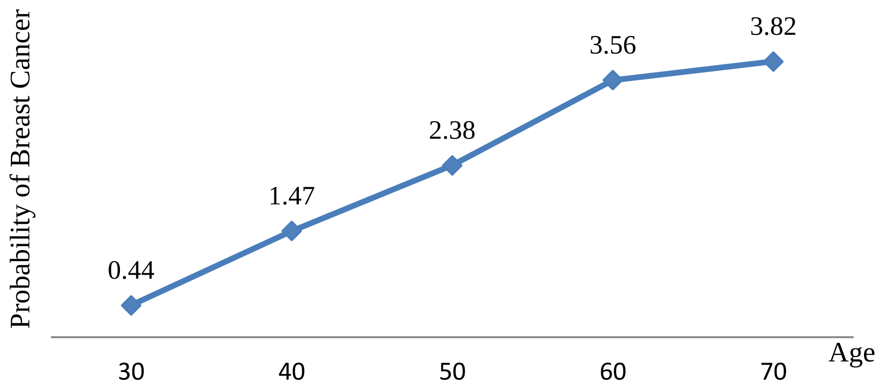

Figure 1.2: Risk of Developing Breast Cancer during the Next 10 Years. Sourse: SEER Cancer Statistics Review, 1975-2009 (Vintage 2009 Populations) , 2012 by Howlader , N. A., Krapcho M, Neyman N, Aminou R, Waldron W, Altekruse SF, Kosary CL, Ruhl J, Tatalovich Z, Cho H, Mariotto A, Eisner MP, Lewis DR, Chen HS, Feuer EJ, Cronin KA. National Cancer Institute.

According to the World Health Organization (WHO), 30% of all cancer cases could be prevented (World Health Organization, 2013). Cancer prevention, as broadly defined by the National Cancer Institute (NCI), is “an action taken to lower the chance of getting cancer” (National Cancer Institute, 2013a). Such actions might include avoiding things known to cause cancer (also known as “risk factors”), changing one’s lifestyle and diet, receiving chemopreventive care, and undergoing routine screening mammography.

1.2.2: Mammography Background

1.2.2.1: The Spread of Screening Mammography in the U.S. A screening mammogram is an x-ray exam that is used to detect breast cancer in asymptomatic women. Since the invention of X-ray in 1895, doctors and researchers have begun using this new technology to look inside the human body (Lerner, 2003). A German surgeon, Albert Solomon, was the first scientist who showed that X-ray could be used to detect breast cancer after he examined more than 3,000 surgically removed breasts (Van Steen & Van Tiggelen, 2007). In the 1930s, another German researcher, W. Vogel, published his research accurately describing how to tell apart cancerous from noncancerous tumors by using X-ray photographs (Van Steen & Van Tiggelen, 2007).

Routine screening mammography became popular in the United States for a number of medical, social, political, and cultural reasons. In the late 1930s, American clinician Jacob Gershon-Cohen, started using mammograms to screen asymptomatic women for breast cancer (American Inventors, 2009). In 1956, Cohen and a group of other researchers began a five-year study to test the accuracy of mammograms. In the study, more than 1,300 women were screened every six months. Out of 1,055 participants of the study, 92 women were diagnosed with benign tumors and 23 with malignant tumors; only 1 diagnosis turned out to be wrong (Gershon-Cohen, Ingleby, Berger, Forman, & Curcio, 1967). This study was a major milestone in mammography promotion and gave strong impetus to the adoption of routine screening for breast cancer. By the 1960s, mammography had become a widely used breast cancer diagnostic tool (Davis, 2009).

Philip Strax, an American radiologist who lost a young wife due to breast cancer, was another enthusiastic advocate for regular screening mammography (Davis, 2009). In 1963, Strax, working with the Health Insurance Plan of New York, conducted the first large randomized trial (consisting of 60,000 women) to assess whether or not mammography saved lives. The trial showed that women over age 50 who had regular mammograms had lower mortality rates from breast cancer in comparison to the control group (Shapiro, Strax, & Venet, 1966). However, for women ages 40-49, the evidence was not as clear (Shapiro et al., 1966), and the screening interval for women in this age group remains a longstanding disagreement among researchers and health organizations (National Comprehensive Cancer Network, 2009).

Popularization of mass screening in the U.S. is also inseparable from the Feminist Women's Health Movement as part of the Women's Liberation Movement in the 1960s and 1970s. Beginning in the 1970s, awareness of women's health issues increased. Organizations like the Feminist Women's Health Centers, National Women's Health Network, and other groups dedicated to increasing women's knowledge and power over their own bodies, started appearing throughout the U.S. (Rainey, 2013). The Feminist Women's Health Centers were grassroots organizations built on the concept of "self-help." Such groups consisted of women who would regularly get together to discuss their health issues and learn how to take care of many of the health issues that usually required a visit to a gynecologist (Kimball, 1981). For example, during such meetings, women were taught how to check their own breasts for lumps (Davis, 2009).

In 1974, Rose Kushner, an immigrant from Eastern Europe and an American journalist interested in healthcare, published "*Breast Cancer: A Personal History and*

Investigative Report," documenting her personal experience with radical mastectomy and providing information about alternative treatment options available at that time in Europe. Rose Kushner, who is considered to be the first American breast cancer activist, played a pivotal role in promoting access to mass screening. In 1972, at the age of 45, Kushner was diagnosed with breast cancer; she underwent radical mastectomy and, later, chemotherapy. She spoke up against one-step radical mastectomy at medical professional meetings, campaigned against aggressive chemotherapy, and was calling for the U.S. federal government to oblige health insurance plans to cover mammograms up until a few days before she died from breast cancer at the age of 60 in 1990. (Lerner, 2001).

In addition, news about First Lady Betty Ford and Margaretta Rockefeller being diagnosed with breast cancer and undergoing radical mastectomies two weeks apart from each other further increased public interest in access to breast cancer screening technology. Between 1973 and 1974, diagnosed incidence of breast cancer rose nearly 15 percent from 82.6 to 94.9 per 100,000 women (Davis, 2009).

In 1972, the American Cancer Society and the National Cancer Institute jointly started the "Breast Cancer Detection Demonstration Project," screening more than 250,000 women over the age of thirty-five (Davis, 2009). By the early 1980s, the American Cancer Society and other organizations began recommending routine annual mammograms for all women in the U.S. over age 40 (American Cancer Society, 2013a).

Perhaps the most important factor in the popularity of routine mammography in the U.S. is the overall enthusiasm and supportiveness of the American public towards breast cancer screening, and in particular, towards frequent screening mammograms for women ages 40-49 (Schwartz, Woloshin, Fowler Jr, & Welch, 2004). Moreover, previous studies have demonstrated a significant bias in the U.S. media in favor of routine mammography for women ages 40-49 (Schwartz & Woloshin, 2002; Wells, Marshall, Crawley, & Dickersin, 2001). This bias is generally attributed to the strong historical influences of breast cancer advocacy efforts in the U.S (Clarke & Everest, 2006; Lantz & Booth, 1998).

*1.2.2.2: Benefits of Screening Mammography***.** Until the 20th century, breast amputations remained the main cure for women diagnosed with breast cancer. Since surgeries were usually performed with a knife and without anesthesia, women were hesitant to seek medical care until late stages of cancer and, as a result, nearly all women who developed the disease died of it (Aronowitz, 2007). Today, early detection of breast cancer through routine screening mammography allows the avoidance of unnecessary surgeries, increases the likelihood of successful treatment, and effectively reduces breast cancer mortality (Kerlikowske et al., 1995). In particular, results of the most recent large randomized clinical trials show that annual screening can help reduce breast cancer mortality by about 25% in women ages 50-69 (Kerlikowske et al., 1995; Nyström et al., 1993). However, studies have yet to prove a significant benefit from routine screening for women ages 40-49 in comparison to those unscreened in the same age group (A. B. Miller, To, Baines, & Wall, 2002; U.S. Preventive Service Task Force, 2009).

1.2.2.3: Cost and Insurance Coverage. The Affordable Care Act mandates that private insurance plans cover the cost of annual mammograms without copayments or deductibles for women over age 40 ("The Patient Protection and Affordable Care Act.," 2010). However, this doesn’t apply to the so-called “grandfathered” health plans that were in place before the law was passed. Many, but not all, states require such plans to provide annual or biannual coverage of mammography for women ages 40-49, and annual coverage for women over age 50. The generosity of coverage varies from state to state: Texas and Mississippi, for example, require plans to offer annual coverage for women over age 35, while Utah doesn't require routine screening coverage whatsoever, and Rhode Island requires the insurance plans cover breast cancer screening in accordance with the American Cancer Society (ACS) guidelines (American Cancer Society, 2014).

Medicare, the national health insurance for people aged 65 and older, covers the full cost of one baseline mammogram between ages 35-39, and annual mammograms for women age 40 and older (Medicare.gov, n.d.). Some state and local health programs provide mammograms free of charge to low-income or uninsured women (National Cancer Institute, 2012). In addition, a screening mammogram for those who pay out-of-pocket is not very expensive: the average cost was $102 in 2012 (Cost Helper, 2012).

*1.2.2.4: Cost-Effectiveness***.** Based on actual breast cancer screening patterns in the U.S. for 1990-2000, the incremental cost of screening versus no screening is about $37,000 per quality-adjusted life-year (QALY) (Stout et al., 2006). If judged against the benchmark of $50,000 commonly used in the cost-effectiveness analysis, then current screening levels are cost-effective. However, as shown in Stout et al. (2006), the actual screening rates are not on the efficient frontier: the same QALYs can be achieved with a lower cost, or, alternatively, more QALYs can be achieved for the same cost. Screening rates that would resemble current guidelines for mammograms (all women 40-80 years old annually) would result in a point on the efficient frontier, but would add about $40,000 in cost per additional QALY (Stout et al., 2006).

1.2.2.5: Potential Harms. Some researchers are concerned that mammography exposes women to small amounts of radiation that can contribute to breast cancer (Davis, 2009). According to the American Cancer Society, the risk of radiation harm is extremely low, as a modern mammography machine uses low radiation doses (0.1 to 0.2 rads per picture) and "expose women to roughly the same amount of radiation as flying from New York to California on a commercial jet"(American Cancer Society, 2013b). Other concerns with routine screening include the high false-positive rates among women age 40-49, a possibility of over-diagnosis (finding and treating cancers that would never cause symptoms or threaten a woman's life), a 10.40% call-back rate for additional screening, and a test sensitivity of only 80% (National Cancer Institute, 2012; U.S. Food and Drug Administration, 2011).

1.2.2.6: Screening Recommendations. In the U.S., recommendations about the frequency of screening and the age at which to begin routine screening differ among the health organizations.

Since 1989, the U.S. Preventive Services Task Force (USPSTF) has recommended screening for breast cancer every 1-2 years for women over age 50. Additionally, starting in 2002, the USPSTF has begun to recommend that all women over age 40 undergo annual or biannual mammography. On November 16, 2009, the USPSTF updated the 2002 recommendations and proposed a less aggressive approach to breast cancer screening. The new 2009 guidelines recommended against routine screening mammography for women ages 40-49 and women age 75 and older, and recommended biennial breast cancer screening for women ages 50-74, instead of screening every 1-2 years ("Screening for Breast Cancer: U.S. Preventive Services Task Force

Recommendation Statement," 2009). Recommendations by the USPSTF are typically endorsed by the American Academy of Family Physicians (AAFP) (Riley, 2013).

In contrast to the USPSTF guidelines, the American Cancer Society (ACS) recommended screening every 1-2 years beginning at age 40 from 1993 till 1997, and, since 1997, has been recommending that women screen annually beginning at age 40 (American Cancer Society, 2013a). Other organizations in favor of annual screening starting at age 40 include the National Cancer Institute (NCI); the American Congress of Obstetricians and Gynecologists (ACOG); the American College of Radiology (ACR) and the Society of Breast Imagine (SBI); the National Comprehensive Cancer Network (NCCN); and the American Medical Association (AMA) (National Guideline Clearinghouse, 2012). Their guidelines also suggest to take individual risk into account, and to make screening decisions after a thoughtful discussion occurs between patient and physician (American Medical Association, 2010).

These U.S. health organizations also disagree on the precise age at which to discontinue routine breast screening. The USPSTF, for example, reports not having sufficient evidence to assess the benefit or harm of receipt of a screening mammogram for women age 75 and older (U.S. Preventive Service Task Force, 2009). The ACS recommends mammography continuation as long as the patient is in good health (American Cancer Society, 2013a). The ACOG guidelines state that women 75 years or older should decide whether or not to continue screening by consulting their physicians (American Congress of Obstetricians and Gynecologists, 2011). While the NCCN states that the appropriate upper age limit has not yet been determined, the ACR recommends continuing until life expectancy reaches less than 5-7 years (National Guideline Clearinghouse, 2012).

Table 1.1: Summary of Current Breast Cancer Recommendations

Organization (year)	**Age to begin screening**	**Frequency**	**Age at which to end routine screening**
U.S.			
ACS (2003)	40	Annual	as long as patient is in good health
NCI (2012)	40	Annual	not specified
AMA (2012)	40	Annual	not specified
ACOG (2011)	40	Annual	consult physician
ACR/SBI (2010)	40	Annual	life expectancy < 5-7 years
NCCN (2013)	40	Annual	not yet established
USPSTF (2009)	50	Biennial	75
AAFP (2009)	50	Biennial	75
Non-U.S.			
CTFPHC (2011)	50	Triennial	75
NHS (2011)	50	Triennial	70 (extending to 73)

Source: National Guideline Clearinghouse 2012. Updated synthesis of recommendations for breast cancer screening can be found at http://www.guideline.gov/syntheses/synthesis.aspx?id=39251

In comparison to other countries, U.S. screening guidelines for breast cancer recommend a more frequent screening interval and an earlier age at which to start routine screening. With the exception of the USPSTF and the AAFP, U.S. organizations agree that annual routine screening mammography should begin at age 40, while both the Canadian Task Force for Preventive Health Care (CTFPHC) and Britain's National Health Service (NHS) recommend beginning triennial screening starting at age 50 (National Guideline Clearinghouse, 2012). Table 1 summarizes current mammography recommendations in the U.S. and abroad.

1.2.2.7: Recent Technological Advances. On January 28, 2000, the Food and Drug Administration (FDA) approved the first digital mammography machine, which, unlike, standard mammography using film, takes an electrical image of breast tissue and stores it on a computer (Conant & Maidment, 2001). Even though standard film mammograms are just as accurate as digital ones (Pisano et al., 2005), digital mammography offers several advantages over conventional film mammography: it allows for remote consultations among radiologists and surgeons, as well as for magnification and modification of images so that differences between normal and abnormal tissues can be more easily recognized (National Cancer Institute, 2012). In addition, digital mammography is more accurate at detecting cancer in younger women (ages 40-49) and in women with dense breasts, in comparison to conventional film mammography (Pisano et al., 2005). Today, most mammogram machines are digital.

Digital Breast Tomosynthesis (or 3-D mammography) was introduced in the U.S. in February 2011. This new technology has been shown to further improve cancer detection rates from 4.28 to 5.25 (per 1,000 patients), to reduce the false-positive rate, and, as a result, to reduce the call-back rate from 10.40% to 8.78% (Nandita M, 2013; U.S. Food and Drug Administration, 2011).

1.3: Literature Review

1.3.1: Social Interactions in Decision Making

The literature on social interactions and economic decision-making started with the seminal paper of Duesenberry (1949), who examined the effects of a reference group on consumer behavior. Since then, social interactions have been shown to have a significant influence on a wide range of social and economic behaviors, including demand for a particular restaurant (Becker, 1991), criminal activity (Glaeser et al., 1996), labor productivity (Falk & Ichino, 2006), labor force participation (Bernheim, 1994; Fajnzylber, 2002), investing in the stock market (Hong, Kubik, & Stein, 2004), micro-financing (S. Li, Liu, & Deininger, 2012), educational outcomes (Graham, 2008; Kremer & Levy, 2008; Sacerdote, 2001; Winston & Zimmerman, 2004), and academic cheating (Carrell, Malmstrom, & West, 2008).

Gary Becker, in his “Note on Restaurant Pricing and Other Examples of Social Influences on Price” (1991), wrote about the existence of goods for which demand is positively related to the quantities demanded by other consumers. His conclusion was inspired by his observation of two very similar seafood restaurants located across the street from each other in California: one restaurant was very popular and had long queues for tables during prime hours; the restaurant across the street, however, had many empty seats most of the time. Despite this, the more popular restaurant would not raise its prices, which would have reduced the queues for seats and increased the profits. He explained this phenomenon by noting that it was the presence of the queues themselves which created the popularity of the restaurant. Becker further explained that people like to eat out at popular places; moreover, they like to be seen eating out at popular places. He also noticed that this tends to be the typical case for other goods that people usually consume together, such as best-selling books, sporting events, or Broadway shows. In addition, Becker noted that heavily advertised goods tend to be the ones that are capable of creating a social multiplier effect, since “the demands of a good by a person depends positively on the aggregate quantity demanded of the good" (Becker, 1991, p.1110-1111).

Similarly, social interactions play a significant role in explaining group criminal behavior, where criminals acting together create an environment which instigates an individual into behaving like the rest of the crowd. In particular, Glaeser et al. (1996) found that peer influences play an important role in explaining a large variation in crime rates across cities, which could not be explained solely by differences in socio-demographic characteristics. According to Glaeser et al. (1996), the effect of social interaction is especially relevant for petty crimes, such as larceny and motor vehicle theft; less relevant for assault, burglary, and robbery; and least relevant for arson, murder, and rape. Glaeser et al., (1996) suggested that a large reduction in crime levels could be achieved by lowering the degree of interaction among members of the groups that have a potential to engage in criminal activity.

Falk and Ichino (2006) presented clear evidence of peer effects in labor productivity by conducting an experiment with high school students, who had to stuff letters in envelopes for money. Students were split up into two possible arrangements: working as a pair and working alone. When working as a pair, each student worked independently, but the desks were located such that the output of the other student could be easily observed. All the students received a fixed payment for their work, regardless of output and the type of working arrangement. Output of students working alone was taken as a level of productivity in the absence of any peer influence. If sharing a room resulted in an increase in the output of an individual student, it was interpreted as evidence that individual behavior was affected by the behavior of the other member of the pair. The results of the experiment showed that those working in the same room had a greater average productivity than those working alone. Not only was the average productivity higher, but output levels were also very similar within pairs, while differing substantially between pairs. In addition, the experiment showed that peer influences affect individuals differently: students who were least productive when working alone were often the ones who would improve the most when paired with another student.

The work of Fajnzylber (2002) provides an example of peer effects in labor force participation. They studied the impact of the Earned Income Tax Credit (EITC) expansion on labor force participation rates among single women of the early 1990s, and found an increase of 2.2 to 3.2 percentage points in labor force participation rate. They further decomposed this increase into a 1.1% private effect (effects attributed to changes in an individual family's incentives, regardless of the decisions taken by other individuals) and a 1.1%-2.1% social spillover effect (the effect of the fraction of working families in a neighborhood on an individual's labor force participation decision).

Li et al. (2012) showed that peer effects are important to the success of microfinance programs in developing countries, where group lending has been an important practice to provide credit to the poor since 1986. In such programs, a loan is given to a group of borrowers and the whole group becomes responsible for the debt of any individual member. This practice allows microfinance programs to rely on mutual trust among borrowers, rather than a financial collateral, to guarantee repayment. The authors estimated that the probability of a member making a full repayment would be 15 percentage points higher if all the other members made a full repayment, in comparison to a scenario in which none of the other members repaid in full.

Perhaps the most prominent example of peer effects is found in education, where a student's performance may be influenced by the performance and characteristics of other students. Sacerdote et al. (2001) examined the existence of such effects in academic outcomes among Dartmouth College freshmen who were randomly assigned to dorms and roommates upon acceptance. They found that the roommate's first year GPA has a strong influence on an individual's first year GPA: having a college roommate whose academic score was in the top 25%, or a roommate who intended to graduate with honors, raised one's own GPA by 0.060 and 0.082 points respectively. Consistent with this evidence, Winston and Zimmerman (2004) found that one's roommate's Scholastic Assessment Test (SAT) score had an effect on an individual's college grades: students in the middle of the SAT distribution may have worse grades if they share a room with a student who is in the bottom 15% of the SAT score distribution. In addition, Kremer and Levy (2008) found that being randomly assigned to share a dorm room with a drinking roommate negatively affected one's college GPA: the effect of a drinking roommate was equivalent to the effect of a reduction of 50 SAT points or 1.2 ACT points in the student's own aptitude test. Finally, Graham (2008) suggested a method for eliciting the presence of social interactions based on conditional variance restrictions and provided evidence of peer influence in the academic achievement of Project STAR kindergarten students.

Another example of social interaction in education is provided by Carrell et al., (2008), who measured the effect of peer cheating on the likelihood of individual cheating among students at the three major U.S. military service academies (Air Force, Army, and Navy), using self-reported academic cheating data. They found that higher levels of peer cheating leads to an increase in the probability that an individual would cheat. Specifically, their results imply that one additional college student who cheated in high school causes cheating of approximately 0.33 to 0.47 college students, while one additional college cheater causes cheating of approximately 0.61 to 0.75 college students to cheat. This suggests that, after a full round of interactions occur, the long-run equilibrium social multiplier in academic cheating is equal to three.

1.3.2: Social Interactions in Health Economics and Public Health

In health economics and public health literature, several papers have examined the social determination of individual health outcomes and behavior, such as individual body weight (Auld, 2011; Christakis & Fowler, 2007; Cohen-Cole & Fletcher, 2008a, 2008b; Renna, Grafova, & Thakur, 2008; Trogdon, Nonnemaker, & Pais, 2008), fertility rates in developing countries (Benefo & Schultz, 1996; Canning, Günther, Linnemayr, & Bloom, 2013; Palloni & Rafalimanana, 1999), and teenage risky behaviors, including smoking, drug and alcohol use, and initiation of sexual activity (Ali, Amialchuk, & Dwyer, 2011; Card & Giuliano, 2012; Clark & Loheac, 2007; Duncan, Boisjoly, Kremer, Levy, & Eccles, 2005; Fletcher, 2010; Krauth, 2007; Powell, Tauras, & Ross, 2005; Wang, Fitzhugh, Westerfield, & Eddy, 1995).

1.3.2.1: Body Weight. Many researchers have studied whether one person's weight is associated with the weight of his/her peers. For example, Christakis and Fowler (2007), using naïve regression design, examined the effects of social network among adults based on the Framingham Heart Study longitudinal data. They found that a person's probabilities of becoming obese increased by 57% if his/her friend became obese during some period of time. To re-examine the issue, Cohen-Cole and Fletcher (2008b) replicated their findings using information on nominated friends within schools from the National Longitudinal Study of Adolescent Health (Add Health) (NLSAH), arriving at the same exact estimates; however, they showed that the peer effects of body weight became insignificant after controlling for shared environment (also known as correlated effects). In addition, Cohen-Cole and Fletcher (2008a) conducted a falsification test of the model presented in Christakis and Fowler (2007), and showed that the naïve specification produced evidence of social effects in health outcomes where such effects are unlikely to occur: acne, headaches, and height. Also using Add Health and employing an instrumental variable and fixed effects approach, Renna et al. (2008) and Trogdon et al. (2008) found evidence in favor of adolescent peer effects in body weight, particularly among females and those with a high body mass index. More recently, Auld (2011) estimated models of social influences in body weight at the county and state levels using BRFSS and methods discussed in Glaeser et al., (2003), Glaeser and Scheinkman (2000), and Graham and Hahn (2005): these methods allow the elicitation of the size of the social multiplier based on differences in the group-level and individual-level effects of exogenous characteristics. The study concluded that while there is no evidence that being underweight is subject to social influences, a small social multiplier in obesity and morbid obesity is plausible.

1.3.2.2: Teenage Risky Behavior. Work by Powel et al. (2005), Fletcher (2010), and Wang et al. (2005) presents strong evidence of peer influences in youth smoking. Fletcher (2010), for example, using an instrumental variables/fixed effects methodology, suggested that increasing the proportion of classmates who smoke by 10% increased the likelihood of an individual smoking by approximately 3 percentage points. Using a similar methodology, Powell et al. (2005) found that moving a student from a school where no children smoke to a school where 25% of children smoke increased the probability of an individual smoking by over 14.5 percentage points. In addition, Wang et al. (1995) found that having a same gender smoker as a best friend was the strongest predictor for adolescents smoking, and that this effect was magnified up to five times when three or four same gender best friends smoke. Furthermore, they showed that having a steady boyfriend/girlfriend who smokes was the next most significant predictor of adolescents smoking, while having a parent or older sibling who smokes had no influence on an adolescent's smoking behavior. In contrast, Krauth (2007), using the influence of the observed characteristics as a proxy for the unobserved influences, provided evidences that the probability of being a smoker goes up by no more than 7.9 percentage points as a result of one close friend becoming a smoker: an estimate somewhat smaller than found in the rest of the literature on peer effects in teen smoking.

Ali and Dwyer (2011) and Card and Giuliano (2012) demonstrated significant peer effects in sexual activity among teenagers. Ali and Dwyer (2011), in particular, found that a 10% increase in the proportion of close friends initiating sex increased the likelihood of sexual behavior by 5% among Add Health survey respondents, taking shared environment into account. They also found that a 10% increase in the number of sexual partners among close peers increased the number of an individual's sexual partners by 5%. Similarly, Card and Giuliano (2012), applying bivariate ordered-choice models to the Add Health panel, reported that the likelihood of initiating intercourse within a year increased by almost 5 percentage points if one's best friend also initiated sexual intercourse. In addition, they found evidence of peer effects in other risky behaviors among teenagers, including truancy, the use of tobacco, and the use of marijuana.

Duncan et al. (2005) used several waves of data from a large public university in the U.S to study peer effects in binge-drinking, marijuana smoking, and sex-initiation among randomly assigned dorm mates. While they showed that nondrinking students are non-susceptible to peer influence in drinking, they found significant peer effects in binge drinking in those who entered college with a history of heavy drinking. Specifically, if a binge-drinking student was randomly assigned a college roommate with a history of binge drinking in high school, they would experience almost 4 times more binge drinking episodes per month in college than if assigned a nonbinge-drinking roommate. However, Duncan et al. (2005) found no multiplier effect for marijuana use or for sexual behavior outcomes. Consistent with this evidence, Clark and Loheac (2007) provided evidence that, controlling for shared environment, there is a significant influence of lagged peer group smoking, alcohol use, and marijuana use on corresponding individual risky behaviors.

1.3.2.3: Fertility in Developing Countries. Canning et al. (2013) examined the social determination of fertility rates in developing countries, where women take expected child mortality rates into account when making individual fertility decisions. They calculated the size of the social multiplier in fertility based on the methodology presented in Glaeser et al. (2003) and Graham and Hahn (2005). Their results suggested that "when one woman lowers her fertility due to a rise in (expected) child survival, social spillovers will lead to reductions in fertility of other women, leading to a cascading process that can add up to much more than the initial effect on the individual," and therefore, lead to a decrease in the rate of population growth (Canning et al., 2013, p.277). This implied that a 1% increase in the expected child survival rates leads to 0.4% fewer children born among individuals within the same group. Their findings were consistent with earlier evidence presented by Benefo and Schultz (1996) and Palloni and Rafalimanana (1999), among others.

A smaller number of published papers highlight the effect of social interactions on the adoption of preventive health behaviors. Among these are, Rutenberg and Watkins (1997); Apouey and Picone (2014); Dearden, Pritchett, and Brown (2004); Kohler (1997); Miguel and Kremer (2002); Montgomery and Casterline (1993); Rogers and Kincaid (1981); and Valente, Watkins, Jato, Van Der Straten, and Tsitsol (1997).

1.3.2.4: Family Planning. Kohler (1997), Rogers and Kincaid (1981), and Rutenberg and Watkins (1997) all examined the role of social networks in the adoption of contraception among women in developing countries. Kohler (1997) and Rogers and Kincaid (1981) presented evidence that Korean women whose networks had largely adopted contraception were themselves more likely to try family planning than women whose networks had not. Rutenberg and Watkins (1997) examined the influence of social network on the contraceptive choices of Kenyan women, who "supplement provider's instruction with the experiences of women whose bodies and circumstances are similar to their own," since providers are socially distant from rural women (Rutenberg and Watkins, 1997, p.1). They suggested that public intervention designers should view women as members of social networks, rather than isolated individuals, since women interact with other women both before and after the formal contact with providers of medical service, creating "a buzz outside the clinics." Consistent with these findings, Montgomery and Casterline (1993) showed that social networks play an important role in a woman's decision to adopt contraception during the introduction of family planning program in Taiwan. However, Valente et al. (1997), presenting evidence from Cameroon, found that it is not the actual use of contraceptive methods by other network members that matters, but rather the perception of use.

1.3.2.5: Child Preventive Health. Dearden et al. (2004) examined social network effects on proper child feeding during episodes of diarrhea in Bolivia and Madagascar. They determined that a mother's ability to prevent the dehydration and possible death of a child during episodes of diarrhea was positively associated with her neighbors' knowledge of the correct action. In Madagascar, in particular, this effect was almost the same as the impact of 4 additional years of schooling or the equivalent of improving the woman's literacy from "cannot read" to "reads with difficulty."

Apouey and Picone (2014) provided evidence of the social influences on malaria prevention in Sub-Saharan Africa by calculating the size of the social multiplier from differences in the individual and aggregate effects of exogenous characteristics. Their results suggested moderate peer effects in the use of insecticide treated bed-nets by children, and a stronger social influence in the adoption of antimalarial drugs by pregnant women. They explained that peer pressure was especially strong in the latter case, since in Africa, the neighborhood can easily observe if a pregnant woman visits neonatal clinics where antimalarial drugs are administered on a strict schedule.

In contrast to successful accounts of public health interventions, Miguel and Kremer (2002) illustrated how social learning may fail such an intervention. They presented evidence from Kenyan schools during the introduction of deworming drugs. In particular, they showed that those who were exposed to more information about the deworming drugs through their social network were less likely to take the drugs, since children believed such drugs were ineffective and were the cause of the abdominal discomfort. This example demonstrates that adoption of a new preventive behavior depends n the acceptance of such behavior not only by an individual, but also by others in the relevant network. If the biggest impact on behavior comes from one's peers, then innovative behaviors may not become widely spread.

*1.3.2.6: Breast Cancer Prevention and Social Support***.** Closer to my own study, several small-scale community and worksite-based studies have examined the association between the level of social support and participation in breast cancer screening. Glanz et al. (1992) found that knowing a co-worker, a friend, or a relative with a history of breast cancer increased the likelihood of individual mammography. Based on data from the Woman to Woman Study, Allen et al. (2008) demonstrated that individual beliefs about the proportion of same-age peers who undergo regular screening had a significant impact on an individual's decision to have a mammogram. Additionally, they found that, for women over age 52, the perception that friends and family approve of annual mammography (or that it has become a social norm) was associated with a 46% increase in the likelihood of getting a mammogram. Finally, Cahalan (1968) and Presser and Stinson (1998) showed that health promotion and disease prevention behaviors, such as cancer screening exams, are seen as socially desirable, similar to activities such as voting, giving to charities, and attending religious services.

To summarize, the existence of peer effects has been well documented in a wide range of economic and health behaviors. However, the effect of large-scale social interactions among women on the decision to undergo annual mammography has not been previously studied.

1.4: Economics of Social Interactions

1.4.1: Terminology

The terminology of social interactions was introduced in "Identification of Endogenous Social Effects: The Reflection Problem" by Manski (1993), and has since become standard in the economics literature. In the words of Manski, *social interactions* are the phenomena that arise when "the propensity of an individual to behave in some way varies with the prevalence of that behavior in some reference group containing that individual" (Manski, 2000, p. 531). When such effects are strong enough, they can lead to the appearance of the so-called *social multiplier*: a situation where a change in an individual's actions creates a spillover that produces a much larger effect at the group level (Manski, 2000). Thus, if social interactions matter, an exogenous shock that affects an individual's incentive to behave in a certain way will have both a direct effect on the individual and an indirect effect on the same individual through his or her peers.

According to Manski, the effect of social interactions can be deconstructed into three elements that potentially explain why people in groups tend to behave similarly: endogenous interactions, contextual interactions, and correlated effects.

Endogenous interactions are effects that occur when an individual's behavior depends on the presence of the same type of behavior from other individuals in the group. For example, a person can be more likely to smoke, eat, or participate in an activity if his/her peers do. In regards to endogenous interactions, a woman's participation in breast cancer screening can depend on her peer group's screening behavior. From the policy perspective, this is the most interesting channel.

Contextual interactions are effects that occur when individuals behave similarly because they have similar exogenous characteristics. Group socioeconomic factors or macro level variables may influence an individual's propensity to have a screening mammogram. For example, a more educated group may encourage preventive behavior through social pressure.

Correlated effects occur when people in the same group tend to behave similarly because they share similar individual characteristics or have similar institutional environments. For example, members of a group may have a similar backgrounds, belong to the same social organization, or be under the care of the same physician. Additionally, correlated effects may appear when people who live in the same geographic area are exposed to area-specific public health interventions that aim at increasing breast cancer screening rates.

Whereas endogenous and contextual interactions represent distinct ways that agents might be influenced by their social environment, correlated effects are a nonsocial phenomenon. Distinguishing among these three effects is important because they imply different predictions for the impact of public policy (Manski, 2000). If endogenous interactions matter, then peer-to-peer interventions are likely to be most effective; in the presence of significant contextual interactions, income subsidization or educational campaigns would be preferable; finally, if correlated effects are extensive, then the appropriate intervention should pertain to the specific factors that cause all people in the group to behave in a similar way.

1.4.2: Social Interactions in Regards to Breast Cancer Screening

When thinking about how people interact, Manski suggested economists examine social effects through the interactions of constraints, expectations, or preferences, the familiar concepts used in economic analysis.

A *constraint interaction* occurs when one person's choices affect the feasible set of another person. For example, the time spent on research and development may not only expand a particular researcher's knowledge, but that of others as well. In regards to rapid advancements in cancer treatment and screening, learning about the latest technologies or changes in screening recommendations can be time-consuming and challenging as individuals age. However, once the information is obtained by any one person, it can be disseminated to others at low or potentially no cost to them. This reasoning provides a validation of educational campaigns about preventive health care that may be conducted at the community level. The Cancer Prevention Foundation, for instance, launched the Community Grants Program in 2006 to support cancer awareness, education, and screening programs in communities across the U.S. Since many Americans over age 50 may move into retirement communities, such programs could prove important in transmitting and sustaining knowledge about cancer prevention among this group.

An *expectations interaction* (or *observational learning*) occurs when an individual learns through observing the actions of others who have more information about the procedure or task at hand. A person who is forming expectations about an action may draw lessons from observation of the actions chosen and outcomes experienced by others (Manski, 2000). Rogers (2010) showed that most individuals are likely to evaluate treatment and preventive innovation through subjective evaluations of their peers who have adopted the innovations, rather than on the basis of scientific research by experts. Moreover, in comparison to men, women are more likely to share their experiences with each other as their interest in having emotional closeness and mutual empathy with others is more prominent at all stages of life (Kohut, 1971; Surrey, 1985; Winnicott, 1971). Consequently, women may be forming their expectations about screening procedures, cancer progression, and cancer treatments based on experiences that other women have shared with them. For example, knowing someone with breast cancer has been shown to increase the likelihood of individual mammography (Allen et al., 2008; Glanz et al., 1992). Likewise, a peer account of low levels of discomfort during breast cancer screening may lead to an expectation of such an experience and encourage a person to seek screening. The opposite may be true for an account of a screening experience that caused discomfort (physical or emotional).

A *preference interaction* occurs when individual preferences about different actions depend on the actions of others. Manski suggested that such everyday ideas as conformism, jealousy, and paternalism point to this form of interaction (Manski, 2000). Women, for example, could engage in conformism by shaming each other into adhering to some preventive health behavior once it became a social norm. Allen et al. (2008) demonstrated that individual beliefs about the proportion of same-age peers who undergo regular screening have a significant impact on an individual's decision for mammography. Furthermore, they found that, for women over age 52, the perception that friends and family approved of annual mammography was associated with a 46% increase in a woman's likelihood of receiving screening. Additionally, Cahalan (1968) and Presser and Stinson (1998) showed that health promotion and disease prevention behaviors, such as breast cancer screening exams, are seen as socially desirable activities, similar to voting, giving to charities, and attending religious services.

Another way in which a woman's preferences over her actions depend on the actions of others arises from the fundamental gender differences in social interactions: as members of a group, men typically seek status, while the ability to make and continue affiliation and relationships is important to women (Benenson (1990); Kohut (1971); J. B. Miller (2012); Surrey (1985); Winnicott (1971)). The success of many group mammography events relies on women's relational nature and their tendency to participate in activities together. Since, for most women, annual mammography is a dreaded event, undergoing the screening with a friend may lessen the anxiety associated with the test results. Among some recent mammography promotion efforts that relied on this phenomenon are social events like "Ladies Night Out," "Mammogram Parties," and "Mamm and Glam," administered by hospitals and imaging clinics. Attendees of such events can have their mammograms while they enjoy complimentary food and beverages, massages, manicures/pedicures, cosmetic services, and the company of other women.

Another manifestation of preference interactions can be seen in women engaging in paternalist behavior by holding each other accountable for a timely screening test. For instance, "Pinky Pledge," a mammography promotion program administered via Facebook and Twitter, aimed to take advantage of such behavior by challenging women to schedule a mammogram and to post a proof of screening at a later time.

In addition to *constraint*, *expectations*, and *preference* interactions, individual choices may be affected by a few sophisticated agents encouraging the rest of the group.

A celebrity or a person of high regard speaking about her screening or personal cancer experience could lead to more individuals seeking screening. To illustrate, in March 2000, two years after her husband's death from colon cancer at age 42, Katie Couric, then the co-host of NBC's "Today Show," underwent a live, on-air colonoscopy. This event, later called by researchers the "Couric Effect," led to a 20% increase in colon cancer screening and was sustained for 40 weeks (Cram et al., 2003). The increase arose from younger women which is similar to the demographics of the "Today Show" viewers, who are 60 percent female with a median age of 47.5 (Hagen, 2012). This suggests that a celebrity spokesperson promoting awareness of a disease can have a significant impact on public behavior related to that disease.

Another celebrity, Amy Robach, a forty-year-old ABC news reporter, discovered stage 2 cancer in both her breasts and lymph nodes after undergoing on-air screening mammography on October 1st, 2013. Robach later wrote that she thought it was nearly impossible that she would have cancer, as she regularly exercised, maintained a healthy diet, and had no family history of cancer (ABC News Network, 2014). After she turned forty, she kept postponing the screening test until she was asked by *"Good Morning America"* producers to have an on-air mammogram for the start of the National Breast Cancer Awareness Month (ABC News Network, 2014). A few weeks after her on-air mammogram, she underwent a double mastectomy, followed by 20-week-long aggressive chemotherapy. During this time, she openly shared her breast cancer battle with her viewers. Mrs. Robach, now a cancer survivor, has since returned to the studio and is hopeful that her story will inspire many U.S. women to get a timely mammogram. She later wrote, "I was also told this: for every person who has cancer, at least 15 lives are saved because people around them become vigilant. They go to their doctors, they get checked" (ABC News Network 2014). Considering that Amy Robach's on-air mammogram is a recent event, its effect on screening rates has yet to be determined.

To summarize, social interactions among women over age 40 may play an important role in cancer prevention, as a woman who frequently socializes with others and shares her mammogram or cancer experience can influence her peers' decisions to undergo screening. If peer effects are an important factor in increasing mammography participation, then providing an incentive to an individual woman to undergo mammography can result in large changes in aggregate screening rates through social spillovers.

It is important to note that Manski cautioned researchers that, if empirical economic analysis is to be useful for policy decision making, it needs to do more than just show the presence of interactions, since the concept of interactions consists of the three distinct channels through which group behavior may affect individual behavior: interactions of constraints, expectations, and preferences. Identifying the exact channel is crucial for policy interventions; for example, providing new information about breast cancer should have no effect on preference interactions, but may change the nature of expectations interactions or cause them to disappear (Manski, 2000). However, if women's preferences depend on each other, then organizing group breast cancer screening events will be an effective way to increase participation rates.

1.4.3: Social Activity among Americans

Many Americans lead active social lives: for example, respondents of the 2008 General Social Survey reported socializing with their relatives (59%), friends outside of their neighborhood (43%), neighbors (31%), or people at the bar (19%) more than once a month (Marsden, 2012). Moreover, for those Americans born after 1920, socializing with friends, neighbors, or at the bar was more common than socializing with relatives in comparison to earlier generations (Marsden, 2012).

Socializing with relatives, friends, and neighbors generally decreases as one becomes older, but in different ways (see Figure 1.3). Socializing with relatives, for example, decreases steadily after the age of 18, but nevertheless accounts for the greatest share of social contact throughout one's life. Socializing with friends declines rapidly between ages 18-40, and then continues to fall, but much more gently. Socializing with neighbors also declines with age, levels off in the 40s and 50s, but then starts to rise again after age 60. After the age of 70, socializing with neighbors becomes more common than socializing with friends (Marsden, 2012).

In addition, people over age 50 may choose to move to a retirement community. Such communities are increasingly being constructed around major cities throughout the U.S., and offer a wide variety of ways to be social for their inhabitants. For example, the Villages, its own city in Florida, is the largest retirement community in the U.S., offering a 108-page-long listing of social clubs and organizations on their website. In addition to numerous socials and fitness and health clubs, some of the popular social organizations include astronomy, genealogy, painting, ballroom dancing, hoola-hooping, quilting, scrapbooking, basket weaving, meditation, golfing, and fishing clubs.

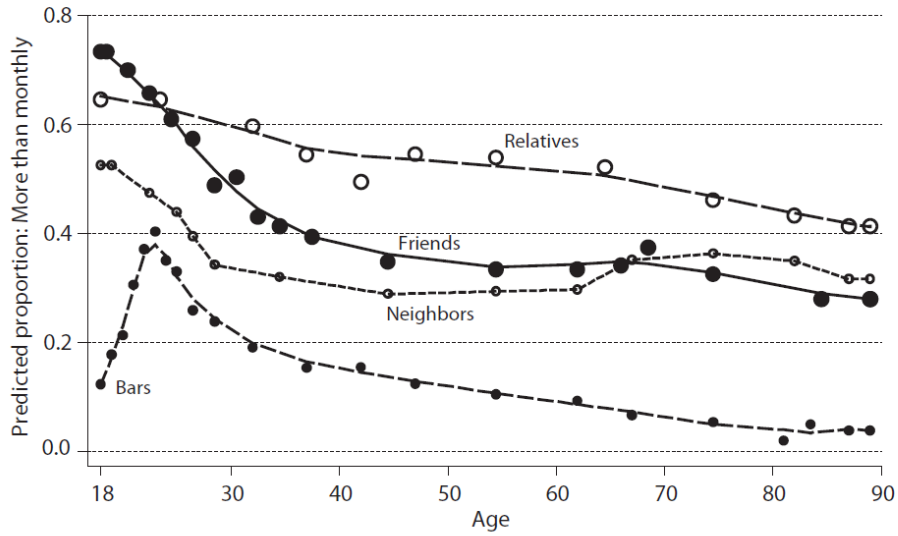

Figure 1.3: Age differences in More-than-monthly socializing. From *Social Trends in American Life: Findings from the General Social Survey since 1972* (page 246), by P. Marsden, 2012, Princeton: Princeton University Press

There are also clubs for people interested in going to movies, concerts, or the theatre; learning a new foreign language, how to play a musical instrument, or photography; flying model airplanes; and playing chess, bridge, cribbage, dominoes, and other card games. In addition, there are a number of groups and organizations that offer support for people dealing with various life events (such as a divorce, marriage, or aging) or medical conditions (such as diabetes or prostate cancer) (TheVillagesActivities.com, 2014). One such support organization, the Red Hat Society, is a sisterhood for women over age 50 that helps women "transition into the mature phase of their lives," cope with the loss of a spouse or parent, and deal with major illness, such as cancer (The Red Hat Society, 2014).

A woman who regularly socializes with others may influence other women's behavior in many ways. For example, if you play cribbage, you might inspire your friend to start playing as well. Such peer influence might also include the decision to have an annual screening mammogram.

1.5: The Model of Social Interactions in Breast Cancer Screening

Several models have been developed in the literature to examine how peer choices affect individual choice. A full description of methods in social interactions is available in Blume et al. (2010). The model presented in this section builds on that of Blume et al. (2011), Glaeser et al. (2003), Glaeser and Scheinkman (2000), and Graham and Hahn (2005). The approach chosen here estimates the steady-state or long-run effect of exogenous characteristics on mammography use, taking social interactions in mammography into account.

Consider a population that is divided into G non-overlapping groups. A woman who is identified by an integer i belongs to some peer group g. At time t, the total number of women in group g is denoted by n_{gt}. Each woman decides each period if she should have a screening test in that period. A_{igt} denotes her decision and can take on the values 0or 1. Each woman observes the average behavior of the other women in her reference group, $\overline{A}_{gt}$. In addition, her actions are affected by individual- and group-level characteristics, θ_{igt}.

Thus, one can write a utility function for a representative woman that depends on her screening choice, her perceptions about the choices of others, and a set of individual and group level characteristics as follows:

$U^i = U^i(\mathrm{A}_{igt}, \overline{\mathrm{A}}_{gt}, \theta_{igt})$, where

$$\overline{A}_{gt} = \frac{1}{n_{gt}-1}\sum_{j\neq i} A_{jgt} .$$

In line with most empirical studies of social interactions, I assume a quadratic utility function, where β serves as a weight for the effect of group average choice on individual utility:

$$U^i = U^i(A_{igt}, \overline{A}_{gt}, \theta_{igt}) = \theta_{igt} A_{igt} - \frac{\beta(A_{igt} - \overline{A}_{gt})^2 + (1-\beta)A_{igt}^2}{2}.$$

If a woman chooses to screen $(A_{igt} = 1)$, then $U_1^i = \theta_{igt} - \frac{\beta(1-\overline{A}_{gt})^2 + (1-\beta)}{2}$,

and if a woman chooses not to screen $(A_{igt} = 0)$, then $U_0^i = -\frac{\beta(0-\overline{A}_{gt})^2}{2} = -\frac{\beta(\overline{A}_{gt})^2}{2}$. If screening is preferred to no screening $(U_1^i > U_0^i)$, then the following inequality should hold:

$$\theta_{igt} - \frac{\beta(1-\overline{A}_{gt})^2 + (1-\beta)}{2} > -\frac{\beta(\overline{A}_{gt})^2}{2}$$

$$2\theta_{igt} - \beta(1-\overline{A}_{gt})^2 - (1-\beta) > -\beta(\overline{A}_{gt})^2$$

$$2\theta_{igt} - \beta(1-2\overline{A}_{gt} + \overline{A}_{gt}^{\,2}) - (1-\beta) > -\beta(\overline{A}_{gt})^2$$

$$2\theta_{igt} - \beta + 2\beta\overline{A}_{gt} - \beta\overline{A}_{gt}^{\,2} - 1 + \beta > -\beta\overline{A}_{gt}^{\,2}$$

$$2\theta_{igt} + 2\beta\overline{A}_{gt} - 1 > 0$$

Thus, if $\theta_{igt} + \beta\overline{A}_{gt} > 1/2$, then individual utility is greater when one chooses to screen ($U_1^i > U_0^i$ and $A_{igt} = 1$). By the same logic, if $\theta_{igt} + \beta\overline{A}_{gt} < 1/2$, then individual utility is greater when one chooses not to screen ($U_1^i < U_0^i$ and $A_{igt} = 0$). Therefore, one can think of A_{igt} as the closest integer to $\theta_{igt} + \beta \overline{A}_{gt}$ that takes on two values, 0 or 1. In other words, $\theta_{igt} + \beta \overline{A}_{gt}$ rounds up to A_{igt}.

$$\mathrm{A}_{igt} \approx \beta \overline{\mathrm{A}}_{gt} + \theta_{igt}.$$

Alternatively, thinking of A_{igt} as a continuous choice variable, one can take the first derivative and set it equal to zero for utility maximization:

$$\frac{\partial U^i}{\partial \mathrm{A}_{igt}} = -\mathrm{A}_{igt} + \beta \mathrm{A}_{igt} - \beta \mathrm{A}_{igt} + \beta \overline{\mathrm{A}}_{gt} + \theta_{igt} = -\mathrm{A}_{igt} + \beta \overline{\mathrm{A}}_{gt} + \theta_{igt} = 0.$$

Doing so will directly produces a linear-in-means model:[1]

$$\mathrm{A}_{igt} = \beta \overline{\mathrm{A}}_{gt} + \theta_{igt}, \qquad (1)$$

where A_{igt} is a woman's screening decision in a given year that depends on the average group screening rate ($\overline{\mathrm{A}}_{gt}$) and a set of individual and group level characteristics (θ_{igt}). Assuming further that θ_{igt} can be decomposed into an individual time variant observable characteristics (X_{igt}), a group level time variant observable characteristics $(\overline{X}_{gt})$, a group level time variant unobservable characteristics (ν_{gt}), and an individual idiosyncratic component (ε_{igt}), written as follows:

$$\theta_{igt} = \alpha + X_{igt}\gamma + \overline{X}_{gt}\delta + \nu_{gt} + \varepsilon_{igt}.$$

Expanding A_{igt} for θ_{igt} then yields the following linear-in-means model:

---

[1]The solution to utility maximization assumes that A_{igt} is continuous. Therefore, I treat Equation (1) as a linearization of some unknown nonlinear function that represents the true solution.

$$\mathrm{A}_{igt} = \alpha + \beta \overline{\mathrm{A}}_{gt} + X_{igt}\gamma + \overline{X}_{gt}\delta + v_{gt} + \varepsilon_{igt}, \text{ where} \tag{2}$$

$$\overline{\mathrm{X}}_{gt} = [\overline{X}_{1gt}, \overline{X}_{2gt} \ldots \overline{X}_{ngt}].$$

In equation (2), β measures the *endogenous effects* – the effects of the group's average screening rate on an individual's screening decision; δ measures the *contextual effects* – the effects of the group's exogenous characteristics on an individual's screening decision; γ represents the effect of individual characteristics on screening; v_{gt} represents the *correlated effects* - the group effects that influence the breast cancer preventive behavior of both the individual and the group (unobservable to the researcher); and, finally, ε_{igt} - measures an unobservable individual component.

There are three main econometric challenges associated with the identification of the linear-in-means models as specified by equation (2): the endogeneity of the peer group, the simultaneity of peer influences, and correlated effects.

The *endogeneity of the peer group* (occurs when people choose friends based on similar characteristics: for example, a smoker may be more likely to become friends with others who smoke). In economic analysis, this issue is typically addressed by finding a suitable instrument for the endogenous variable. In regards to breast cancer screening, endogeneity of peer group formation is not likely to be a problem, since there is no reason to believe that women select friends based on their mammography status. However, there may be a cross-product between the group-level exogenous characteristics and individual behavior. In this particular case, since annual mammography is a socially desirable behavior, a more educated group will be more likely to adhere to screening characteristics and may exert peer pressure.

The simultaneity of peer influences is also known as the "reflection problem" (Manski, 1993). This problem arises from the fact that each individual's behavior depends on his/her expectations about behavior of others, but the individual's choice also affects the group average behavior. For example, if an individual woman is exposed to an exogenous shock that results in the increase in her probability of breast cancer screening, this will increase the group expected screening rates. In a small peer group, once the group expected screening rate goes up, it will lead to an increase in the probability of screening of each woman in the group. The reflection problem is not likely to be a concern in this case because of large peer groups considered: even if an individual woman experiences an exogenous shock that influences the probability of her screening for breast cancer, the expectations of the county or state screening rate is not likely to increase.

Correlated effects arise from shared environmental influences. In this particular case, the unobserved group effects in v_{gt} are likely to be correlated with $\overline{A}_{gt}$ and $\overline{X}_{gt}$. If physicians have significant differences in their screening practices that are unrelated to the health status and demographic characteristics of their patients, but are related to institutional or regional practice customs, the group mammography rate will be endogenous. Furthermore, v_{gt} may include any breast cancer screening promotion efforts in geographic area *g* at time *t*. At the same time, area unobserved characteristics incorporated in v_{gt} may cause migration of both patients and physicians with similar characteristics, such as age, income, education, and race. For these reasons, one cannot estimate equation (2) directly. Instead, taking the expected value of both sides of equation

(2) and solving for $\overline{A}_{gt}$ leads to the following Bayes-Nash social equilibrium equation (Blume et al., 2010):

$$\overline{\mathrm{A}}_{gt} = \frac{\alpha}{1-\beta} + \overline{X}_{gt}\left(\frac{\gamma+\delta}{1-\beta}\right) + \frac{v_{gt}}{1-\beta}, \text{ where } \overline{\mathrm{X}}_{gt} = [\overline{X}_{1gt}, \overline{X}_{2gt} \ldots \overline{X}_{ngt}]. \tag{3}$$

This equation defines the group screening rates $(\overline{A}_{gt})$ in terms of the group level exogenous characteristics $(\overline{X}_{gt})$. Since the true population averages are unknown, I replace $\overline{X}_{gt}$ and $\overline{A}_{gt}$ with their sample counterparts $\overline{X}_{gt} = \frac{1}{m_{gt}}\sum_i X_{igt}$ and $\overline{A}_{gt} = \frac{1}{m_{gt}}\sum_i A_{igt}$, where $m_{gt} < n_{gt}$ is the number of women actually observed. This yields the following group level model:

$$\overline{\mathrm{A}}_{gt} = \frac{\alpha}{1-\beta} + \overline{X}_{gt}\left(\frac{\gamma+\delta}{1-\beta}\right) + \frac{v_{gt}}{1-\beta} + \overline{\varepsilon}'_{gt}, \text{ where} \tag{4}$$

$$\overline{\varepsilon}'_{gt} = \frac{\beta[\widetilde{A}_{gt} - \overline{A}_{gt}] + \delta[\widetilde{X}_{gt} - \overline{X}_{gt}] + \overline{\varepsilon}_{gt}}{1-\beta}.$$

However, replacing the population means with sample averages in equation (2) potentially leads to bias caused by measurement error in both the explanatory and dependent variables. Measurement error in the dependent variable may create bias if women overstate their screening frequency, since receiving annual mammograms is a socially desirable behavior (Cahalan, 1968; Presser & Stinson, 1998), and telephone respondents may be more likely to present themselves in socially desirable ways than respondents of a face-to-face interview (Holbrook, Green, & Krosnick, 2003). In addition, sampling error in the group level explanatory variables can create an attenuation bias due to the classical error-in-variables problem. If this measurement error is not corrected, then the model will systematically underestimate the coefficients in the group level regressions as well as the magnitude of the social multipliers.

Next, substituting (3) into (2), replacing the true averages with their sample counterparts, and solving for A_{igt} results in the following individual-level equation (see Appendix C for more details):

$$\mathrm{A}_{igt} = \frac{\alpha}{1-\beta} + X_{igt}\gamma + \overline{X}_{gt}\left(\frac{\beta\gamma+\delta}{1-\beta}\right) + \frac{v_{gt}}{1-\beta} + \varepsilon^{*}{}_{igt}, \text{ where} \tag{5}$$

$$\overline{\mathrm{X}}_{gt} = [\overline{X}_{1gt}, \overline{X}_{2gt} \ldots \overline{X}_{ngt}] \text{ and } \varepsilon^{*}_{igt} = \left[\tilde{X}_{gt} - \overline{X}_{gt}\right]\left(\frac{\beta\gamma+\delta}{1-\beta}\right) + \varepsilon_{igt}.$$

Equation (5) defines the individual screening decision (A_{igt}) in terms of exogenous variables, and allows for the estimation of γ consistently. The following two assumptions are necessary for the unobserved individual component:

1. The unobservable individual effects are uncorrelated with the rest of the individual characteristics, or $E(\varepsilon_{igt} \mid X_{igt}, \overline{X}_{gt}, \overline{A}_{gt}, i \in g) = 0$.
2. There is no co-variation between individual unobserved characteristics of members of different peer groups; that is, for each *i, j, g,* and *h,* such that $i \neq j$ and $g \neq h$, $Cov\,(\varepsilon_{igt}\varepsilon_{jht} \mid X_{igt}, \overline{X}_{gt}, \overline{A}_{gt}, i \in g, X_{jht}, \overline{X}_{ht}, \overline{A}_{ht}, j \in h) = 0$. Such an assumption may not be ideal in this application, as it implies no social spillovers across geographic areas. Since such spillovers are likely to exist, the social effects in this case are likely to be underestimated.

Finally, following the approach of Canning et al. (2013), Apouey and Picone (2014), Glaeser et al. (2003), and Glaeser and Scheinkman (2000), I calculate a vector of social multipliers as the ratio between the group-level exogenous variable coefficients, $\left(\frac{\gamma+\delta}{1-\beta}\right)$, from equation (3), and individual level coefficients, γ, estimated from equation (2), associated with each explanatory variable. The intuition behind this approach is that a one-unit increase in an individual characteristic will increase the individual probability of screening by γ, while in equilibrium, after multiple rounds of interactions take place, a one-unit increase in the group average characteristic will increase each person's probability by $\left(\frac{\gamma+\delta}{1-\beta}\right)$. Thus, after all interactions occur, the social multiplier associated with characteristic X_j should be equal to $\left(\frac{\gamma+\delta}{1-\beta}\right)_j \Big/ \gamma_j$. The primary empirical goal is to estimate this vector of multipliers.

Whenever both endogenous and exogenous effects are present ($0<\beta<1$ and $\delta \neq 0$), and γ and δ have the same sign[2], the multiplier is greater than one. The assumption that γ and δ have the same sign is reasonable in my application, as it means that, in equation (1), the effect of an individual characteristic on an individual screening decision should have the same sign as the effect of the mean of the characteristic in the geographic area on individual behavior. For example, a woman's age should have a positive impact on the probability of screening, since the risk of contracting the disease increases as a woman gets older; by the same logic, the mean age of women in the

[2] For most variables, we expect that these two coefficients do have the same sign, but general equilibrium effects may sometimes induce a different sign at the aggregate level than at the individual level.

reference group should also have a positive impact on the individual's probability of taking the test, since a woman whose reference group is older (and therefore is more likely to have regular screening and to be diagnosed with breast cancer) will be more likely herself to have a screening mammogram, all else equal. In the presence of endogenous effects $(0 < \beta < 1)$, but absent contextual effects ($\delta = 0$), the ratio equals $\frac{1}{1-\beta}$, and is also greater than one. If screening participation is influenced entirely by contextual effects, that is $\beta = 0$ and $\delta \neq 0$, the ratio equals $1+\frac{\delta}{\gamma} > 1$ since γ and δ have the same sign. Thus, if the ratio is greater than one, one can conclude that social interactions associated with a particular explanatory variable are present in mammography decisions; however, I will not be able to distinguish between contextual and endogenous effects. On the other hand, in the absence of social interactions ($\delta = 0$ and $\beta = 0$), the ratio is equal to one, since the effect of the group-level characteristic is the same as the individual-level effect.

1.6: Estimation Strategy

1.6.1. The Main Approach to Estimating the Social Multipliers

I considered a woman's reference group to be defined by the women of the same age in the geographical area. Given the nature of the data, my group analysis was on the county and state levels. Defining peer group in this way, required the assumption that women are more likely to be influenced by the women with whom they have frequent contact: co-workers, neighbors, and people who belong to local clubs and associations. In addition, I am assuming no social spillovers across different geographic groups. With this assumption in mind, the proposed social multipliers will only measure the interactions occurring within counties and states. Therefore, the estimates should be interpreted as a lower bound on the social interactions.

First, to obtain the denominator of the social multiplier, γ , I estimated the individual-level equation (5) as a Linear Probability Model (LPM):

$$\mathrm{A}_{igt} = \frac{\alpha}{1-\beta} + X_{igt}\gamma + \overline{X}_{gt}\left(\frac{\beta\gamma+\delta}{1-\beta}\right) + \frac{v_g}{1-\beta} + \frac{v_t}{1-\beta} + \varepsilon_{igt}\text{, where the}$$

probability that $A_{igt} = 1$ is a linear function of the explanatory variables. The advantages of using LPM over nonlinear binary response methods, such as probit and logit, are described in detail in Angrist and Pischke (2008). Each coefficient is interpreted as the effect of a one unit change in the explanatory variables on the probability that $A_{igt} = 1$. Unbiased and efficient estimates were obtained by using Ordinary Least Squares (OLS) with robust standard errors clustered by geographical clusters. In addition, I assumed that v_{gt} can be deconstructed into v_g - group-specific unobserved effects that are time invariant and affect everyone in the geographic area in the same way, and v_t - time variant unobserved effects that influence screening behavior of all groups. To account for such unobserved influences on the individual decision to undergo screening, I included time- and state-level fixed effects. It is important to note that including group fixed effects, however, did not allow for the estimation of the impact of $\overline{X}_{gt}$, because they are time-specific group averages and were be cancelled out.

To access the magnitude of omitted variable biases of county-level fixed effects, I estimated the same equation using group fixed effects on a county level, the smallest level of geographical disaggregation. In addition, to account for the growing popularization of mass breast cancer screening and to allow time fixed effects to differ among states, I estimated a separate model with and without time trend and its square interacted with state dummy variable. For example, a nation-wide year-specific intervention can have differing effects on individual screening rates in different geographic areas.

I then averaged the data across women by county and state within each year to obtain the sample counterparts of group averages, $\overline{X}_{gt} = \frac{1}{m_{gt}} \sum_{t} X_{igt}$ and $\overline{A}_{gt} = \frac{1}{m_{gt}} \sum_{t} A_{igt}$.

This step allows for construction of a quasi-panel data at the group-level, since there were be multiple years of group-level observations. To identify the numerator of the social multiplier, $\left(\frac{\gamma + \delta}{1 - \beta}\right)$, I estimated equation (4) using a fixed effects estimator with robust standard errors clustered by geographical clusters (county or state), where the true population means are replaced with their sample counterparts, $\overline{X}_{gt}$ and $\overline{A}_{gt}$:

$$\overline{\mathrm{A}}_{gt} = \frac{\alpha}{1-\beta} + \overline{X}_{gt}\left(\frac{\gamma + \delta}{1-\beta}\right) + \frac{\nu_g}{1-\beta} + \frac{\nu_t}{1-\beta} + \overline{\varepsilon}^{*}_{gt} \ .$$

Including the group-specific and time-specific fixed effects controlled for the correlated effects incorporated in v_{gt} and minimized the omitted variable bias. Time fixed effects captured time variant effects that influenced all groups in the same way. Such effects can account for changes in technology that would make people more/less likely to undergo screening (e.g. the introduction of digital mammography in the early 2000s), and control for any time-specific national public health interventions and breast cancer screening campaigns. State or county fixed effects controlled for the unobserved factors that influence breast cancer prevention specific to geographic area. These factors may include institutional differences across groups, styles of health care practices, intensity of screening promotion efforts, and the amount of public health interventions.

Next, I calculated the social multipliers as ratios of group level coefficients on $\overline{X}_{gt}$ from equation (4) to individual-level coefficients on X_{igt} from equation (5). To get the standard errors and the 95% confidence intervals for the ratios, I used a panel bootstrap method discussed in H. Li and Maddala (1999), and implemented by Canning et al. (2013) and Apouey and Picone (2014), among others. Lastly, I tested the hypothesis that the obtained ratios were significantly greater than unity.

Each year of the surveys comes with the weights that could be used to account for the unequal sampling probabilities of each woman in the population. I used an unweighted OLS estimator since, by the Gauss-Markov theorem, least squared are more efficient than weighted estimators under the same set of assumptions (Deaton, 1997).

1.6.2: Empirical Specification

Dependent variable: I considered annual (as opposed to biennial or triennial) mammography visits to be the dependent variable, since recommendations of an annual mammography are uniform among all the U.S. health organizations for the time period I analyzed (1993-2008). At the individual-level analysis, the dependent variable was a binary indicator of a mammography test within the twelve months of the survey. At the group level, the dependent variable was the average mammography rate for same-aged women in the county or state, based on the individual-level data.

Explanatory variables: Explanatory variables were divided into the following categories: individual-level, group-level (county and state), group fixed effects, and time fixed effects.

Individual-level: The main control variables of interest were education and age, as I expected the social multiplier to work primarily through these two channels. I expected age to have a positive effect on the probability of having an annual mammography, as breast cancer risk increases with age. A woman's education is a binary indicator of at least high school completion. I expected this variable to also have a positive effect on the probability of having undergone mammography in the past twelve months, since educated women are more likely to understand the advantages of frequent screenings and encourage their peers to have a timely screening exam.

Additional controls included income, ethnicity, marital status, employment status, general health, and insurance status. Income was calculated using interval midpoints, and adjusted for inflation using the all-item Consumer Price Index (CPI). Marital status, a binary variable, indicates whether a woman is married or is a member of an unmarried couple. A health plan dummy variable captured the effect of having any health insurance coverage, private or public. I control for racial/ethnic differences in screening participation rates by including a set of dummy variables for black, Hispanic, Asian/Pacific Islander, American Indian/Alaskan Native, and other races/ethnicities (including multiracial and other non-Hispanic), with white being the omitted category. The employment status indicator controlled for women who are either working for wages or self-employed. A dummy variable for self-reported poor health status was included to account for the effect of perceived general health on mammography use.

Group-level variables: Corresponding county- and state-level means were constructed from individual-level variables. It is important to note that, with the exception of the average age and income, the calculated means represented the proportion of the population in the geographic area with certain characteristics. A summary of all explanatory variables used in the analysis is reported in Table 1.2.

1.6.3: Falsification Test

It is possible, however, that group and time fixed effects do not fully account for all group-specific and time-variant factors that influence screening behavior, and that there might still be an omitted variable bias. In addition, there might be other reasons why aggregate coefficients turn out to be larger than the individual effects. To test the reliability of the main methods, I re-calculated the model using height in inches as a new dependent variable. Since the height of one's peer group is not likely to affect an individual's own height, I should have found no evidence of social effects in determining individual height. Self-selection into peer groups of similar height was not likely to be a concern, since peer groups are geographically defined. If inferring the effect of social interactions based on differences in the magnitude of the effect of an exogenous variable on the dependent variable at the individual and aggregate levels produced reliable estimates, the ratios of the coefficients when height is used as a dependent variable would have been equal to or close to unity.

Table 1.2: Explanatory Variables Used in the Regression Analysis

Variable	Description
Age	Age in years, continuous
Health Plan	Dummy variable =1 if individual has any health insurance coverage (public or private), =0 otherwise
Married	Dummy variable =1 if individual reported being married or living as a couple, = 0 otherwise
Education	Dummy variable =1 if individual completed high school or college education, =0 otherwise
Hispanic	Dummy variable =1 if Hispanic, = 0 otherwise
Black	Dummy variable =1 if black, = 0 otherwise
Other	Dummy variable =1 if Multiracial and Other Non-Hispanic, =0 otherwise
Asian/Pacific	Dummy variable =1 if Asian/Pacific Islander, =0 otherwise
Indian/Alaskan	Dummy variable =1 if American Indian/Alaskan Native, =0 otherwise
Employed	Dummy variable =1 if individual reported being employed or self-employed, =0 otherwise
Poor Health	Dummy variable =1 if individual reported being in poor general health, =0 otherwise
Income	Continuous, adjusted to 2010 purchasing power
Year	Dummies indicating the year individual is observed
County	Dummies controlling for the county individual observation comes from
State	Dummies controlling for the state individual observation comes from
Time trend	Continuous, time period count

1.6.4: Correcting for Measurement Error Using a Split-Sample Instrumental Variable

To correct for the attenuation bias in the group level regressions caused by the measurement error in the explanatory variables, I used a split-sample instrumental variable method proposed by Angrist and Krueger (1995) and implemented by Auld (2010), and Apouey and Picone (2014).

In this procedure, the sample within each year and group (county or state) was randomly split into two independent subgroups, and submeans of their exogenous characteristics ($\overline{X}_{g1t}$ and $\overline{X}_{g2t}$) were calculated. Since assignment to a subgroup is random, the measurement error in $\overline{X}_{g2t}$ was uncorrelated with the measurement error in $\overline{X}_{g1t}$, and I could instrument $\overline{X}_{g1t}$ by $\overline{X}_{g2t}$ to get consistent estimates of the group-level coefficients. I implement this method by using the observations from subgroup 2 to estimate the first-stage regression coefficients and to construct predicted values of $\overline{X}_{g1t}$. In the second stage, group mammography rates are regressed on these predicted values using the observations only from subgroup 1 and controlling for time and state fixed effects.

1.7: Data and Summary Statistics

1.7.1 Data Sources

My analysis used data from the Behavioral Risk Factor Surveillance System (BRFSS) surveys for 1993-2008. The BRFSS is a nationally representative annual cross-sectional survey of adults regarding their health practices and health-related risky behaviors. The surveys are conducted by state health departments under the administration of the Center of Disease Control (CDC) and are used to monitor the nation's progress towards the Healthy People 2020 objectives. Currently, BRFSS is the largest ongoing multi-mode (mail, landline phone, and cell phone) survey in the world, and is publicly available online for 1983-2012. Nelson et al. (2000) provide a more detailed information on the sampling design in BRFSS.

The BRFSS includes three parts: 1) the core component; 2) optional modules; and 3) state-added questions. All states agree to ask the questions in the core component, which includes questions about current health–related perceptions, conditions, and behaviors, as well as demographic questions. Optional modules include questions on specific topics (e.g., cardiovascular disease, arthritis, or women's health) that states can elect to use. The state-added questions are developed by the states, allowing them the flexibility to ask questions specific to their needs.

In addition to the BRFSS, I used data on the Consumer Price Index (CPI) for 1993-2008, obtained from the U.S. Department of Labor, Bureau of Labor Statistics website, to adjust the income variable to the 2008 purchasing power.

1.7.2. Sample Selection

The first year I used in the analysis is 1993, when the BRFSS became a nationwide system. Between 1993 and 2000, and during even years since 2000, mammography questions were asked in all of the states as part of the BRFSS fixed core questionnaire. I excluded the odd years after the year 2000, as during those years, mammography questions were asked only in the optional modules, and could introduce selection bias if, for example, a state where breast cancer incidence or mortality is particularly high chose to add a women's health module to the core questions (see Figure 1.5). In view of the 2009 changes in the USPSTF recommendations regarding the frequency of routine breast cancer screening, 2008 was the last year I used in the analysis. Therefore, the sample consisted of 12 years of nationally representative surveys, taken when screening recommendations were consistent between different U.S. health organizations. States and U.S. territories that did not participate in the surveys in some of the years between 1993-2008 (Rhode Island, Wyoming, Guam, Puerto Rico, and the Virgin Islands) were omitted from the analysis, which ultimately yielded 48 states and 2,413 distinct counties.

As can be seen from Figure 1.4, the number of women surveyed from 1993-2008 has been steadily increasing: this increase is reflective of the expansion of the BRFSS surveys over the years. The whole sample consisted of 598,489 individual women age 40 and older. Women ages 50-75 accounted for more than half of the sample (55.10% or 329,781 observations), followed by women ages 40-49 (31.16% or 186,502 observations), and women age 75 and older (13.74% or 82,206 observations). These numbers can be found in Table 1.3.

1.7.3 Descriptive Statistics

Table 1.3 presents summary statistics for the individual level data. Column (1) shows the summary statistics for all women over age 40, whereas columns (2), (3), and (4), contain the summary statistics for women ages 40-49, ages 50-74, and age 75 and older, respectively.

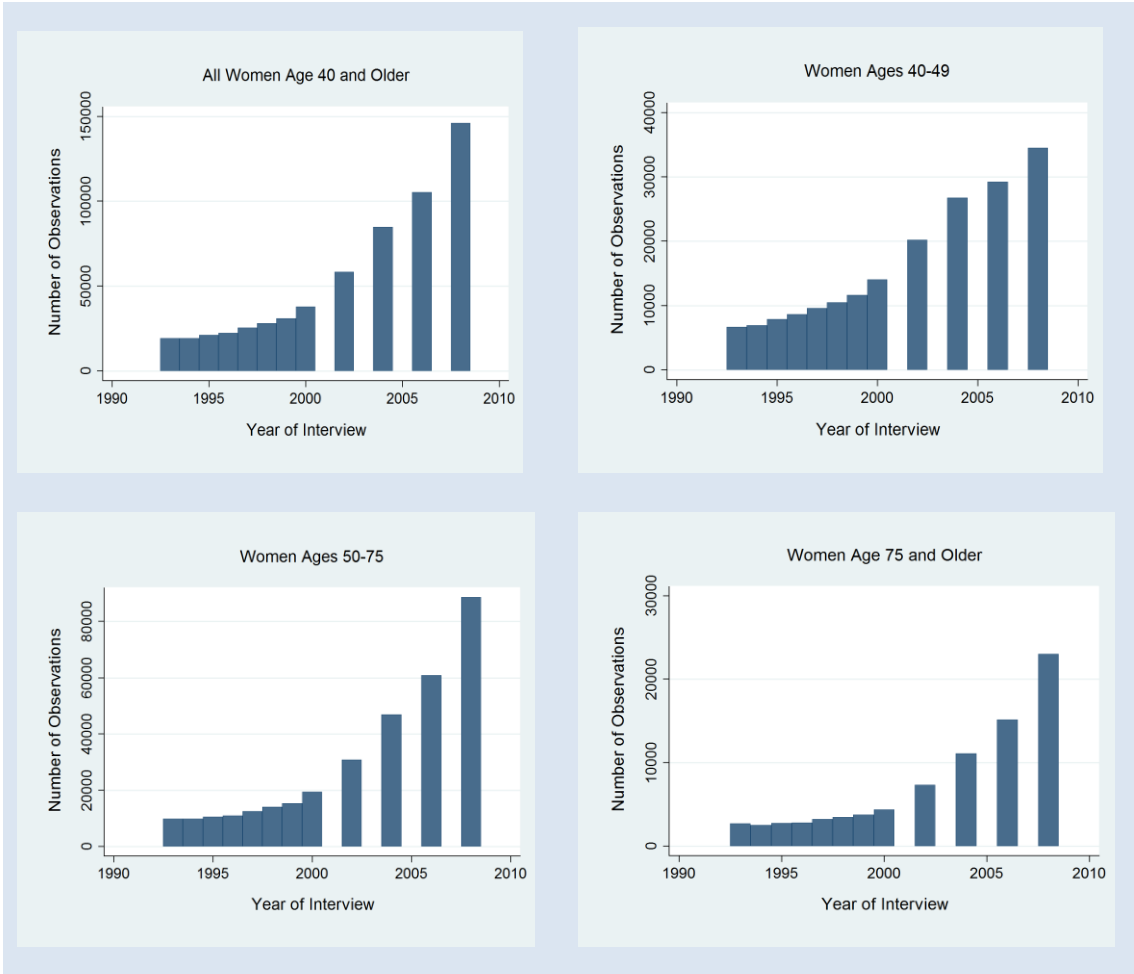

Figure 1.4: Mammography Sample Size by Year and Age Group, 1993-2008

Dependent variable: For 1993-2008, the mean rate of mammogram receipt in the 12 months prior to the interview for women age 40 and older was 59.9%. The mean screening rate varied greatly by age group, with 52% of women ages 40-49, 65.5% of women ages 50-74, and 55.9% of women age 75 and older reporting a mammogram in the past 12 months of the survey.

Explanatory variables: Column (1) shows that the average woman's age was around 60 years. A little over 8% of all women were uninsured, 51.4% reported working for wages or being self-employed, and 52% were married or cohabitated as an unmarried couple. The average household income was $48,560. About 10% of women did not complete high school. The women in the sample were in good overall health: only 6.20% reported poor general health. About 83.3 % of women reported being white, 4.7% Hispanic, 8.0% black, 1.7% Asian/Pacific Islanders, 0.08% American Indian/Alaskan Native, and 1.5% other ethnicities.

Column (2) reports descriptive statistics for the youngest group of women: the group aged 40-49. In comparison to women in the other age groups, women ages 40-49 had the highest proportion of both uninsured (12.1%) and healthy (96.6%) individuals. In addition, women in this age group were the most likely to be married (63.4%), have at least a high school level of education (94.1%), be employed (77.6%), and have high household income (mean of $59,040). Finally, the proportion of women who identified themselves as being of any other ethnicity but white was also the highest in this group (20.47% all other ethnicities versus 79.53% white).

In contrast, the oldest group of women, those ages 75 and older, had the highest proportion of individuals with health insurance (98.6%), but also individuals in poor general health (10.2%). Only 22.2% of women over age 75 were married or lived as a couple, and only 4.4% were still employed. This group had the highest proportion of high school drop-outs (21.1%), which is not surprising since the average woman in this group was born in 1928 and lived through WWII, and many had also lived through WWI. In comparison to women in the other age groups, women over age 75 had the lowest average household income ($29,390). Close to 90% of women in this age group were white.

Table 1.3: Individual Level Descriptive Statistics by Age Group, 1993-2008

	All Ages	Ages 40-49	Ages 50-74	75 and Older
Mammogram in the past 12 months	0.599	0.520	0.655	0.559
	(0.490)	(0.500)	(0.475)	(0.497)
Age	58.22	44.43	60.45	80.54
	(12.79)	(2.864)	(7.116)	(4.493)
Health Plan	0.916	0.879	0.920	0.986
	(0.277)	(0.326)	(0.271)	(0.116)
Married	0.520	0.634	0.530	0.222
	(0.500)	(0.482)	(0.499)	(0.415)
Education	0.896	0.941	0.895	0.799
	(0.305)	(0.236)	(0.306)	(0.401)
Hispanic	0.0466	0.0638	0.0424	0.0245
	(0.211)	(0.244)	(0.201)	(0.155)
Black	0.0801	0.0942	0.0796	0.0501
	(0.271)	(0.292)	(0.271)	(0.218)
Asian/Pacific Islander	0.0170	0.0223	0.0151	0.0127
	(0.129)	(0.148)	(0.122)	(0.112)
American Indian / Alaskan Native	0.00784	0.00889	0.00813	0.00432
	(0.0882)	(0.0939)	(0.0898)	(0.0656)
Other	0.0153	0.0155	0.0158	0.0127
	(0.123)	(0.124)	(0.125)	(0.112)
Employ	0.514	0.776	0.483	0.0444
	(0.500)	(0.417)	(0.500)	(0.206)
Poor Health	0.0619	0.0342	0.0676	0.102
	(0.241)	(0.182)	(0.251)	(0.303)
Income ($10,000)	4.856	5.904	4.742	2.939
	(2.957)	(2.977)	(2.867)	(2.090)
Observations	598,489	186,502	329,781	82,206

Notes. Mean coefficients. Standard deviations in parenthesis.

Table 1.4: County Level Descriptive Statistics, 1993-2008

	All Ages	Ages 40-49	Ages 50-75	75 and Older
Mammogram in the past 12 months	0.578 (0.124)	0.503 (0.202)	0.634 (0.153)	0.530 (0.288)
Age	58.30 (3.460)	44.46 (1.122)	60.63 (2.175)	80.41 (2.462)
Health Plan	0.908 (0.0763)	0.861 (0.153)	0.913 (0.0891)	0.985 (0.0669)
Married	0.536 (0.123)	0.655 (0.194)	0.547 (0.155)	0.217 (0.230)
Education	0.872 (0.103)	0.932 (0.109)	0.867 (0.129)	0.750 (0.268)
Hispanic	0.0407 (0.0871)	0.0532 (0.119)	0.0372 (0.0905)	0.0229 (0.0935)
Black	0.0740 (0.119)	0.0877 (0.159)	0.0718 (0.125)	0.0503 (0.140)
Asian/Pacific Islander	0.00851 (0.0370)	0.0116 (0.0442)	0.00755 (0.0407)	0.00464 (0.0469)
American Indian / Alaskan Native	0.00705 (0.0304)	0.00896 (0.0512)	0.00705 (0.0320)	0.00411 (0.0382)
Other	0.0115 (0.0266)	0.0120 (0.0488)	0.0114 (0.0326)	0.0104 (0.0549)
Employ	0.498 (0.129)	0.769 (0.177)	0.457 (0.159)	0.0412 (0.110)
Poor Health	0.0692 (0.0649)	0.0380 (0.0794)	0.0749 (0.0839)	0.117 (0.189)
Income ($10,000)	4.637 (1.056)	5.618 (1.416)	4.510 (1.140)	2.800 (1.225)
Observations	9,944	9,761	9,921	9,317

Notes. Mean coefficients. Standard deviations in parenthesis.

Table 1.5: State Level Descriptive Statistics, 1993-2008

	All Ages	Ages 40-49	Ages 50-75	75 and Older
Mammogram in the past 12 months	0.577 (0.0605)	0.504 (0.0669)	0.641 (0.0623)	0.522 (0.104)
Age	57.92 (1.722)	44.32 (0.299)	60.59 (0.890)	80.33 (0.692)
Health Plan	0.913 (0.0314)	0.882 (0.0470)	0.923 (0.0303)	0.986 (0.0172)
Married	0.528 (0.0392)	0.628 (0.0563)	0.522 (0.0530)	0.209 (0.0600)
Education	0.863 (0.0675)	0.940 (0.0334)	0.869 (0.0649)	0.751 (0.115)
Hispanic	0.0410 (0.0543)	0.0565 (0.0716)	0.0391 (0.0540)	0.0239 (0.0386)
Black	0.0754 (0.0781)	0.101 (0.0997)	0.0848 (0.0834)	0.0595 (0.0709)
Asian/Pacific Islander	0.0165 (0.0661)	0.0206 (0.0576)	0.0160 (0.0684)	0.0145 (0.0856)
American Indian / Alaskan Native	0.00507 (0.0165)	0.00573 (0.0196)	0.00450 (0.0151)	0.00247 (0.00906)
Other	0.0100 (0.0183)	0.0112 (0.0227)	0.00994 (0.0183)	0.00844 (0.0166)
Employ	0.511 (0.0625)	0.788 (0.0540)	0.468 (0.0720)	0.0414 (0.0288)
Poor Health	0.0632 (0.0264)	0.0312 (0.0176)	0.0657 (0.0272)	0.106 (0.0529)
Income ($10,000)	4.750 (0.648)	5.974 (0.702)	4.723 (0.623)	2.941 (0.598)
Observations	575	575	575	575

Notes. Mean coefficients. Standard deviations in parenthesis.

Tables 1.4 and 1.5 contain descriptive statistics at the county- and state-defined group level. The means at the county and state levels are similar to the means at the individual level. Note that 598,489 individual-level observations aggregate into 9,944 county-level observations and 575 state-level observations.

Table 1.6 provides more detail about the mean screening rate for different age groups of women in the U.S. for 1993-2008. For all years combined, 59.9% of all women over age 40 reported having a mammogram within 12 months of the interview. About 52% of women ages 40-49 reported having a breast cancer screening exam in the past 12 months. For women ages 50-74, the average mammography rate for the past 12 months was 65.5%: within this group, women eligible for Medicare (ages 65-74), reported the highest screening rate of all groups (66.5%). The use of mammography declined with age to 59% among women 75-84 years old, and further fell to 42.6% among women 85-99 years old.

Table 1.6: Mammography Receipt within Twelve Months of Interview by Age Group, 1993-2008

Characteristic	Number	Screening Rate	(95 %CI)
40 and Older	598,489	59.94%	(59.82% - 60.10%)
40-49	186,502	51.96%	(51.73% - 52.18%)
50-74	329,781	65.47%	(65.31% - 65.63%)
50-64	225,189	65.01%	(64.81% - 65.20%)
65-74	104,592	**66.46%**	(66.17% - 66.75%)
75 and Older	82,206	55.89%	(55.55% - 56.23%)
75-84	66,678	58.98%	(58.61% - 59.36%)
85-99	15,528	42.61%	(41.84% - 43.39%)

Table 1.7 shows the overall proportion of women by age group who reported having a mammogram within 12 months of the BRFSS interview for 1993-2008, sorted by select demographic characteristics. Women age 40 and older who reported the highest rates of screening within the study period identified themselves as black (62.20%), reported having at least a college degree (65.43%), and had a household income above $75,000/year (67.21%) and health insurance coverage (62.33%). The lowest use of mammography was reported by American Indian and Alaskan Native women (52.55%), women without high school education (50.27%), women with an annual household income less than $15,000 (48.68%), and women with no health insurance (33.79%). Such patterns of screening were consistent across all age groups, with one exception pertaining to women over age 75: women who identified themselves as Asian/Pacific Islanders reported the highest mammography rates, in comparison to other ethnic groups.

Table 1.7: Mammography Receipt within Twelve Months of Interview by Select Demographic Characteristics, 1993-2008

	Age 40 and Older	Ages 40-49	Ages 50-75	Age 75 and Older
Race/Ethnicity				
White	60.03% (0.0006)	51.82% (0.0013)	65.55% (0.0009)	55.85% (0.0018)
Black	**62.20%** (0.0022)	**55.62%** (0.0037)	**67.51%** (0.0029)	56.40% (0.0077)
Hispanic	57.54% (0.0030)	50.74% (0.0046)	63.80% (0.0041)	54.24% (0.0111)
Asian/Pacific	59.60% (0.0049)	50.23% (0.0078)	66.59% (0.0067)	**63.60%** (0.0149)
Indian/Alaskan	52.55% (0.0073)	44.15% (0.0122)	57.35% (0.0095)	55.49% (0.0264)

Table 1.7 (Continued): Mammography Receipt within Twelve Months of Interview by Select Demographic Characteristics, 1993-2008

Other	54.62%	48.52%	58.40%	52.72%
	(0.0052)	(0.0093)	(0.0068)	(0.0154)
Education				
No High School	50.27%	41.52%	55.27%	45.67%
	(0.0020)	(0.0047)	(0.0027)	(0.0039)
High school	58.31%	48.24%	63.57%	56.02%
	(0.0011)	(0.0022)	(0.0015)	(0.0028)
Some college	59.55%	50.62%	65.23%	58.68%
	(0.0012)	(0.0021)	(0.0016)	(0.0034)
College graduate	**65.43%**	**57.40%**	**71.61%**	**63.36%**
	(0.0011)	(0.0019)	(0.0015)	(0.0040)
Income				
<$15,000	48.68%	40.07%	52.70%	46.19%
	(0.0018)	(0.0043)	(0.0025)	(0.0036)
$15,000 - $35,000	55.26%	42.57%	59.69%	55.59%
	(0.0012)	(0.0026)	(0.0016)	(0.0024)
$35,000 - $50,000	61.31%	48.86%	67.10%	63.80%
	(0.0015)	(0.0028)	(0.0019)	(0.0043)
$50,000 - $75,000	63.94%	53.71%	70.78%	65.34%
	(0.0015)	(0.0026)	(0.0020)	(0.0064)
> $75,000	**67.21%**	**59.39%**	**74.46%**	**66.17%**
	(0.0013)	(0.0019)	(0.0016)	(0.0071)
Health Insurance				
Yes	**62.33%**	**55.24%**	**67.84%**	**56.07%**
	(0.0007)	(0.0012)	(0.0008)	(0.0017)
No	33.79%	28.19%	38.20%	43.16%
	(0.0021)	(0.0030)	(0.0030)	(0.0148)

Notes. Proportions are reported. Standard errors in parenthesis.

7.4: Geographic Variation in Mammography Use

For 1993-2008, the average mammogram rate varied significantly between different states. For example, in 2008, the rate of mammography use within twelve months of the interview ranged from 50.36% (Utah) to 72.95% (Massachusetts). Table A.1 of the Appendix reports the unadjusted state-level screening rates for each state for 1993-2008. Previous years' screening rates exhibit similar pattern in geographic. Among factors that researchers commonly cite as responsible for this variation are the availability of large university hospital systems, the geographic density of healthcare providers, the level of insurance coverage in the population, the accessibility of mammography facilities, and levels of annual income (J. W. Miller, King, Joseph, & Richardson, 2012).

Figure 1.5 shows state-level screening rates regression adjusted for such characteristics as state average age, race, number of married couples, number of insurance, level of education, health status, employment, and income by age group. There appears to be a large amount of geographic variation between the states for 1993-2008 that cannot be explained by demographic characteristics alone.

In addition, screening rates also varied significantly across time within states. Reports of a mammogram in the past 12 months of the interview in Louisiana, for instance, increased by 19.73 percentage points (from 45.60% in 1993 up to 65.33% in 2008), while Alabama's screening rate only increased by 0.13 percentage points (from 58.91% in 1993 up to 59.04% in 2008).

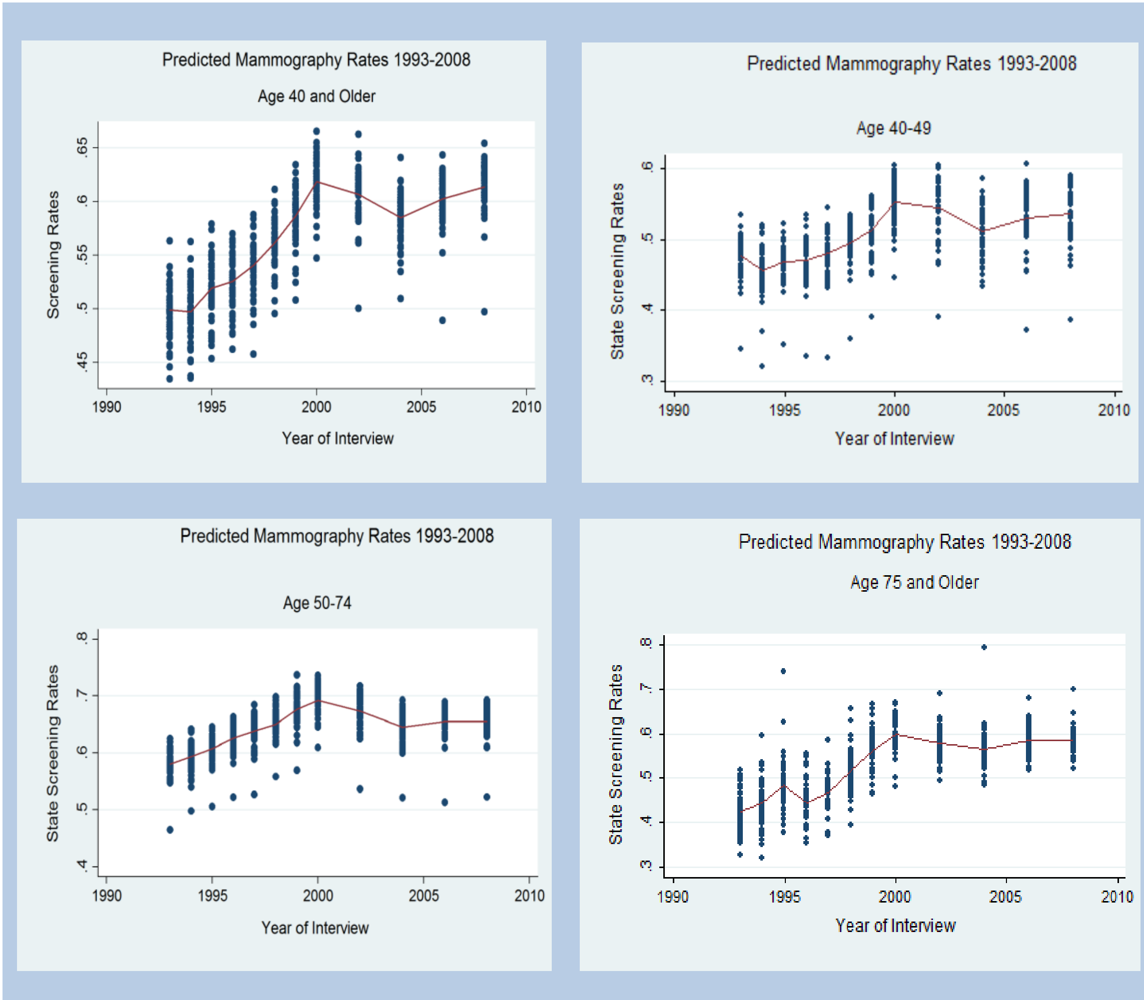

Figure 1.5: Geographic Variation in Mammotraphy Rates by Age Group, 1993-2008. State mammography rates adjusted for age, race, marital status, health insurance, education, health status, employment, and income.

1.8: Results

1.8.1: Determinants of Individual Mammography Receipt

Results of the individual-level regressions of mammography use in the past 12 months are reported in Table 1.8. Column (1) presents results for all women over age 40, whereas columns (2), (3), and (4) contain the results for women ages 40-49, ages 50-75, and age 75 and older respectively. The effects of the explanatory variables on the receipt of a mammogram in the past 12 months differed between the age groups.

All women age 40 and older: Some of the factors positively associated with the probability of mammogram receipt for women age 40 and older were age, having health insurance, being married, having completed at least a high school level of education, and having a higher household income. Health insurance status appears to be the biggest predictor of a mammogram: having any type of coverage, public or private, increased the probability of screening by 22.25 percentage points. This finding supports previous research that shows that a physician's recommendation for mammography is the most important influence on a woman's decision to have the exam (Schueler et al., 2008; Zapka et al., 2004). Age, the most significant risk factor for breast cancer, only moderately influenced the probability of individual mammography: a 0.35 percentage point increase each year among all women over age 40. Being married increased the probability of women having had a mammogram in the past 12 months by 3.36 percentage points. One possible explanation for this positive effect is that a spouse may provide encouragement, support, and reminders, as well as help in overcoming barriers to screening (such as finding time or transportation). Likewise, spousal adherence to routine cancer screening recommendations (for example, colorectal cancer screening), overall general preventive behavior, and health status may also influence an individual woman's likelihood of screening. Moreover, in comparison to single women, married women may feel more pressure from family members to have a timely mammogram. The likelihood of breast cancer screening increased by 6.11 percentage points if a woman had at least a high school level of education. The positive effect of education is expected, since educated women are more likely to understand the benefits of frequent screenings and adhere to routine mammography recommendations. In addition, an increase in one's household income by $10,000 implied an increase in the probability of breast cancer screening by 1.76 percentage points.

For all women over age 40, being in poor general health was negatively associated with the probability of breast cancer screening. In particular, women who reported poor general health were 4.1 percentage points less likely to report a mammogram in the past 12 months. These findings are consistent with results found elsewhere in the literature. Feldstein et al. (2011), for example, showed that obese women were more likely to report experiencing "too much pain" during mammograms, and therefore, might be more reluctant to schedule a timely screening test. One other possible explanation of the negative effect of poor health is that, in the presence of many competing health risks, it could be difficult to see the benefit of any one particular preventive action, such as breast cancer screening.

In comparison to white women over age 40, Hispanic and black women were 6.7 and 8.6 percentage points more likely to report having received a mammogram in the past 12 months. While identifying oneself as being other ethnicity/race reduced an individual woman's likelihood of screening by 2.5 percentage points. The differences in the likelihood of screening among American Indian/Alaskan Native and Asian/Pacific Islanders as compared to white women were not statistically significant.

Women ages 40-49: Similarly to the results for women in other age groups, having health insurance was the most important determinant of screening, resulting in a 21.84 percentage point higher probability of a mammogram. For women ages 40-49, the probability of screening increased by 1.8 percentage points for every year they were older: much stronger than the effect for women ages 50-75, which was only 0.35

percentage points per year. The large positive effect of age for women in this age group might be explained by a significant gain in life expectancy due to early detection of the disease, in comparison to older women. Women ages 40-49 who had completed high school were almost 2.0 percentage points more likely to have had a test than high school drop-outs, while possessing an additional $10,000 of household income increased the probability of screening by 1.7 percentage points. The effect of identifying oneself as Hispanic (8.0 percentage points) or black (8.5 percentage points) was also significant and positive.

In contrast to findings for women of all other age groups, employment among women ages 40-49 was positively related to screening, increasing the probability of reporting a mammogram in the past 12 months of the interview by 1.6 percentage points. In addition, unlike women of all other age groups, being married or co-habiting had no significant effect on the probability of screening for women in this age group. Poor health status also was not a significant predictor of screening in the past 12 months.

Women ages 50-75: Factors that had a positive effect on the probability of screening in the past 12 month included age (a 0.3 percentage point increase), health insurance (a 24.0 percentage point increase), having a spouse (a 2.8 percentage point increase), having completed at least a high school level of education (a 5.2 percentage point increase), being Hispanic or black (a 6.8 and 8.6 percentage point increase, respectively), and reporting a higher household income (a 1.9 percentage point increase).

Employment negatively affected the probability of mammography for women in this age group. In particular, being employed reduced the probability of screening in the 12 months before the interview by almost 1.8 percentage points. The negative effect of employment can perhaps be explained by the opportunity cost of a screening visit: previously published research reports that simply being too busy is commonly cited by women as a barrier to mammography use (Feldstein et al., 2011). Identifying oneself as being other ethnicity reduced the probability of screening by 3.4 percentage points. Finally, being in poor health reduced the likelihood of an individual screening by almost 5.0 percentage points for women in this age group.

Women age 75 and older: In contrast to women in other age groups, age was negatively associated with having a mammogram in the past 12 months: turning one year older reduced the probability of screening by 1.6 percentage points among women age 75 and older. The negative effect of age may be due to little perceived benefit from early detection of breast cancer in terms of life-years gained. In comparison to other age groups, health insurance only moderately affected the probability of screening for women age 75 and older (an increase of 9.0 percentage points). Being married (3.4 percentage points) and having completed at least a high school education (7.5 percentage points) had a stronger positive impact on the likelihood of a mammogram for women age 75 and older, as compared to other age groups. Similar to women ages 50-75, employment was negatively associated with a mammogram in the past 12 months and reduced the probability of screening by 3.4 percentage points. Women in poor health were 6.7 percentage points less likely to report a mammogram.

To assess the sensitivity of the results to the choice of controls associated with time and group fixed effects, Tables A.2-A.5 of the Appendix present alternative specifications for women age 40 and older, ages 40-49, ages 50-75, and age 75 and older. Each table is organized as follows: column (1) controls solely for the main explanatory variables; column (2) includes the effects of state dummies and year dummies in addition to the main variables, the same specification used in Table 1.8; column (3) includes state dummies, time trend, and its square, as well as state-specific trends to allow the influence of time-specific unobserved effects to differ among states; lastly, to assess the magnitude of county-level omitted variable bias, column (4) presents results based on regression with county and year dummies.

Individual regression results appear to be robust to the choice of controls associated with time, as the coefficients on the explanatory variables are not considerably different across columns (1)-(4). The bias from omitted county-level unobserved characteristics was minimal, since county-level fixed effects estimation (column (4)) leads to very similar results to those obtained when using state fixed effects regression in column (2).

1.8.2: Evidence of Social Spillover in Breast Cancer Screening

Table 1.9 presents the individual- and group-level regression results side by side for women age 40 and older. Column (1) reports individual-level regression coefficients from column of (2) Table 1.8, whereas columns (2) and (3) report the respective coefficients from county- and state-level regressions. Note that the number of observations decreases sharply moving from column (1) to columns (2) and (3): there are 598,489 women in column (1), but they are aggregated into 9,944 county-level observations in column (2) and 575 state-level observations in column (3). Tables 1.10, 1.11, and 1.12 present results for women ages 40-49, ages 50-74, and age 75 and older in the same way.

Table 1.8: Determinants of Individual Mammography Receipt within Twelve Months of Interview by Age Group, U.S. Women 1993-2008 (OLS)

	40 and Older	Ages 40-49	Ages 50-75	75 and Older
Age	0.0035***	0.0188***	0.0028***	-0.0167***
	(0.0002)	(0.0005)	(0.0002)	(0.0005)
Health Plan	0.2225***	0.2184***	0.2405***	0.0906***
	(0.0044)	(0.0037)	(0.0058)	(0.0127)
Married	0.0336***	-0.0000	0.0282***	0.0337***
	(0.0017)	(0.0034)	(0.0018)	(0.0036)
Education	0.0611***	0.0197***	0.0521***	0.0752***
	(0.0037)	(0.0061)	(0.0038)	(0.0058)
Hispanic	0.0674***	0.0801***	0.0689***	0.0152
	(0.0068)	(0.0074)	(0.0075)	(0.0121)
Black	0.0864***	0.0850***	0.0856***	0.0445***
	(0.0047)	(0.0051)	(0.0059)	(0.0090)
Asian/Pacific	-0.0081	-0.0150	0.0051	0.0797
	(0.0221)	(0.0151)	(0.0132)	(0.0665)
Indian/Alaskan	0.0049	0.0008	0.0011	0.0159
	(0.0158)	(0.0201)	(0.0164)	(0.0359)
Other	-0.0251***	-0.0087	-0.0336***	-0.0223
	(0.0055)	(0.0102)	(0.0066)	(0.0162)
Employed	-0.0027	0.0163***	-0.0178***	-0.0340***
	(0.0023)	(0.0031)	(0.0022)	(0.0092)
Poor Health	-0.0406***	0.0028	-0.0497***	-0.0672***
	(0.0026)	(0.0055)	(0.0035)	(0.0063)
Income	0.0176***	0.0169***	0.0193***	0.0184***
	(0.0007)	(0.0010)	(0.0007)	(0.0011)
Constant	-0.0285**	-0.6562***	0.0326**	1.6097***
	(0.0117)	(0.0232)	(0.0140)	(0.0435)
Observations	598,489	186,502	329,781	82,206
R-squared	0.0537	0.0649	0.0570	0.0617
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county/state) robust standard errors in parentheses

Comparison of group- and individual-level regression results for all U.S. women over age 40 provides evidence in favor of social spillover in breast cancer screening associated with education, as the effect of this variable was much larger at the county and state levels than at the corresponding individual level. In particular, the effect of education was almost twice larger at the county level (0.11) than the direct effect of education on the probability of individual screening (0.06), and more than three times greater than that at the state level (0.20). This suggests that it is not only a woman's own education, but also the education of other women in her geographic area, that influences individual her screening decision. In other words, since a woman's education has both direct effect on her behavior and an indirect effect on the behavior of her peers, the effect of this variable is much larger at the group equilibrium level than at the individual level.

In addition, for all women over age 40, the coefficients on the dummy variables associated with a woman's ethnicity, in particular black and other, also increased in magnitude with the level of aggregation. The coefficient for reporting being black increased from 0.09 at the individual level to 0.11 at the county level, and to 0.13 at the state level, whereas the coefficient on the dummy variable for other ethnic background increased in magnitude from negative 0.03 to 0.15 at the county level and to 0.44 at the state level.

Similarly to the results obtained for all women age 40 and older, the results across all age groups suggested strong evidence of spillover associated with a woman's education. In the case of women ages 40-49, the increase in education appeared particularly strong: the county-level effects (0.07) was more than three times the individual-level effect (0.02), with the state level effect (0.18) almost 9 times the individual effect. In addition to evidence of spillover associated with education, for women ages 40-49, there was a modest increase in the coefficient on having a health plan: an increase from 0.21 at the individual level to 0.26 at both the county and state levels. The effect of being employed also increased with the level of aggregation from 0.02 at the individual level to 0.04 at the county level and 0.10 at the state level, although no longer significant.

For women ages 50-75, the results were very similar to those reported for all women over age 40. The factors that have a larger effect at the group level, in comparison to the individual level, included education and identifying oneself as being black or other ethnicity/race. The magnitude of these effects was also very similar to those found for all women over age 40.

For women over age 75, there were also three significant explanatory variables through which social interactions might influence the likelihood of an individual woman's breast cancer screening. The effect of education increased from 0.08 at the individual level to 0.21 at the state level. In addition, unique to this group was the spillover associated with being married and age. The effect of being married or living as a couple was statistically significant at all levels, and increased in magnitude from 3.4 percentage points at the individual level to 5.1 percentage points at the county and 16 percentage points at the state level. This suggests that the proportion of same-aged married individuals has a positive effect on the probability of screening for a woman age 75 and older. Finally, for women over age 75, turning one year older decreased the likelihood of a mammogram by 1.67 percentage points. At the group level, the effect of age was much larger: if the group average age rose by one, then the probability of screening for every woman in the group decreased by 2.0 percentage points at the county level, and further decreased by 2.8 percentage points at the state level. This suggests that it is not only a woman's own age, but also the age of other women in her geographic area that influences an individual woman's decision to gradually discontinue screening.

1.8.3: The Social Multipliers in Mammography Use

The social multipliers in breast cancer screening are presented in Table 1.13. The vectors of social multipliers were computed by dividing the coefficients from the group-level regressions in columns (2) and (3) by the coefficients of the same explanatory variable from the individual-level regression in columns (1). In the presence of social spillovers, this ratio should be significantly larger than unity. I used a bootstrap method with 1,000 replications to calculate the 95% confidence intervals of the social multipliers (Li and Maddala, 1999).

The significance levels were based on the tests of whether or not the ratios are larger than unity. A ratio greater than unity implies that an explanatory variable had both a direct effect on a woman's breast cancer screening behavior and an indirect effect on the behavior of her peers; therefore, in equilibrium, after all interactions have been accounted for, the observed effect of that variable at the group level should be larger than the effect at the individual level. The presence of social multipliers in mammography suggests that interventions that take advantage of social influences in decision to screen for breast cancer can potentially result in a much larger effect on the aggregate screening rates, and therefore may be an effective way to reach the screening objective of 81.1% of women adhering to guidelines.

Table 1.9: Individual and Group Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Age 40 and Older, U.S. 1993-2008 (OLS-FE)

	Individual Level OLS (1)	County OLS-FE (2)	State OLS-FE (3)
Age	0.0035***	0.0034***	0.0007
	(0.0002)	(0.0008)	(0.0042)
Health Plan	0.2225***	0.2127***	0.0879
	(0.0044)	(0.0319)	(0.1611)
Married	0.0336***	0.0236	-0.0493
	(0.0017)	(0.0196)	(0.0755)
Education	**0.0611*** **	**0.1087*** **	**0.2010** **
	(0.0037)	(0.0291)	(0.0956)
Hispanic	0.0674***	0.0456	-0.0209
	(0.0068)	(0.0436)	(0.1405)
Black	**0.0864*** **	**0.1063*** **	**0.1336* **
	(0.0047)	(0.0264)	(0.0757)
Asian/Pacific	-0.0081	-0.1875	-0.2739*
	(0.0221)	(0.1867)	(0.1434)
Indian/Alaskan	0.0049	-0.0726	-0.2097*
	(0.0158)	(0.1008)	(0.1185)
Other	**-0.0251*** **	**-0.1524** **	**-0.4385*** **
	(0.0055)	(0.0692)	(0.1056)
Employed	-0.0027	0.0252	0.1276
	(0.0023)	(0.0214)	(0.1057)
Poor Health	-0.0406***	-0.0155	0.1270
	(0.0026)	(0.0350)	(0.1794)
Income	0.0176***	0.0127***	0.0130*
	(0.0007)	(0.0034)	(0.0073)
Constant	-0.0285**	-0.0743	0.1321
	(0.0117)	(0.0638)	(0.3681)
Observations	598,489	9,944	575
R-squared	0.0537	0.6051	0.7642
Groups	n/a	2,413	48
County FE		Yes	
State FE	Yes		Yes
Year FE	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state) robust standard errors in parentheses.

Table 1.10: Individual and Group Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Ages 40-49, 1993-2008 (OLS-FE)

	Individual Level OLS (1)	County OLS-FE (2)	State OLS-FE (3)
Age	0.0188***	0.0182***	0.0046
	(0.0005)	(0.0031)	(0.0116)
Health Plan	**0.2184*** **	**0.2597*** **	**0.2560** **
	(0.0037)	(0.0270)	(0.0967)
Married	-0.0000	-0.0085	-0.1391**
	(0.0034)	(0.0210)	(0.0566)
Education	**0.0197*** **	**0.0661* **	**0.1764* **
	(0.0061)	(0.0377)	(0.1038)
Hispanic	0.0801***	0.0488	0.0059
	(0.0074)	(0.0426)	(0.1261)
Black	0.0850***	0.0550	0.0388
	(0.0051)	(0.0382)	(0.0837)
Asian/Pacific	-0.0150	-0.0125	-0.3273***
	(0.0151)	(0.0830)	(0.1126)
Indian/Alaskan	0.0008	0.0879	-0.3986***
	(0.0201)	(0.1219)	(0.0819)
Other	-0.0087	0.0435	-0.3422***
	(0.0102)	(0.0867)	(0.0736)
Employed	**0.0163*** **	**0.0428** **	**0.0977**
	(0.0031)	(0.0218)	(0.0663)
Poor Health	0.0028	0.0614	-0.2212
	(0.0055)	(0.0527)	(0.1494)
Income	0.0169***	0.0133***	0.0182***
	(0.0010)	(0.0037)	(0.0065)
Constant	-0.6562***	-0.7425***	-0.2015
	(0.0232)	(0.1436)	(0.5380)
Observations	186,502	9,761	575
R-squared	0.0649	0.5135	0.6767
Groups	n/a	2,251	48
County FE		Yes	
State FE	Yes		Yes
Year FE	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state) robust standard errors in parentheses.

Table 1.11: Individual and Group Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Ages 50-74, 1993-2008 (OLS-FE)

	Individual Level OLS (1)	County OLS-FE (2)	State OLS-FE (3)
Age	0.0028***	0.0007	-0.0043
	(0.0002)	(0.0014)	(0.0042)
Health Plan	0.2405***	0.2077***	0.1715
	(0.0058)	(0.0299)	(0.1153)
Married	0.0282***	0.0157	-0.1351***
	(0.0018)	(0.0192)	(0.0492)
Education	**0.0521*** **	**0.0900*** **	**0.1620***
	(0.0038)	(0.0260)	(0.0831)
Hispanic	0.0689***	0.0800	0.0283
	(0.0075)	(0.0525)	(0.1210)
Black	**0.0856*** **	**0.1208*** **	**0.1372***
	(0.0059)	(0.0291)	(0.0785)
Asian/Pacific	0.0051	-0.2474*	-0.1885*
	(0.0132)	(0.1502)	(0.1120)
Indian/Alaskan	0.0011	-0.1215	-0.2044*
	(0.0164)	(0.0831)	(0.1199)
Other	**-0.0336*** **	**-0.1462** **	**-0.4765*** **
	(0.0066)	(0.0633)	(0.1271)
Employed	-0.0178***	-0.0411*	-0.0401
	(0.0022)	(0.0220)	(0.0609)
Poor Health	-0.0497***	-0.0765**	0.0212
	(0.0035)	(0.0349)	(0.1037)
Income	0.0193***	0.0205***	0.0177**
	(0.0007)	(0.0032)	(0.0086)
Constant	0.0326**	0.1620	0.5460
	(0.0140)	(0.0991)	(0.3377)
Observations	329,781	9,921	575
R-squared	0.0570	0.5254	0.6913
Groups	n/a	2,393	48
County FE		Yes	
State FE	Yes		Yes
Year FE	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state) robust standard errors in parentheses.

Table 1.12: Individual and Group Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Age 75 and Older, 1993-2008 (OLS-FE)

	Individual Level OLS (1)	County OLS-FE (2)	State OLS-FE (3)
Age	**-0.0167***** (0.0005)	**-0.0201***** (0.0021)	**-0.0282***** (0.0079)
Health Plan	0.0906*** (0.0127)	0.0491 (0.0805)	0.6022*** (0.2163)
Married	**0.0337***** (0.0036)	**0.0510**** (0.0219)	**0.1599*** (0.0823)
Education	**0.0752***** (0.0058)	**0.0569***** (0.0213)	**0.2116***** (0.0693)
Hispanic	0.0152 (0.0121)	-0.0849 (0.0618)	0.2398 (0.1689)
Black	0.0445*** (0.0090)	0.0297 (0.0410)	0.3734*** (0.0844)
Asian/Pacific	0.0797 (0.0665)	-0.0196 (0.1481)	0.1674 (0.5725)
Indian/Alaskan	0.0159 (0.0359)	0.0504 (0.1267)	-0.5394* (0.2916)
Other	-0.0223 (0.0162)	0.0274 (0.0844)	0.1721 (0.2445)
Employed	-0.0340*** (0.0092)	0.0025 (0.0490)	-0.1599 (0.1484)
Poor Health	-0.0672*** (0.0063)	-0.0394 (0.0270)	0.0252 (0.1247)
Income	0.0184*** (0.0011)	0.0173*** (0.0046)	0.0182** (0.0084)
Constant	1.6097*** (0.0435)	1.8525*** (0.1915)	1.8310** (0.7694)
Observations	82,206	9,317	575
R-squared	0.0617	0.3966	0.6333
Groups	n/a	2,183	48
County FE		Yes	
State FE	Yes		Yes
Year FE	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state) robust standard errors in parentheses

All women age 40 and older: Panel A presents results for women ages 40 and older. For all women over age 40, I found a county-level multiplier in education of 1.780 and a state-level multiplier of 3.291. Both multipliers associated with education were statistically significant and greater than unity. This finding suggests that a woman's educational attainment has not only a direct positive influence on an individual woman's screening decision, but also a very large indirect effect on her peers' screening behavior. This multiplier is consistent with the idea that frequent screening mammograms are seen as a socially desirable behavior among women in the U.S: an educated woman is more likely to act as a role model for her peers and to provide advice and encouragement. At the same time, a more educated group of women is more likely to apply peer pressure on the individual woman to undergo an annual screening mammogram, once such behavior becomes an accepted social norm.

I also found significant evidence of peer effects in mammography among black and other race/ethnicity women. In particular, the county-level multiplier among black women equaled 1.2 and the state-level multiplier equaled 1.6. The corresponding social multipliers associated with being other race/ethnicity were 6.07 and 17.5. These multipliers indicates that, as the proportion of individuals with the same ethnic background (namely, black and other) in a geographic area increases, the effect of that ethnicity on the peer group's screening rates becomes magnified. This implication is in line with the idea that people form social preferences within groups that share a common language, ethnicity, and religion (Coale & Watkins, 1986; Munshi & Myaux, 2006).

Women ages 40-49: Panel B of Table 1.13 contains social multipliers for women ages 40-49. For women in this age group, there was a modest, statistically significantly greater-than-unity multiplier associated with having health insurance at the county (1.2) and state (1.2) levels. This multiplier might indicate the presence of endogenous interactions associated with visiting a health care provider: observing an individual woman's screening behavior, rather than her characteristics, might influence the probability of other women ages 40-49 seeking screening through observational learning. Thus, as the proportion of women who have health insurance in a geographic area increases, the proportion of women ages 40-49 that screen for breast cancer annually should also increase.

For women ages 40-49, the multiplier associated with education equaled 3.4 at the county level and 8.9 at the state level. This was the largest-in-magnitude multiplier associated with education, in comparison to women of other age groups. This suggests that education plays an especially important role in the decision to undergo mammography for women in this age group.

Additionally, there was a statistically significant social multiplier associated with being employed. One possible explanation for this employment multiplier is that turning 40 years old is a significant milestone in every woman's life that is usually observable to others, including co-workers. Having turned forty - the age of the baseline mammogram - a woman might experience social pressure from co-workers of the same gender to undergo a screening mammogram as a rite of passage. As a consequence, knowledge about a college's preventive behavior increased the effect of employment by 2.6 and 6.0 times at the county and state levels in comparison to the individual-level effect of employment.

Women ages 50-57: Panel C contains the social multipliers for women ages 50-75. For women in this age group, I found significant evidence of multipliers associated with education and ethnicity. The multiplier in education was statistically significant and greater than unity at the county (1.7) and state (3.1) levels. In addition, I found a larger-than-unity multiplier associated with being black (1.4 and 1.6) and identifying oneself as other race/ethnicity (4.4 and 14.2). The social multipliers for breast cancer screening in this age group were associated with the same explanatory variables as for all women over age 40.

Women age 75 and older: Lastly, panel D presents social multipliers for women age 75 and older. The three social multipliers in this age group were associated with age, being married, and education.

The county-level age multiplier equaled 1.2 and the state-level age multiplier equaled 1.7. The age multiplier implies that the decision to undergo mammography does not only depend on one's own age, but also on the age of other women in one's peer group. For this age group, however, age was negatively associated with the likelihood of screening. Such a relationship is plausible, since an individual woman will be less likely to undergo screening if she sees little benefit from early detection in terms of life-years gained. Since the group-level coefficient was also negative and became larger in magnitude with level of aggregation, it implies that older women are learning from each other to discontinue screening after a certain age. Thus, as the proportion of women age 75 and older in the geographic area increases, the proportion of women in this particular age group who have breast cancer screenings every 12 months will decrease.

The social multiplier associated with being married was moderate in size (1.2 at the county level and 1.7 at the state level) and statistically significantly greater than unity. Such a multiplier indicates that being married has an indirect effect on an individual woman's decision to undergo screening. Such an effect is intuitive for a number of reasons. First, given that a spouse may help in overcoming barriers to screening (such as finding transportation), and may remind the woman to have a timely screening, it is possible that there is an endogenous multiplier in the decision to have a mammogram. Second, a larger proportion of married individuals over age 75 in the geographic area may induce an individual to pursue a healthy lifestyle, and therefore, increase the probability of a screening exam. In addition, since friends often discuss their spousal situations, an older man who frequently socializes with other men may have an indirect influence on his peers' wives' decisions to seek screening through sharing the information about his own wife's preventive behavior or breast cancer status. Lastly, women over age 75 who are married or live as an unmarried couple might be more likely to socialize than single women in this age group. For these reasons, among others, being married or living as an unmarried couple when one is age 75 or older will have a larger effect on breast cancer prevention in the long run than is predicted by individual-level models.

Finally, I found a significant social multiplier associated with education for women age 75 and older at the state level. In equilibrium, the effect of education on breast cancer screening was 2.8 times larger than the individual-level effect. However, I did not find a multiplier associated with education at the county level for this age group.

Therefore, it is not completely clear whether education among women age 75 or older affects the decision of other women in their peer group to have a mammogram.

It is important to note that, in most cases, the multipliers increased with the level of aggregation. As explained in Glaeser et al., (2003), such a pattern is likely to occur since, the bigger the group, the greater the share of social influences that each person will have.

1.8.4: Falsification Test Results

Table 1.14 reports the ratios of group-level effects to individual-level effects when using height as a new dependent variable. Overall, the results indicated that there were no social spillovers associated with an individual's height. The negative ratios provided evidence against the existence of a multiplier in height, since they violate the assumption that γ and δ have the same sign. In the cases where I find positive ratios at the county and state levels, I fail to reject the hypothesis that the obtained ratios are statistically significantly greater than unity.

Although there may exist other reasons for aggregate effects of exogenous variables in mammography screening to be greater than their individual effects, the placebo test provides evidence in support of the reliability of the main approach for estimating social multipliers in breast cancer screening at both the county and state levels.

1.8.5: Split-Sample Instrumental Variable Results

Table 1.15 contains the results of the split sample instrumental variable (SSIV) method that corrects for the measurement error in $\overline{X}_{gt}$ and $\overline{A}_{gt}$ in the group level

Table 1.13: Social Multipliers in Breast Cancer Screening among US Women

	Individual Effect (1)	County Effect (2)	State Effect (3)	County Multiplier (4)	State Multiplier (5)
Panel A: Women Ages 40 and Older					
Education	0.061*** (0.004)	0.109*** (0.029)	0.201** (0.096)	**1.780***** (0.103) [1.577 - 1.982]	**3.291***** (0.122) [3.052 - 3.529]
Black	0.086*** (0.005)	0.106*** (0.026)	0.134* (0.076)	**1.230***** (0.040) [1.152 - 1.307]	**1.545***** (0.044) [1.460 - 1.631]
Other	-0.025*** (0.006)	-0.152** (0.069)	-0.439*** (0.106)	**6.070***** (1.638) [2.860 - 9.281]	**17.463***** (4.484) [8.675 - 26.251]
Panel B: Women Ages 40 -49					
Health Plan	0.218*** (0.0037)	0.260*** (0.027)	0.256** (0.0967)	**1.189**** (0.039) [1.1122- 1.266]	**1.172**** (0.019) [1.135 - 1.209]
Education	0.020*** (0.006)	0.066* (0.038)	0.176* (0.1038)	**3.350***** (1.270) [0.860 -5.841]	**8.935***** (3.441) [2.190 - 15.679]
Employed	0.016*** (0.003)	0.0428** (0.022)	0.098 (0.066)	**2.635***** (0.694) [1.276 - 3.996]	**6.012***** (1.187) [3.686 - 8.337]
Panel C: Women Ages 50-75					
Education	0.052*** (0.004)	0.090*** (0.0260)	0.162* (0.083)	**1.727***** (0.163) [1.407 - 2.048]	**3.110***** (0.175) [2.767 - 3.452]
Black	0.086*** (0.004)	0.121*** (0.026)	0.137* (0.083)	**1.410***** (0.076) [1.262 - 1.559]	**1.603***** (0.060) [1.485 - 1.720]

Table 1.13 (Continued): Social Multipliers in Breast Cancer Screening among US Women

Other	-0.034*** (0.007)	-0.146** (0.063)	-0.477*** (0.127)	**4.355***** (1.145) [2.110 - 6.600]	**14.193***** (3.691) [6.959 - 21.427]
Panel D: Women Age 75 and Older					
Age	-0.017*** (0.001)	-0.020*** (0.002)	-0.028*** (0.008)	**1.204***** (0.059) [1.088 - 1.321]	**1.687***** (0.048) [1.593 - 1.782]
Married	0.034*** (0.004)	0.051** (0.022)	0.160* (0.082)	**1.514*** (0.368) [0.792 - 2.236]	**4.744***** (0.654) [3.462 - 6.027]
Education	0.075*** (0.006)	0.057*** (0.021)	0.211*** (0.069)	0.757 (0.129) [0.504 - 1.010]	**2.815***** (0.185) [2.451 - 3.178]

Notes: *** denotes significance at 1% level. ** denotes significance at 5% level. * denotes significance at 10% level. Significance levels with regards to coefficients means significantly different from zero. Significance levels with regards to ratios mean significantly greater than 1. Standard errors are reported in parentheses. […] denotes 95% confidence intervals. I bootstrapped the standard errors and confidence Intervals for the ratios, applying a panel bootstrap using 1000 replications.

regressions. Column (1) reports the coefficients obtained from state-level OLS fixed effects regression (from Tables 1.9-1.12), whereas column (2) shows the coefficients from the state-level regressions using the SSIV method with fixed effects. The coefficients in the group-level regressions for all the dependent variables associated with social spillover were of the same sign, which provides additional evidence in support of the existence of large social multipliers in breast cancer screening. The coefficients on the dependent variables in the SSIV model were generally bit larger than those obtained by OLS, which implies a downward bias in the original estimates of the social multipliers.

Table 1.14: Results of the Falsification Test: Social Multipliers in Height

	County/ Individual Ratio	State/ Individual Ratio		County/ Individual Ratio	State/ Individual Ratio
Panel A: Women Ages 40 and Older			Panel C: Women Ages 50-75		
Education	0.898	-0.057	Education	0.507	0.345
	(0.084)	(0.003)		(0.077)	(0.022)
Black	0.403	1.051	Black	1.097	-2.051
	(0.172)	(0.508)		(17.944)	(27.967)
Other	-8.953	-7.711	Other	-18.402	-36.495
	(174.000)	(41.793)		(128.674)	(923.474)
Observations	598,489	598,489	*Observations*	329,781	329,781
Panel B: Women Ages 40 -49			Panel D: Women Age 75 and Older		
Health Plan	1.074	0.760	Age	0.558	-0.815
	(0.218)	(0.085)		(0.281)	(0.208)
Education	0.494	-0.329	Married	-0.442	6.370
	(0.187)	(0.027)		(67.214)	(90.628)
Employment	-3.815	0.461	Education	0.372	0.334
	(13.345)	(0.794)		(0.102)	(0.049)
Observations	186,502	186,502	*Observations*	82,206	82,206

Notes. Height in inches is the new dependent variable. Significance levels of ratios tests whether ratios are significantly larger than unity. Standard errors in parenthesis.

Table 1.15: Group Level Regressions for Breast Cancer Screening for US Women (OLS and Split-Sample IV)

	State OLS-FE (1)	State SSIV-FE (2)
Panel A: Women Ages 40 and Older		
Education	0.201**	0.692***
	(0.096)	(0.101)
Black	0.134*	0.143***
	(0.076)	(0.050)
Other	-0.439***	-0.116
	(0.106)	(0.182)
Observations	575	575
R-squared	0.510	0.195
Number of (split) groups	48	48
First Stage F-stat for Education [P-value]		132.08 [0.0000]
First Stage F-stat for Black [P-value]		572.99 [0.0000]
First Stage F-stat for Other [P-value]		263.21 [0.0000]
Anderson canon. corr LM statistic		68.546
Panel B: Women Ages 40 -49		
Health Plan	0.256**	0.455*
	(0.0967)	(0.286)
Education	0.176*	0.837***
	(0.1038)	(0.125)
Employed	0.098	0.325 ***
	(0.066)	(0.144)
Observations	575	575
R-squared	0.307	0.088
Number of Split groups	48	48
First Stage F-stat for Health Plan[P-value]		63.96 [0.0000]
First Stage F-stat for Education [P-value]		19.24 [0.0000]
First Stage F-stat for Employed [P-value]		35.63 [0.0000]
Anderson canon. corr LM statistic		50.494

Table 1.15 (Continued): Group Level Regressions for Breast Cancer Screening for US Women (OLS and Split-Sample IV)

Panel C: Women Ages 50-75

Education	0.162*	0.313 ***
	(0.083)	(0.125)
Black	0.137*	0.102**
	(0.083)	(0.057)
Other	-0.477***	-0.500***
	(0.127)	(0.253)
Observations	575	575
R-squared	0.400	0.218
Number of Split groups	48	48
First Stage F-stat for Education [P-value]		86.70 [0.0000]
First Stage F-stat for Black [P-value]		293.72 [0.0000]
First Stage F-stat for Other [P-value]		154.14 [0.0000]
Anderson canon. corr LM statistic		11.364

Panel D: Women Age 75 and Older

Age	-0.028***	-0.111***
	(0.008)	(0.048)
Married	0.160*	0.324
	(0.082)	(1.344)
Education	0.211***	0.578***
	(0.069)	(0.283)
Observations	575	575
R-squared	0.336	0.443
Number of Split groups	48	48
First Stage F-stat for Age [P-value]		3.55 [0.0000]
First Stage F-stat for Married [P-value]		74.97 [0.0000]
First Stage F-stat for Education [P-value]		20.67 [0.0000]
Anderson canon. corr LM statistic		15.92

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level. * denotes significance at 10% level. Standard errors are reported in parentheses. I use state averages of the variables constructed from only half of the original data. The averages of the remaining half of the data are used as instruments.

1.9: Concluding Remarks

1.9.1: Conclusion

Breast cancer screening rates are below the current public policy goal. In this chapter, I examined whether social interactions explain individual behavior to have a mammogram and thus help reach adequate levels of prevention. The results indicate the possibility of large social multipliers associated with education and ethnicity for women across all age groups. In addition, I found significant group-specific multipliers for women ages 40-49 and women age 75 and older.

The main channel of social influence in breast cancer screening behavior that affects women of all ages is an individual's education. This supports the effectiveness of mammography promotion efforts that focus on raising awareness of breast cancer and the benefits of early detection through frequent screenings, since women may influence each other's screening decisions through knowledge dissemination, role modeling, and experience sharing. Given that mammography is a socially desirable behavior, it is plausible that a more educated group of women will be more likely to convince a woman to have a timely routine mammogram, once such behavior becomes a norm in the peer group. In addition, for women across all age groups, I found significant evidence for peer effects in mammography within ethnicities, particularly black women and women who reported other race/ethnicity. This finding suggests that, as the proportion of women who share the same ethnic background increases in a geographic area, interactions of women of the same background will lead to a magnified effect, positive or negative, of this characteristic on breast cancer screening behavior. In addition, I found that social interactions do not affect women in different age groups in the same way. To this end, the decision to undergo screening for women age 40-49 is subject to social influence through a woman's place of employment and ownership of health insurance, while for women age 75 and older, social influence in regards to mammography is related to being married and aging.

The overarching finding that what other women do matters for an individual, suggests that establishing a belief that most women undergo a timely annual mammography will influence women to make it a habit. This might be achieved through creative public communications featuring women talking about how they made routine mammography a habit, or by influential members of society sharing their screening experiences. Furthermore, my findings also support the idea that public intervention designers should view women as members of social networks, rather than as isolated individuals, since women interact with other women both before and after their formal contact with medical service providers. Thus, the social events that offer group screening, such as "Lady's Night Out" at screening clinics, are likely to increase mammography participation, as they appeal to a woman's relational nature.

It is important we understand the importance of social interactions versus other inputs in increasing mammography rates, such as physicians' advice and education. In order to improve screening participation, we need to know which inputs matter. Given the existence of social multipliers in mammography, any policy impact on health behavior, whether positive or negative, will be magnified through the influence of peers. Therefore, it is not enough to evaluate the effect of a policy on group screening rates: the social spillovers will lead to the existence of a group equilibrium outcome that will be different from the individual reaction. What may seem like an initially small effect from public health intervention may actually result in large changes after multiple rounds of interactions.

1.9.2: Study Limitations

The findings presented here must be interpreted with some caution. First, the nature of the data does not allow for distinguishing between routine screenings versus diagnostic mammography. I also cannot control for family history of breast cancer or past individual screening experiences. Second, one cannot completely rule out an omitted variable bias in the aggregate regressions. Third, this paper gives estimates of the social multiplier but does not identify the precise channel of the social spillovers, since exogenous and endogenous social interactions are indistinguishable with the data that I have at the disposal. The fourth limitation stems from the fact that annual mammography is perceived to be a socially desirable behavior, and that telephone respondents are more likely to present themselves in socially desirable ways than face-to-face interview respondents (Holbrook et al., 2003). Lastly, research shows that women, especially Non-Hispanic and non-white women, tend to over-report mammography participation (Holt et al., 2006; Fiscella et al., 2006)

Additionally, as discussed in Manski (2000), outcome data does not necessarily provide adequate information for empirical research in social interactions. Thus, data that specifies the composition of a woman’s peer group and their preventive behavior is needed to be able to study the effect of social interactions on screening decisions, such as having a mammogram, with a greater degree of precision.

1.9.3: Future Research

Continuing research in this area should focus on obtaining data that will allow for the construction of friendship connections among women. Such data is necessary in order to distinguish between the endogenous and exogenous peer effects in breast cancer prevention and inform policy makers about appropriate interventions.

As a follow-up to this work, empirical work could also be extended to study the importance of social interactions in other cancer preventive behaviors, such as colorectal cancer screening. This analysis might provide some insight into the significance of gender differences on peer influence in cancer screening.

Future research could also consider examining the effect of celebrities on breast cancer screening rates in the U.S. For example, researchers could study the effect of Amy Robach's on-air mammography or Angelina Jolie's double mastectomy on annual mammography rates.

Finally, exploring the applicability of other methods of identification of social interactions, such as the variance-based approach developed by Graham (2008), within the context of breast cancer screening presents another opportunity for further research.

Chapter 2: The Effect of US Preventive Services Task Force Breast Cancer Screening Recommendations on Mammography Rates

2.1: Introduction

Starting in 2002, the U.S. Preventive Task Force has recommended that all women over age 40 have annual or biannual mammography. On November 16, 2009 the USPSTF updated their recommendations and proposed a less aggressive approach to breast cancer screening. The new 2009 guidelines recommended against routine screening mammography for women ages 40-49 and women age 75 and older, and recommended biennial breast cancer screening for women ages 50-74, instead of every 1-2 years.("Screening for Breast Cancer: U.S. Preventive Services Task Force Recommendation Statement," 2009).

The new USPSTF screening mammography recommendations were not received well by cancer societies, public advocacy groups, politicians, and medical community leaders. Many who had stated their support for annual screening called the newest recommendations “ill-advised” (American Medical Association, 2010). During the development of the 2010 U.S. health reform, many were concerned that the USPSTF recommendations were an example of how health care would be rationed under the Affordable Care Act if the legislation was to pass (Squiers et al., 2011). In response to the public criticism, the U.S. Senate passed amendments to its proposed health care reform, that required the government to ignore the 2009 USPSTF recommendations and to provide no-cost breast screening for women over age 40 as part of the Affordable Care Act ("The Patient Protection and Affordable Care Act.," 2010).

On December 4th, 2009, the USPSTF updated the recommendation regarding women under age 50. The updated guidelines stated: “The decision to start regular, biennial screening mammography before the age of 50 years should be an individual one and take patient context into account, including the patient's values regarding specific benefits and harms” (U.S. Preventive Service Task Force, 2009). In addition, the USPSTF concluded that the evidence was insufficient to recommend for or against routine screening mammography in women older than 75 years (U.S. Preventive Service Task Force, 2009). The Appendix provides more detail on the USPSTF recommendations.

An extensive analysis of news articles, social media posts, and internet-based surveys of women in the weeks immediately following the 2009 USPSTF announcement showed that while the new recommendation have helped roughly 6% of women understand better when to get a mammogram, it confused about 30% of women, and that confusion over the screening intervals was greatest among women ages 40-49 (Squiers et al., 2011).

Prior research has found that neither annual nor biannual screening rates were affected immediately following the 2009 revision of the USPSTF breast cancer screening recommendations (Howard & Adams, 2012). In this chapter, I improve upon these published studies by using population-based survey data to compare self-reported mammography screening in the years before and after the USPSTF announcement.

My results show a significant reduction in screening rates following the change in recommendations.

2.2: Relevant Literature

Other authors have studied the impact of changing recommendations on receipt of mammography. For example, Calvocoressi et al., (2008) showed that, after the NCI and ACS changed their recommendations in favor of routine annual screening mammography in 1997 among women ages 40-49, the screening rates immediately increased.

Howard and Adams (2012) examined the effect of the 2009 USPSTF breast cancer screening guidelines on receipt of mammography. They used close to 30,000 observations from the Medical Expenditure Panel Survey (MEPS) for 2006 to 2010, and employed a logistic regression approach to estimate the probability of mammography use in the past one and two years. The impact of the revised recommendations was estimated by comparing regression-adjusted screening rates for 2006 to 2009 and 2010.The study concluded that neither annual nor biannual mammography rates were significantly affected by the new recommendations.

My analysis improves on the study of Howard and Adams (2012) in several ways. First, I am using the BRFSS, a large nationally representative survey, with a two-year follow-up period to study the effect of the USPSTF announcement on breast cancer screening rates. The advantage of using BRFSS, a large cross-sectional data, over the MEPS is that, I can avoid the issue associated with the natural aging of the cohort that could affect the probability of having a mammogram. Second, respondents of the BRFSS surveys are women themselves, which is not necessarily the case in the MEPS: any member of the household can be answering the question about the mammography participation of women in the house, which may be less accurate than women's direct responses.

2.3: Methodology

I used surveys from BRFSS for 1993-2012 to examine the effect of the 2009 USPSTF updated recommendations on the use of mammography. Mammography rates were calculated as a proportion of women who reported they had a mammogram within one and two years of the interview. See the Appendix for the exact question wording. Since the BRFSS has conducted national-wide mammography surveys only in the even years since 2000, I have 2 years of follow-up data after the USPSTF revised the screening recommendation: 2010 and 2012.

I used logistic regression to employ the same specification as in Howard & Adams (2012) for comparability of the results. In particular, the regression model estimated the probability that a woman had a mammogram in the past one and two years as a function of age, race, marital status, health insurance, college degree, and employment status. I controlled for regional unobserved effects by constructing 4 regions (Northeast, Midwest, South, and West) using states' FIPS codes that come with the BRFSS and the U.S. Census Region Codes and Names. To control for time specific influences on mammography rates, I used year dummy variables for 1993-2012, with 2006 being the omitted category, again to make the results comparable to Howard and Adams (2012). All observations were weighted to account for the unequal probabilities of sample selection. The analysis was stratified by age group: women ages 40-49, ages 50-75, and 75 and older. Summary of the weighted explanatory variables is presented in Table 2.1.

Table 2.1: Descriptive Statistics of Explanatory Variables, 1993-2012

	Ages 40-49	Ages 50-75	Age 75 and older
	Mean (Standard deviation)	Mean (Standard deviation)	Mean (Standard deviation)
Age	44.51	60.74	80.75
	(2.878)	(7.030)	(4.610)
Any Insurance	0.873	0.918	0.987
	(0.333)	(0.274)	(0.115)
Married	0.641	0.533	0.229
	(0.480)	(0.499)	(0.420)
College Degree	0.385	0.308	0.189
	(0.487)	(0.461)	(0.391)
Employed	0.761	0.474	0.0476
	(0.427)	(0.499)	(0.213)
White	0.784	0.831	0.889
	(0.412)	(0.375)	(0.314)
Black	0.0969	0.0843	0.0540
	(0.296)	(0.278)	(0.226)
Hispanic	0.0699	0.0434	0.0254
	(0.255)	(0.204)	(0.157)
Asian	0.0226	0.0145	0.0128
	(0.149)	(0.120)	(0.112)
Indian/Alaskan	0.00965	0.00909	0.00478
	(0.0978)	(0.0949)	(0.0689)
Other	0.0174	0.0178	0.0141
	(0.131)	(0.132)	(0.118)
Northeast	0.132	0.123	0.122
	(0.339)	(0.328)	(0.328)
Midwest	0.296	0.293	0.326
	(0.457)	(0.455)	(0.469)
South	0.317	0.335	0.312
	(0.465)	(0.472)	(0.463)
West	0.254	0.249	0.240
	(0.435)	(0.432)	(0.427)
Observations	250,313	531,065	135,889

Notes. Mean coefficients; standard deviations in parentheses

2.4: Results

Table 2.2 and Table 2.3 report the odds ratios of having a mammogram in the past twelve and twenty-four months of the interview, respectively. The coefficients of interest were those on indicator variables for 2010 and 2012.

The regression results indicated that the odds ratios on the 2010 year dummy were significantly different from 1, suggesting that the 2009 USPSTF revised recommendation had an immediate impact on the twelve-month prevalence of mammography across all the age groups. In particular, women ages 40-49 were 5.1 percentage points less likely to report screening in the past 12 months in 2010, whereas women ages 50-75 and those older than 75 were less likely to report a mammogram by 9 and 11 percentage points, respectively. The revised breast cancer screening recommendation also caused an immediate reduction in the proportion of women who reported screening in the past twenty-four months. The biannual prevalence of mammography declined by 6 percentage points for women ages 40-49, by 11 percentage points for women ages 50-75, and by 9 percentage points for women age 75 and older. The reduction in the prevalence of screening rates across all age groups was non-trivial and very clear: none of the 95% confidence intervals included unity. These results contradict the conclusion made by Howard and Adams (2012), who, using a Medical Expenditure Panel Survey (MEPS) and the same study design, found no significant changes in the screening rates in 2010 across all age groups.

In addition, the two year follow-up period to changes in the recommendation suggested a further decline in screening rates across all age groups. Biannual prevalence declined by 9, 13, and 15 percentage points as compared to the 2006 biannual rates for

Table 2.2: Logistic Regression Results of Mammography Receipt within Twelve Months of Interview by Age Group, 1993-2012

	Age 40-49	Age 50-75	75 and Older
	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age	1.085*** (1.082 - 1.088)	1.011*** (1.010 - 1.012)	0.929*** (0.927 - 0.932)
Any Insurance	3.036*** (2.955 - 3.120)	3.255*** (3.187 - 3.325)	1.584*** (1.439 - 1.743)
Married	1.192*** (1.172 - 1.213)	1.388*** (1.372 - 1.405)	1.304*** (1.269 - 1.339)
College Degree	1.278*** (1.256 - 1.300)	1.362*** (1.344 - 1.380)	1.375*** (1.337 - 1.415)
Employ	1.151*** (1.129 - 1.173)	1.051*** (1.037 - 1.065)	0.949** (0.900 - 0.999)
Black	1.399*** (1.359 - 1.440)	1.445*** (1.413 - 1.477)	1.137*** (1.082 - 1.195)
Hispanic	1.313*** (1.270 - 1.357)	1.199*** (1.165 - 1.234)	0.947 (0.883 - 1.015)
Asian/Pacific	1.000 (0.947 - 1.057)	1.074*** (1.022 - 1.128)	1.323*** (1.197 - 1.463)
Indian/Alaskan Native	0.910** (0.836 - 0.991)	0.866*** (0.816 - 0.919)	0.789*** (0.674 - 0.923)
Other	0.958 (0.900 - 1.019)	0.829*** (0.795 - 0.865)	0.872*** (0.795 - 0.956)
2008	1.015 (0.982 - 1.048)	1.005 (0.983 - 1.028)	1.026 (0.984 - 1.071)
2010	0.949*** (0.919 - 0.981)	0.914*** (0.895 - 0.934)	0.893*** (0.857 - 0.930)
2012	0.949*** (0.918 - 0.981)	0.889*** (0.870 - 0.908)	0.824*** (0.791 - 0.859)
Northeast	1.593*** (1.549 - 1.638)	1.579*** (1.546 - 1.612)	1.334*** (1.283 - 1.387)
Midwest	1.268*** (1.240 - 1.296)	1.158*** (1.139 - 1.176)	1.088*** (1.055 - 1.121)
South	1.281*** (1.253 - 1.310)	1.150*** (1.132 - 1.168)	1.131*** (1.097 - 1.166)
Constant	0.007*** (0.006 - 0.007)	0.213*** (0.199 - 0.227)	274.666*** (218.780 - 344.828)
Observations	250,313	531,065	135,889

Odds Ratios. 95% confidence intervals in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Omitted categories: Omitted categories: 2006 (year), West (region), white (race), uninsured. Additional controls also include dummy variables for 1993-2004

Table 2.3: Logistic Regression Results of Mammography Receipt within Twenty Four Months of Interview by Age Group, 1993-2012

	Age 40-49	Age 50-75	75 and Older
	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age	1.128*** (1.124 - 1.131)	1.008*** (1.007 - 1.009)	0.924*** (0.922 - 0.927)
Any Insurance	3.299*** (3.215 - 3.385)	3.930*** (3.847 - 4.014)	1.757*** (1.596 - 1.935)
Married	1.251*** (1.228 - 1.275)	1.508*** (1.487 - 1.529)	1.361*** (1.320 - 1.404)
College Degree	1.392*** (1.366 - 1.419)	1.490*** (1.466 - 1.515)	1.414*** (1.369 - 1.461)
Employ	1.206*** (1.182 - 1.231)	1.082*** (1.065 - 1.099)	0.893*** (0.843 - 0.946)
Black	1.444*** (1.398 - 1.491)	1.691*** (1.645 - 1.738)	1.209*** (1.144 - 1.279)
Hispanic	1.321*** (1.275 - 1.369)	1.293*** (1.250 - 1.337)	0.928* (0.860 - 1.001)
Asian/Pacific	0.965 (0.909 - 1.023)	0.998 (0.942 - 1.058)	1.338*** (1.193 - 1.500)
Indian/Alaskan Native	0.957 (0.877 - 1.045)	0.914*** (0.855 - 0.978)	0.745*** (0.631 - 0.880)
Other	0.884*** (0.828 - 0.944)	0.791*** (0.754 - 0.829)	0.801*** (0.725 - 0.883)
2008	0.993 (0.958 - 1.029)	0.950*** (0.925 - 0.976)	1.001 (0.955 - 1.050)
2010	0.939*** (0.906 - 0.973)	0.892*** (0.869 - 0.915)	0.912*** (0.871 - 0.955)
2012	0.906*** (0.874 - 0.939)	0.869*** (0.846 - 0.892)	0.841*** (0.803 - 0.880)
Northeast	1.631*** (1.581 - 1.683)	1.586*** (1.545 - 1.628)	1.290*** (1.235 - 1.347)
Midwest	1.244*** (1.214 - 1.274)	1.097*** (1.077 - 1.118)	1.037** (1.004 - 1.071)
South	1.260*** (1.230 - 1.290)	1.106*** (1.086 - 1.126)	1.117*** (1.081 - 1.155)
Constant	0.002*** (0.002 - 0.002)	0.470*** (0.435 - 0.507)	805.962*** (634.605 - 1,023.587)
Observations	250,313	531,065	135,889

Odds Ratios. 95% confidence intervals in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Omitted categories: Omitted categories: 2006 (year), West (region), white (race), uninsured. Additional controls also include dummy variables for 1993-2004 women ages 40-49, 50-75, and 75 and older, respectively. Since 100% of women would be "due" for a mammogram by 2012, the results provide strong evidence of a decline in screening rates after the 2009 USPSTF guidelines had changed.

Figure 2.1 reports regression-adjusted mammography rates for each year. The screening rates were adjusted for the same demographic and socioeconomic characteristics, and regional variables included in the regression. Each one of the nodes was calculated by predicting marginal effects at the means of the explanatory variables for each year using the above regression coefficients.

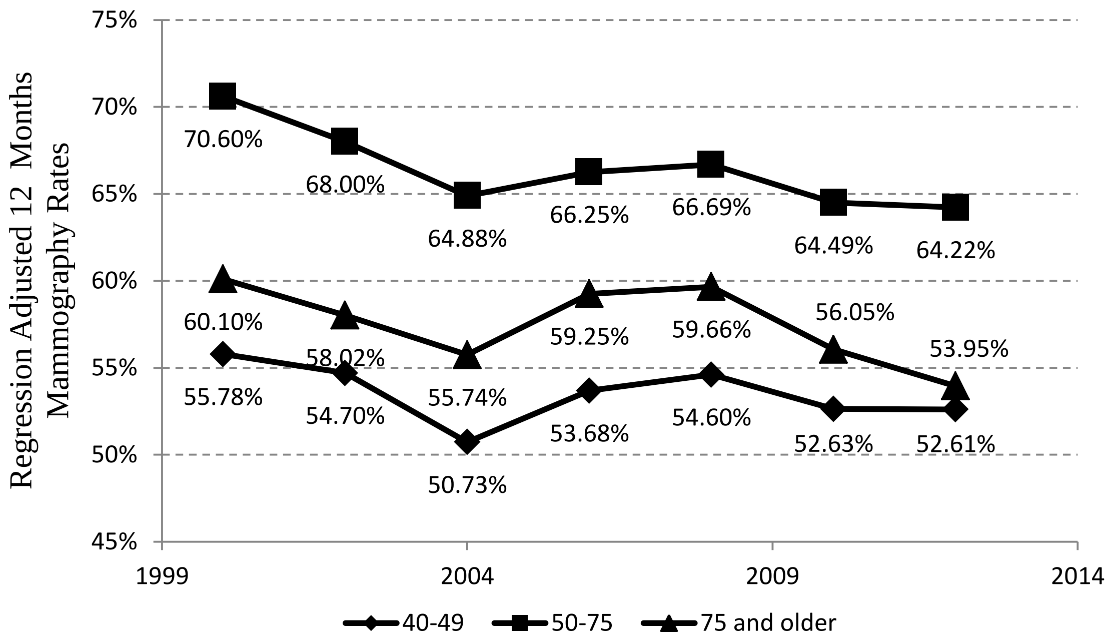

Figure 2.1: Regression Adjusted Twelve Months Mammography Rates, 1993-2012. The graph displays the proportion of women who reported having a mammogram in the past 12 months of the interview, adjusted for demographics, socioeconomic status, and region.

For women ages 40-49, the rate of mammography reported within the past 12 months of the interview fell from 54.60% in 2008 to 52.63% in 2010. The reduction of 1.97 percentage points (95% confidence interval [CI]: - 2.75 to -1.2). Among women ages 50-74, the rate fell from 66.69% in 2008 to 64.49%. The decrease was 2.20

percentage points (95% confidence interval [CI]: - 2.64 to -1.77). For women age 75 and older, the mammography rate in 2008 was 59.66%, whereas the rate in 2010 was 53.95%. The reduction of 3.61 percentage points (95% confidence interval [CI]: - 4.49.64 to - 2.72). The differences of predicted rates of mammography can be found in Table 2.4.

Table 2.4: Contrast of Predicted Rates of Mammography Receipt within Twelve Months of Interview, 2008-2012

Year	Contrast	Delta Method Standard Error	95% Confidence Interval
Ages 40-49			
2010 vs 2008	-0.0197	0.0040	(-0.0275 - -0.0120)
2012 vs 2008	-0.0199	0.0040	(-0.0279 - -0.0120)
Ages 50-74			
2010 vs 2008	-0.0220	0.0022	(-0.0264- - 0.0177)
2012 vs 2008	-0.0247	0.0022	(-0.0291- -0.0203)
Ages 75 and Older			
2010 vs 2008	-0.0360	0.0045	(-0.0449- -0.0272)
2012 vs 2008	-0.0570	0.0045	(-0.0656- -0.0481)

Notes: The contrasts were obtained by pairwise comparison of predicted mammography rates, by year and age group, using the regression coefficients. Standard errors and 95% confidence intervals were obtained using Delta method.

Figures 2.2, 2.3 and 2.4 plot predicted mammography rates within 12 months of the interview with 95% confidence intervals for women ages 40-49, ages 50-74, and age 75 and older, respectively, by year. Comparing the 95% confidence intervals for 2008 and 2010 clearly demonstrates that the two means (before and after) were statistically different from one another for women across all age groups: the 95% confidence intervals do not overlap. The graphs present clear evidence that the 2009 revision of screening recommendations have significantly reduced the prevalence of 12-month mammography among U.S. women of all age groups.

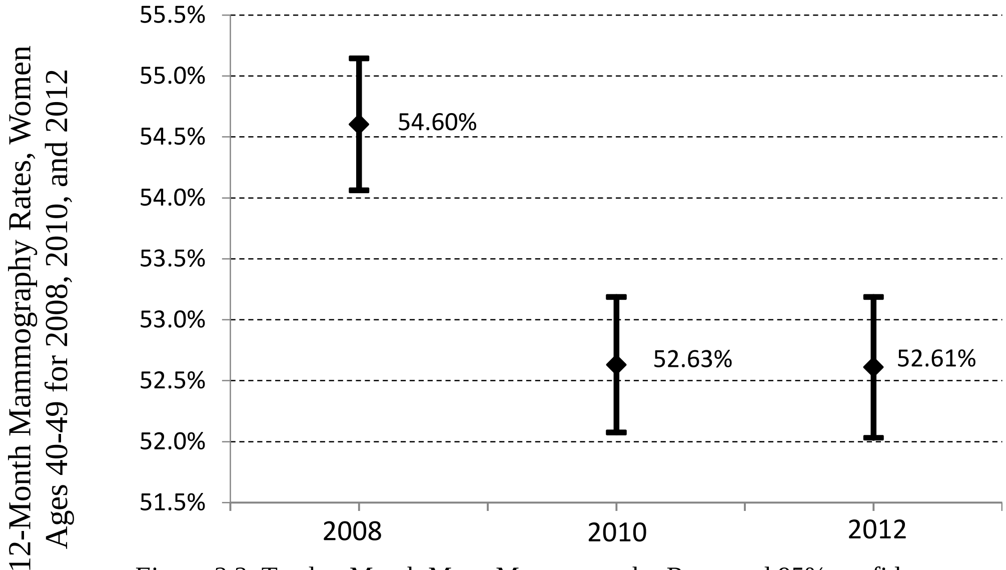

Figure 2.2: Twelve-Month Mean Mammography Rates and 95% confidence interval for Women Ages 40-49 for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women age 40-49 who reported having a mammogram in the past 12 months of the interview.

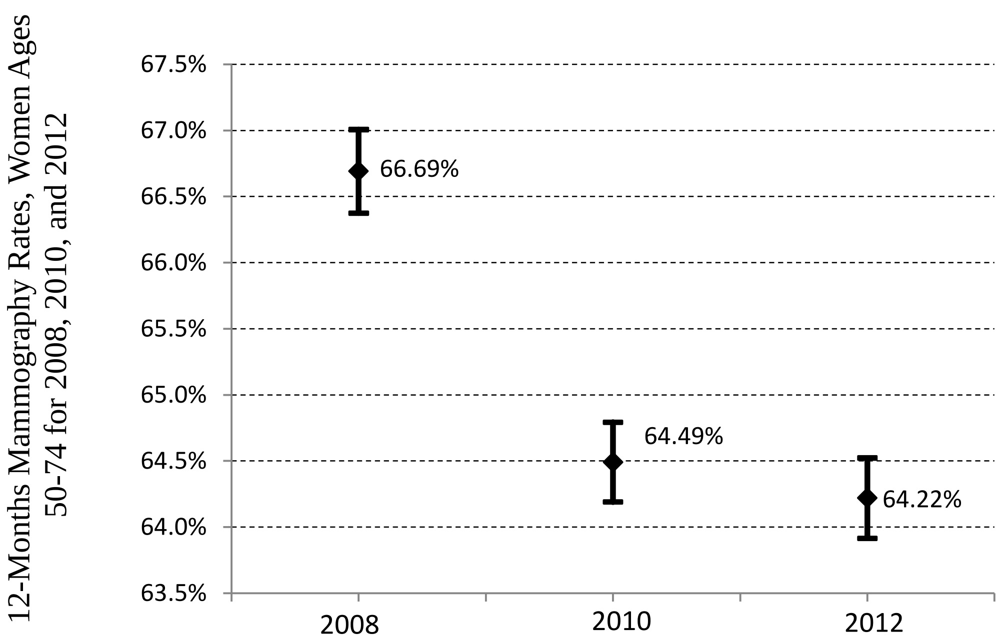

Figure 2.3: Twelve-Month Mean Mammography Rates and 95% confidence interval for Women Ages 50-74 for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women ages 50-74 who reported having a mammogram in the past 12 months of the interview.

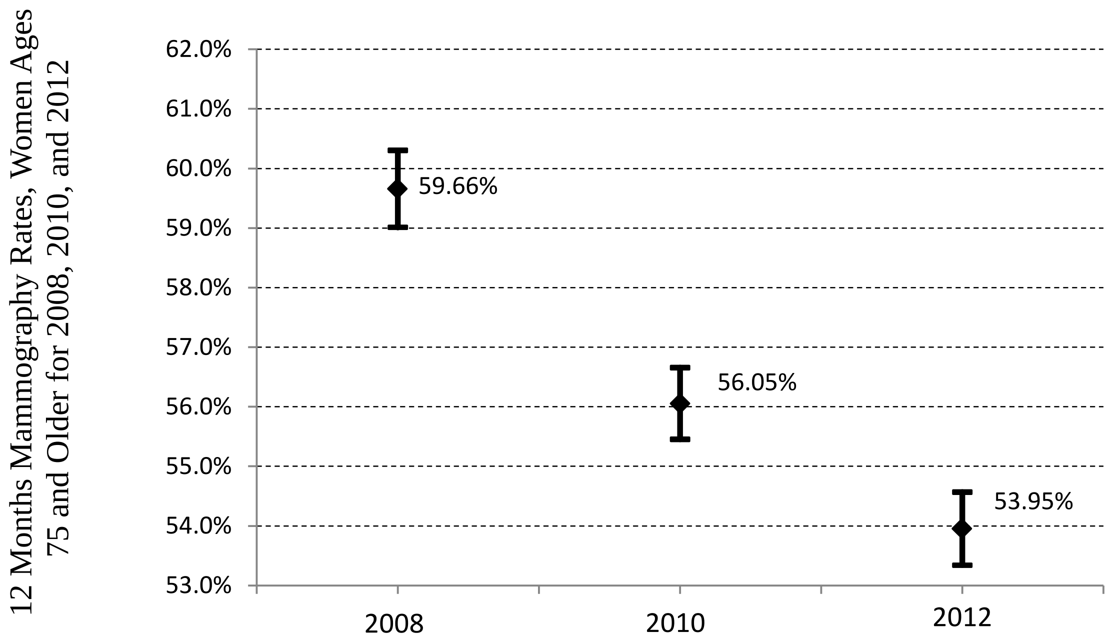

Figure 2.4: Twelve-Month Mean Mammography Rates and 95% Confidence Interval for Women Age 75 and Older for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women age 75 and older who reported having a mammogram in the past 12 months of the interview.

Moreover, there was a significant drop in rates of mammography receipt in the past 24 months among women of all ages immediately following the 2009 announcement. For women ages 40-49, the rate of mammography reported within the past 24 months of the interview fell from 71.30% in 2008 to 69.83% in 2010. The decrease of 1.47 percentage points (95% confidence interval [CI]: - 2.18 to -0.76). Among women ages 50-74, the rate declined from 81.58% in 2008 to 80.52%. The reduction of 1.05 percentage points (95% confidence interval [CI]: - 1.04 to -0.07). Finally, for women age 75 and older, the 24-month mammography receipt in 2008 was 74.80%, whereas the rate in 2010 was 72.88%. The difference was 1.92 percentage points (95% confidence interval [CI]: - 2.71 to -1.15) (See Appendix Table A.6 and Figures B.1-B.4).

2.5: Conclusion

Mammography rates declined after the USPSTF revised breast cancer screening recommendations in 2009. Twelve-month mammography receipt decreased by 1.97 (women ages 40-49), 2.20 (ages 50-74), and 3.61 percentage points (age 75 and older). Twenty-four month mammography receipt decreased by 1.47 (women ages 40-49), 1.05 (ages 50-74), and 1.92 percentage points (age 75 and older). The results indicate a significant immediate impact on mammography rates following the 2009 announcement. A two-year follow-up period provides further support to this conclusion, since the 2012 BRFSS survey respondents were 100% due to have a screening mammogram, and the 2012 screening rates were similar to those in 2010. These results are in contrast to findings in Howard and Adams (2012) of no significant “differences in mammography rates between 2010 and earlier years” (Howard and Adams, 2012, p. 487).

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Appendices

Appendix A: Additional Tables

Table A.1: Unadjusted State Level Means of Self-Reported Mammography Receipt within the Past Twelve Months of Interview,1993-2008

	Year of Interview											
State	1993	1994	1995	1996	1997	1998	1999	2000	2002	2004	2006	2008
AL	58.91%	49.21%	50.41%	48.31%	54.75%	55.66%	58.53%	58.81%	66.55%	62.20%	60.90%	59.04%
AK	50.00%	48.03%	53.31%	52.85%	54.91%	55.88%	59.11%	60.92%	53.74%	50.27%	55.40%	54.25%
AZ	50.11%	53.08%	56.56%	55.45%	43.51%	46.92%	62.90%	60.14%	58.59%	60.22%	59.77%	59.98%
AR	40.13%	42.61%	47.46%	46.50%	42.45%	49.94%	50.85%	59.39%	53.30%	52.66%	56.78%	58.87%
CA	55.89%	55.37%	56.24%	57.59%	56.03%	57.63%	58.83%	63.22%	61.35%	58.13%	62.20%	64.63%
CO	51.93%	45.32%	49.93%	53.67%	54.39%	53.97%	52.41%	55.27%	58.88%	56.43%	56.12%	58.42%
CT	57.17%	54.95%	55.32%	58.11%	58.39%	62.74%	68.91%	73.07%	67.70%	67.08%	68.67%	70.19%
DE	53.90%	57.76%	57.26%	55.78%	61.87%	64.01%	67.64%	73.64%	68.37%	69.54%	68.44%	70.46%
FL	50.10%	54.35%	58.93%	57.53%	60.95%	62.53%	63.65%	65.50%	66.27%	59.91%	62.55%	63.35%
GA	51.34%	53.27%	48.36%	53.45%	55.32%	55.49%	59.49%	59.67%	60.35%	58.74%	63.98%	65.65%
HI	58.68%	53.38%	61.12%	57.98%	56.22%	61.37%	58.48%	64.56%	60.51%	69.77%	62.32%	62.63%
ID	43.70%	39.96%	46.29%	42.60%	45.39%	49.45%	46.73%	50.24%	48.78%	47.98%	51.10%	52.93%
IL	47.50%	51.97%	51.94%	53.64%	53.29%	55.11%	55.12%	63.76%	60.39%	58.91%	57.00%	60.06%
IN	48.35%	49.47%	44.73%	50.67%	50.47%	53.69%	58.20%	59.10%	58.48%	54.18%	55.42%	58.07%
IA	47.46%	47.67%	49.58%	44.44%	47.42%	53.63%	56.85%	60.81%	65.35%	62.06%	64.57%	62.93%
KS	54.02%	56.25%	47.86%	50.09%	56.13%	56.56%	60.02%	60.47%	61.69%	63.38%	60.36%	63.59%
KY	44.33%	44.01%	46.20%	50.68%	52.32%	51.78%	55.90%	59.99%	59.69%	60.01%	55.99%	57.05%
LA	45.60%	47.46%	50.52%	49.69%	56.34%	52.68%	59.16%	64.38%	65.15%	59.04%	61.44%	65.33%
ME	51.64%	52.62%	52.81%	55.82%	62.37%	61.41%	63.13%	67.33%	67.53%	63.88%	68.06%	69.90%
MD	58.07%	62.48%	62.24%	62.79%	66.64%	63.65%	67.06%	68.67%	67.65%	62.55%	64.52%	63.44%
MA	57.14%	59.23%	61.22%	60.90%	70.20%	67.11%	65.08%	70.29%	69.09%	68.60%	70.42%	72.95%
MI	54.14%	53.69%	59.59%	57.87%	59.97%	61.73%	65.62%	69.04%	61.79%	62.70%	64.27%	64.64%

Table A.1: (Continued): Unadjusted State Level Means of Self-Reported Mammography Receipt within the Past Twelve Months of Interview,1993-2008

Year of Interview:

State	1993	1994	1995	1996	1997	1998	1999	2000	2002	2004	2006	2008
MN	50.16%	52.45%	52.73%	50.67%	53.27%	45.22%	56.05%	60.98%	64.45%	64.66%	66.67%	61.20%
MS	40.16%	38.87%	46.91%	43.51%	50.10%	49.71%	47.59%	52.48%	53.85%	50.97%	51.45%	55.51%
MO	50.00%	45.91%	52.43%	44.27%	51.67%	48.93%	49.59%	56.22%	55.79%	51.43%	54.69%	57.08%
MT	42.67%	46.65%	46.18%	52.20%	47.93%	50.58%	56.16%	58.70%	55.07%	54.01%	57.65%	57.83%
NE	41.84%	43.17%	47.78%	47.92%	52.66%	52.46%	60.29%	62.15%	59.14%	58.32%	57.30%	54.93%
NV	47.10%	48.87%	50.44%	47.45%	49.42%	52.05%	55.87%	56.86%	56.48%	51.15%	52.04%	53.55%
NH	54.42%	55.42%	58.23%	58.13%	61.01%	60.68%	64.09%	66.15%	67.18%	64.36%	67.26%	68.22%
NJ	48.00%	48.86%	41.30%	53.02%	56.91%	59.88%	62.41%	66.58%	62.96%	60.62%	63.26%	61.88%
NM	51.71%	52.38%	54.86%	53.24%	49.33%	50.59%	52.75%	60.63%	51.76%	51.59%	51.62%	54.27%
NY	57.42%	55.21%	59.69%	58.66%	60.02%	61.71%	64.79%	66.70%	62.98%	59.88%	64.88%	66.66%
NC	52.05%	52.09%	49.35%	52.51%	56.10%	57.79%	64.99%	65.13%	69.04%	61.60%	64.17%	64.30%
ND	50.09%	49.01%	49.37%	51.61%	53.63%	57.83%	58.31%	62.60%	59.84%	56.61%	62.84%	64.45%
OH	50.88%	46.56%	55.20%	50.21%	55.84%	59.98%	60.29%	63.55%	62.18%	59.64%	63.83%	61.34%
OK	40.28%	37.66%	49.85%	47.02%	47.75%	57.71%	51.05%	54.98%	55.49%	50.89%	49.20%	51.69%
OR	52.47%	51.79%	49.50%	58.14%	56.61%	57.48%	60.93%	62.30%	60.37%	57.27%	63.05%	63.56%
PA	49.30%	47.47%	49.00%	53.22%	55.34%	58.93%	62.74%	64.23%	62.25%	57.46%	60.01%	62.74%
SC	51.24%	48.52%	53.76%	54.57%	47.78%	58.37%	59.83%	63.21%	58.95%	56.25%	57.77%	61.56%
SD	47.61%	48.78%	46.55%	48.90%	54.33%	60.27%	59.24%	61.42%	63.09%	61.15%	58.47%	63.12%
TN	42.99%	43.37%	53.90%	53.16%	56.30%	58.86%	58.58%	63.50%	64.44%	62.81%	59.52%	58.27%
TX	49.63%	42.94%	48.79%	49.58%	51.44%	51.91%	56.89%	56.13%	51.74%	50.13%	58.08%	59.44%
UT	49.68%	48.60%	45.15%	47.54%	46.62%	49.94%	51.88%	52.28%	51.33%	49.10%	49.30%	50.38%
VT	48.83%	50.20%	53.15%	51.52%	52.93%	59.38%	59.24%	61.93%	63.70%	59.48%	64.07%	67.69%
VA	48.64%	53.62%	55.20%	57.90%	55.56%	59.30%	58.09%	58.74%	58.41%	59.71%	62.83%	63.53%
WA	54.38%	54.81%	54.45%	51.27%	51.96%	52.68%	56.07%	59.92%	57.06%	54.53%	59.19%	61.38%
WV	47.52%	45.50%	50.24%	54.47%	49.39%	56.02%	56.67%	61.27%	59.73%	58.28%	62.12%	61.63%
WI	45.60%	46.47%	49.64%	56.19%	51.52%	54.47%	57.78%	60.95%	63.22%	57.68%	60.46%	61.15%

Table A.2: Determinants of Individual Mammography Receipt within Twelve Months of Interview, Women Age 40 and Older, 1993-2008 (OLS)

	(1)	(2)	(3)	(4)
Age	0.0036***	0.0035***	0.0035***	0.0034***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Health Plan	0.2243***	0.2225***	0.2227***	0.2206***
	(0.0023)	(0.0044)	(0.0045)	(0.0027)
Married	0.0326***	0.0336***	0.0336***	0.0358***
	(0.0014)	(0.0017)	(0.0017)	(0.0015)
Education	0.0661***	0.0611***	0.0607***	0.0601***
	(0.0022)	(0.0037)	(0.0037)	(0.0025)
Hispanic	0.0619***	0.0674***	0.0669***	0.0653***
	(0.0031)	(0.0068)	(0.0066)	(0.0047)
Black	0.0918***	0.0864***	0.0860***	0.0811***
	(0.0023)	(0.0047)	(0.0046)	(0.0030)
Asian/Pacific	-0.0090*	-0.0081	-0.0091	-0.0116
	(0.0048)	(0.0221)	(0.0215)	(0.0130)
Indian/Alaskan	0.0039	0.0049	0.0062	0.0125
	(0.0073)	(0.0158)	(0.0168)	(0.0105)
Other	-0.0188***	-0.0251***	-0.0237***	-0.0257***
	(0.0052)	(0.0055)	(0.0056)	(0.0051)
Employed	0.0000	-0.0027	-0.0028	-0.0024
	(0.0015)	(0.0023)	(0.0023)	(0.0017)
Poor Health	-0.0393***	-0.0406***	-0.0406***	-0.0400***
	(0.0028)	(0.0026)	(0.0026)	(0.0028)
Income	0.0176***	0.0176***	0.0176***	0.0172***
	(0.0003)	(0.0007)	(0.0007)	(0.0004)
Constant	0.0139***	-0.0285**	-0.1636***	-0.0972***
	(0.0051)	(0.0117)	(0.0132)	(0.0079)
Observations	598,489	598,489	598,489	598,489
R-squared	0.0443	0.0537	0.0541	0.0602
Year FE		Yes		Yes
State FE		Yes	Yes	
County FE				Yes
Average Xs		Yes	Yes	Yes
Time			Yes	
Time Sq			Yes	
Time x State FE			Yes	
Time Sq. x State FE			Yes	

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state level) robust standard errors in parentheses.

Table A.3: Determinants of Individual Mammography Receipt within Twelve Months of Interview, Women Ages 40-49, 1993-2008 (OLS)

	(1)	(2)	(3)	(4)
Age	0.0194***	0.0188***	0.0188***	0.0189***
	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Health Plan	0.2234***	0.2184***	0.2181***	0.2163***
	(0.0035)	(0.0037)	(0.0038)	(0.0035)
Married	0.0003	-0.0000	-0.0000	0.0030
	(0.0027)	(0.0034)	(0.0034)	(0.0029)
Education	0.0209***	0.0197***	0.0196***	0.0205***
	(0.0050)	(0.0061)	(0.0061)	(0.0053)
Hispanic	0.0713***	0.0801***	0.0794***	0.0736***
	(0.0048)	(0.0074)	(0.0072)	(0.0062)
Black	0.0930***	0.0850***	0.0849***	0.0789***
	(0.0040)	(0.0051)	(0.0051)	(0.0047)
Asian/Pacific	-0.0195**	-0.0150	-0.0155	-0.0186
	(0.0078)	(0.0151)	(0.0147)	(0.0130)
Indian/Alaskan	-0.0038	0.0008	0.0063	0.0026
	(0.0121)	(0.0201)	(0.0219)	(0.0153)
Other	-0.0013	-0.0087	-0.0063	-0.0096
	(0.0092)	(0.0102)	(0.0105)	(0.0089)
Employed	0.0158***	0.0163***	0.0160***	0.0166***
	(0.0029)	(0.0031)	(0.0031)	(0.0028)
Poor Health	0.0057	0.0028	0.0030	0.0049
	(0.0065)	(0.0055)	(0.0056)	(0.0064)
Income	0.0165***	0.0169***	0.0169***	0.0165***
	(0.0005)	(0.0010)	(0.0010)	(0.0006)
Constant	-0.6803***	-0.6562***	-0.6067***	-0.7035***
	(0.0182)	(0.0232)	(0.0236)	(0.0206)
Observations	186,502	186,502	186,502	186,502
R-squared	0.0540	0.0649	0.0655	0.0786
Year FE		Yes		Yes
State FE		Yes	Yes	
County FE				Yes
Average Xs		Yes	Yes	Yes
Time			Yes	
Time Sq			Yes	
Time x State FE			Yes	
Time Sq. x State FE			Yes	

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state level) robust standard errors in parentheses.

Table A.4: Determinants of Individual Mammography Receipt within Twelve Months of Interview, Women Ages 50-75, 1993-2008 (OLS)

	(1)	(2)	(3)	(4)
Age	0.0027***	0.0028***	0.0028***	0.0028***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Health Plan	0.2433***	0.2405***	0.2408***	0.2383***
	(0.0032)	(0.0058)	(0.0059)	(0.0037)
Married	0.0251***	0.0282***	0.0284***	0.0309***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)
Education	0.0541***	0.0521***	0.0516***	0.0511***
	(0.0030)	(0.0038)	(0.0037)	(0.0031)
Hispanic	0.0604***	0.0689***	0.0682***	0.0671***
	(0.0042)	(0.0075)	(0.0073)	(0.0055)
Black	0.0869***	0.0856***	0.0852***	0.0813***
	(0.0030)	(0.0059)	(0.0057)	(0.0037)
Asian/Pacific	-0.0009	0.0051	0.0045	-0.0002
	(0.0067)	(0.0132)	(0.0129)	(0.0099)
Indian/Alaskan	-0.0070	0.0011	0.0013	0.0086
	(0.0096)	(0.0164)	(0.0171)	(0.0125)
Other	-0.0366***	-0.0336***	-0.0335***	-0.0338***
	(0.0067)	(0.0066)	(0.0068)	(0.0069)
Employed	-0.0150***	-0.0178***	-0.0177***	-0.0174***
	(0.0019)	(0.0022)	(0.0022)	(0.0020)
Poor Health	-0.0498***	-0.0497***	-0.0499***	-0.0493***
	(0.0035)	(0.0035)	(0.0035)	(0.0036)
Income	0.0198***	0.0193***	0.0194***	0.0187***
	(0.0004)	(0.0007)	(0.0007)	(0.0004)
Constant	0.1117***	0.0326**	-0.1176***	0.0014
	(0.0095)	(0.0140)	(0.0137)	(0.0118)
Observations	329,781	329,781	329,781	329,781
R-squared	0.0486	0.0570	0.0576	0.0667
Year FE		Yes		Yes
State FE		Yes	Yes	
County FE				Yes
Average Xs		Yes	Yes	Yes
Time			Yes	
Time Sq			Yes	
Time x State FE			Yes	
Time Sq. x State FE			Yes	

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state level) robust standard errors in parentheses.

Table A.5: Determinants of Individual Mammography Receipt within Twelve Months of Interview, Women Age 75 and Older, 1993-2008 (OLS)

	(1)	(2)	(3)	(4)
Age	-0.0161***	-0.0167***	-0.0167***	-0.0168***
	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Health Plan	0.0856***	0.0906***	0.0917***	0.0857***
	(0.0148)	(0.0127)	(0.0130)	(0.0143)
Married	0.0381***	0.0337***	0.0336***	0.0355***
	(0.0043)	(0.0036)	(0.0037)	(0.0043)
Education	0.0907***	0.0752***	0.0747***	0.0726***
	(0.0045)	(0.0058)	(0.0058)	(0.0048)
Hispanic	0.0174	0.0152	0.0147	0.0167
	(0.0111)	(0.0121)	(0.0119)	(0.0128)
Black	0.0495***	0.0445***	0.0424***	0.0376***
	(0.0079)	(0.0090)	(0.0089)	(0.0098)
Asian/Pacific	0.0717***	0.0797	0.0783	0.0828**
	(0.0149)	(0.0665)	(0.0650)	(0.0362)
Indian/Alaskan	0.0348	0.0159	0.0184	0.0348
	(0.0262)	(0.0359)	(0.0370)	(0.0303)
Other	-0.0101	-0.0223	-0.0203	-0.0187
	(0.0153)	(0.0162)	(0.0165)	(0.0144)
Employed	-0.0283***	-0.0340***	-0.0348***	-0.0334***
	(0.0083)	(0.0092)	(0.0092)	(0.0087)
Poor Health	-0.0689***	-0.0672***	-0.0673***	-0.0680***
	(0.0058)	(0.0063)	(0.0062)	(0.0058)
Income	0.0180***	0.0184***	0.0184***	0.0176***
	(0.0009)	(0.0011)	(0.0011)	(0.0010)
Constant	1.6449***	1.6097***	0.9386***	0.9200***
	(0.0349)	(0.0435)	(0.0451)	(0.0367)
Observations	82,206	82,206	82,206	82,206
R-squared	0.0462	0.0617	0.0627	0.0921
Year FE		Yes		Yes
State FE		Yes	Yes	
County FE				Yes
Average Xs		Yes	Yes	Yes
Time			Yes	
Time Sq			Yes	
Time x State FE			Yes	
Time Sq. x State FE			Yes	

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Geographically clustered (county or state level) robust standard errors in parentheses.

Table A.6: Contrast of Predicted Rates of Mammography Receipt within Twenty Four Months of Interview, 2008-2012

Year	Contrast	Delta Method Standard Error	95% Confidence Interval
Ages 40-49			
2010 vs 2008	-0.0147	0.0036	(-0.0218 - -0.0076)
2012 vs 2008	-0.0225	0.0037	(-0.0297 - -0.0152)
Ages 50-75			
2010 vs 2008	-0.0105	0.0018	(-0.0141- - 0.0070)
2012 vs 2008	-0.0117	0.0018	(-0.0153- -0.0082)
Ages 75 and Older			
2010 vs 2008	-0.0193	0.0040	(-0.0271- -0.0115)
2012 vs 2008	-0.0375	0.0041	(-0.0454- -0.0295)

Notes: The contrasts were obtained by pairwise comparison of predicted mammography rates, by year and age group, using the regression coefficients. Standard errors and 95% confidence intervals were obtained using Delta method.

Appendix B: Additional Figures

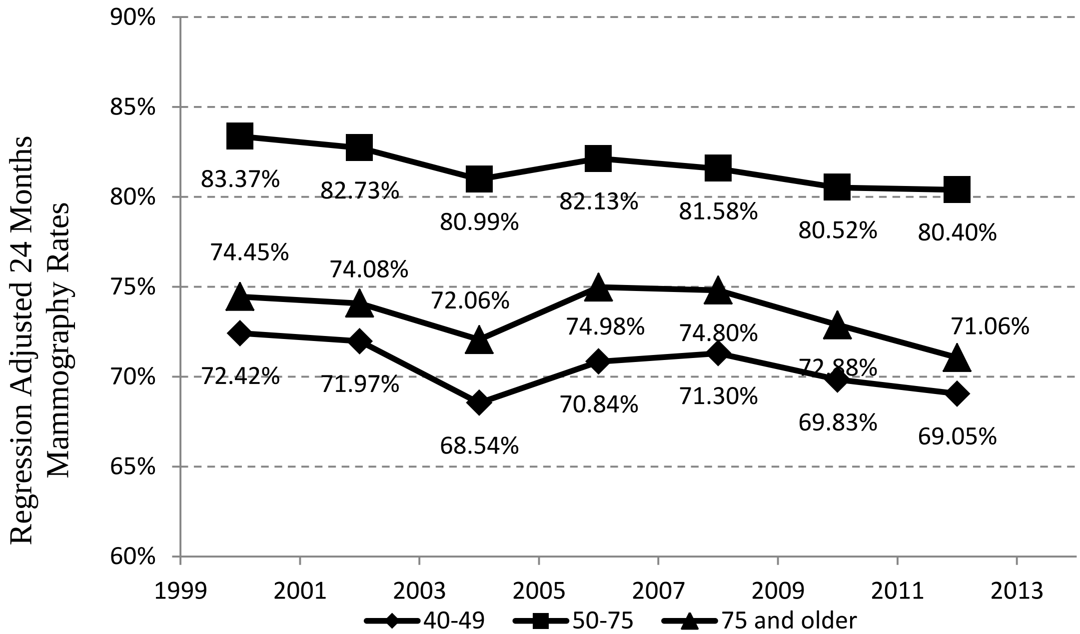

Figure B.1: Regression Adjusted Twenty-Four-Months Mammography Rates, 1993-2012. The graph displays the proportion of women who reported having a mammogram in the past 24 months of the interview, adjusted for demographics, socioeconomic status, and region.

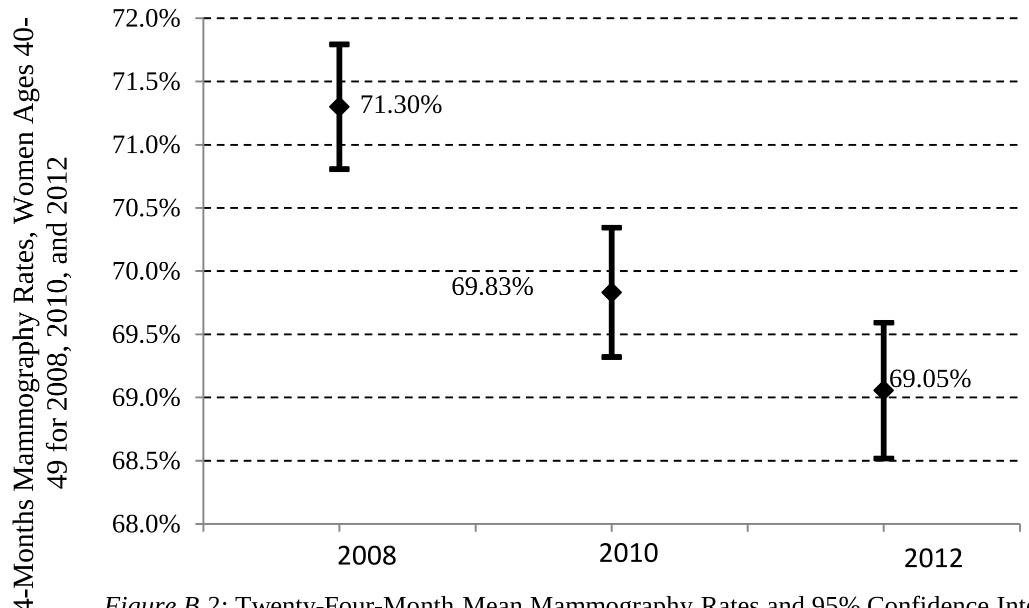

Figure B.2: Twenty-Four-Month Mean Mammography Rates and 95% Confidence Interval for Women Ages 40-49 for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women ages 40-49 who reported having a mammogram in the past 24 months of the interview for the years of 2008, 2010, and 2012

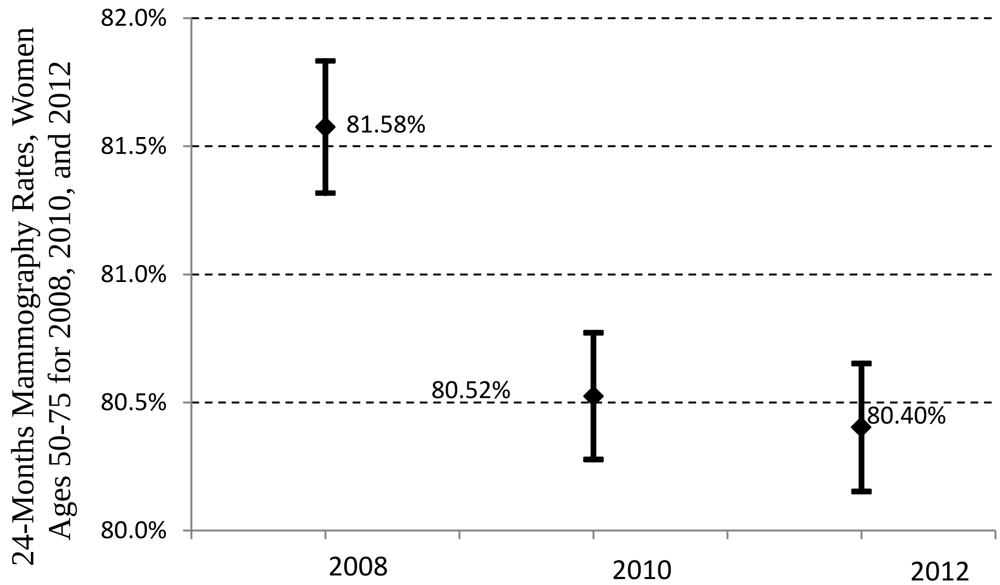

Figure B.3: Twenty-Four-Month Mean Mammography Rates and 95% Confidence Interval for Women Ages 50-74 for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women ages 50-74 who reported having a mammogram in the past 24 months of the interview for the years of 2008, 2010, and 2012

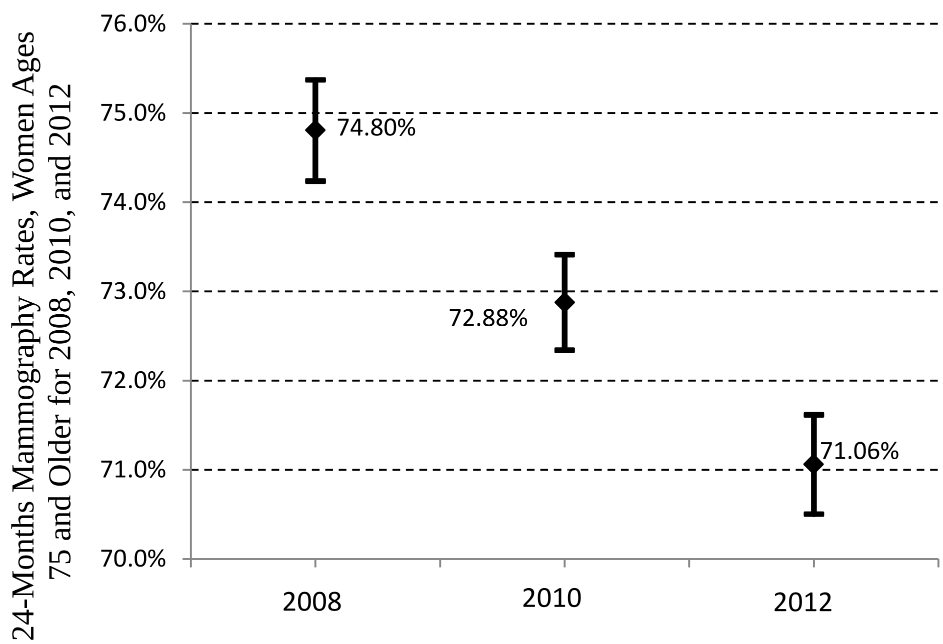

*Figure B.4:*Twenty-Four-Month Mean Mammography Rates and 95% Confidence Interval for Women Age 75 and Older for 2008, 2010, and 2012. The graph displays the 95% confidence intervals for the proportion of women ages 75 and older who reported having a mammogram in the past 24 months of the interview for the years of 2008, 2010, and 2012

Appendix C: Derivations of Equation 5

$$A_{igt} = \alpha + \beta\overline{A}_{gt} + \gamma X_{igt} + \delta\overline{X}_{gt} + v_{gt} + \varepsilon_{igt} \tag{2}$$

Taking expected value of both sides, obtain the following equation:

$$\overline{A}_{gt} = \alpha + \beta\overline{A}_{gt} + \gamma\overline{X}_{gt} + \delta\overline{X}_{gt} + v_{gt}$$

Rearranging and solving for $\overline{A}_{gt}$

$$\overline{A}_{gt} = \frac{\alpha}{1-\beta} + \frac{\overline{X}_{gt}(\gamma+\delta)}{1-\beta} + \frac{v_{gt}}{1-\beta} \tag{3}$$

Substituting back into previous equation:

$$A_{igt} = \alpha + \frac{\alpha\beta}{1-\beta} + \frac{\overline{X}_{gt}\beta(\gamma+\delta)}{1-\beta} + \frac{\beta v_{gt}}{1-\beta} + \gamma X_{igt} + \delta\overline{X}_{gt} + v_{gt} + \varepsilon_{igt}$$

$$= \frac{\alpha(1-\beta)+\alpha\beta}{1-\beta} + \frac{\overline{X}_{gt}\beta\gamma + \overline{X}_{gt}\beta\delta}{1-\beta} + \frac{\overline{X}_{gt}\delta(1-\beta)}{1-\beta} + \gamma X_{igt} + \frac{\beta v_{gt}}{1-\beta} + \frac{v_{gt}(1-\beta)}{1-\beta} + \varepsilon_{igt}$$

$$= \frac{\alpha - \alpha\beta + \alpha\beta}{1-\beta} + \frac{\overline{X}_{gt}\beta\gamma + \overline{X}_{gt}\beta\delta + \overline{X}_{gt}\delta - \overline{X}_{gt}\beta\delta}{1-\beta} + \gamma X_{igt} + \frac{\beta v_{gt} - \beta v_{gt} + v_{gt}}{1-\beta} + \varepsilon_{igt}$$

$$= \frac{\alpha}{1-\beta} + \frac{\overline{X}_{gt}\beta\gamma + \overline{X}_{gt}\delta}{1-\beta} + \gamma X_{igt} + \frac{v_{gt}}{1-\beta} + \varepsilon_{igt}$$

$$= \frac{\alpha}{1-\beta} + \frac{\overline{X}_{gt}(\beta\gamma+\delta)}{1-\beta} + \gamma X_{igt} + \frac{v_{gt}}{1-\beta} + \varepsilon_{igt} \tag{5}$$

Appendix D: USPSTF Breast Cancer Screening Recommendations

2002	All ages: The U.S. Preventive Services Task Force (USPSTF) recommends screening mammography, with of without clinical breast examination (CBE), every 1 to 2 years for women ages 40 and older
2009	**Aged 40 to 49**: The USPSTF recommends against routine screening mammography in women aged 40 to 49 years. The decision to start regular, biennial screening mammography before the age of 50 years should be an individual one and take patient context into account, including the patient's values regarding specific benefits and harms. **Aged 50 to 74**: The USPSTF recommends biennial screening mammography for women aged 50 to 74 years. **Ages 75 and older**: The USPSTF concludes that the current evidence is insufficient to assess the additional benefits and harms of screening mammography in women 75 years or older.
Current	The U.S. Preventive Services Task Force (Task Force) has started the process of updating its recommendation on screening for breast cancer.

Appendix E: Mammography Receipt Question as it Appears in BRFSS

If respondent is male, go to next section.

I. A mammogram is an x-ray of each breast to look for breast cancer. Have you ever had a mammogram?

1. Yes 1
2. No [Go to next question] 2
3. Don't know / Not sure [Go to next question] 3
4. Refused [Go to next question] 4

How long has it been since you had your last mammogram?

Read only if Necessary

1. Within the past year (1 to 12 months ago)..1
2. Within the past 2 years (1 to 2 years ago)..2
3. Within the past 3 years (2 to 3 years ago)..3
4. Within the past 5 years (3 to 5 years ago)..4
5. 5 or more years ago...5
6. Don't know/Not sure..7
7. Refused 9

About the Author

Natallia Gray graduated magna cum laude from the University of Southern Maine with a B.S. in Economics in 2008. In 2009, she was accepted into the University of South Florida's (USF) Ph.D. in Economics program and was awarded a graduate fellowship for her first year of doctoral studies. Her fields of study included health economics, public finance, and urban and regional economics.

Mrs. Gray received a distinction by the economics department in passing her microeconomics/mathematical economics qualifying exam. In 2013, Mrs. Gray was awarded the Dissertation Completion Fellowship by the USF Graduate School in recognition of the importance and quality of her research. She was employed by the Economics Department as a teaching assistant for the period of 2010-2013.