Social Interactions and Breast Cancer Prevention:

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Abstract

A large body of literature has documented the influence of peer group behavior on individual choices. This paper examines 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 in 12 months prior to being interviewed, including ordinary least squares, fixed effects, the split sample instrumental variable approach, and a falsification test.

The results support the hypothesis that social interactions impact the decision to have a mammogram. For all women over age 40, I find a strong evidence of social interactions associated with individual's education, employment, and select ethnicities. In addition, uniquely for women ages 40-49, the decision to have screening is subject to peer influences through the ownership of health insurance. Lastly, for women age 75 and older, being married and aging are significantly associated with peer influences a decision to have a mammogram. Peer effects are strongest for women over age 75 when state was considered as a peer group.

JEL Classification: I12, I19, A14
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1. Introduction

Breast cancer is one of the most feared diseases among women: 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 is the second leading cause of cancer deaths, with more than 40,000 deaths annually (American Cancer Society, 2013). Getting a screening mammogram on a regular basis is recognized as the most effective way of early detection of breast cancer. Currently, majority of the health organizations in the U.S. recommend that women ages 50-74 undergo routine annual mammography[2] (Table A1), 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 ages 50-74 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 encourage action by lowering the price of participation. However, since annual screening mammography is 100% covered under the Patient Protection and Affordable Care Act (2010), less conventional methods may be needed to reach the current policy goal.

Previously published 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

[2] November 16, 2009, the U.S. Preventive Services Task Force (USPSTF) recommended biennial screening for women ages 50-74 and recommended against routine screening for women ages 40-49 .The new recommendation is consistent with the World Health Organization (WHO) guidelines. However, since the announcement generated a huge public outcry in the U.S., the 2009 recommendation did not affect the insurance coverage. Under the Affordable Care Act (2010), annual mammograms for all women over 40 are reimbursed at 100%. There is also no general agreement among the organizations about the age at which to discontinue routine screening. A summary of the most recent recommendations by organizations in the U.S. is provided in the Appendix.

(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 paper 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 merely establish whether social effects are present in breast cancer screening decisions and to measure their magnitude by calculating the so-called “social multiplier”.

To estimate the social multiplier, I employ a strategy developed by E. Glaeser and Scheinkman (2001) 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.

The literature on social interaction and economic decision-making started with the seminal paper of Duesenberry (1949), who examined the effects of a reference group on consumer behavior. Since 1949, social interactions have been shown to be 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, 1995), labor productivity (Falk & Ichino, 2006), labor force participation (Bernheim, 1994;

Fajnzylber, 2002), investing in the stock market (Hong, Kubik, & Stein, 2004), the success of micro-financing programs (S. Li, Liu, & Deininger, 2012), educational outcomes (Winston & Zimmerman, (2004); Sacerdote (2001); Kremer and Levy (2008)), and academic cheating (Carrell, Malmstrom, & West, 2008).

In the health economics literature, several papers examine the social determination of individual health outcomes and behavior, such as body weight (Auld, 2011), fertility rates in developing countries (Canning, Günther, Linnemayr, & Bloom, 2013), teen smoking (Fletcher, 2010; Krauth, 2007; Powell, Tauras, & Ross, 2005; Wang, Fitzhugh, Westerfield, & Eddy, 1995), drug and alcohol use (Duncan, Boisjoly, Kremer, Levy, & Eccles, 2005), and initiation of sexual activity (Ali & Dwyer, 2011; Card & Giuliano, 2012).

A smaller number of published works look at the effect of social interactions on the adoption of preventive health behaviors. Among these, Rutenberg et al., (1997) present evidence from Kenya, and Rogers et al., (1981) from Korea, that women whose networks largely adopted contraception were themselves more likely to use contraceptives than women whose networks had not tried family planning. Miguel et al., (2003) find significant evidence of social learning among children during the introduction of deworming drugs in Kenyan schools. Dearden, Pritchett, and Brown (2004) determine that a mother's ability to prevent dehydration and possible death of a child during episodes of diarrhea in Bolivia and Madagascar was positively associated with her neighbors' knowledge of the correct preventive health actions. Finally, Apouey and Picone (2014) provide evidence of the social spillovers in prenatal care and malaria preventive behavior in Sub-Saharan Africa.

Closer to my study, several small-scale community-and worksite-based studies examine the association between the level of social support and participation in breast cancer screening. Glanz et al. (1992) find that knowing someone with breast cancer increases the likelihood of individual mammography. Allen et al. (2008) demonstrate 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. Additionally, they find that for women over age 52, the perception that friends and family approve of mammography is associated with a 46% increase in likelihood of mammography. Finally, Cahalan (1968) and Presser and Stinson (1998) show 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.

My results support the hypothesis that social interactions impact the decision to have a mammography. 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.

2. A 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:

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

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

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:

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

If a woman chooses to screen $(A_{igt} = 1)$, then $U_1^i = \theta_{igt} - \dfrac{\beta(1-\overline{\mathrm{A}}_{gt})^2 + (1-\beta)}{2}$, and if a woman chooses not to screen $(A_{igt} = 0)$, then $U_0^i = -\dfrac{\beta(0-\overline{\mathrm{A}}_{gt})^2}{2} = -\dfrac{\beta(\overline{\mathrm{A}}_{gt})^2}{2}$. If screening is preferred to no screening $(U_1^i > U_0^i)$, then the following inequality should hold:

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

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

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

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

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

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, we 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:[3]

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

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 (v_{gt}) , and an individual idiosyncratic component (ε_{igt}) , written as follows:

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

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

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

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

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

[3]The solution to utility maximization assumes that A_{igt} is continuous, which may not be realistic. Therefore, I treat Equation (1) as a linearization of some unknown nonlinear function that represents the true solution.

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 formation, the simultaneity of peer influences, and correlated effects.

The *endogeneity of the peer group* formation occurs when people choose friends based on similar characteristics (smokers may be more likely to become friends with other people who smoke, for example). In economic analysis, this issue is typically addressed by finding a suitable instrumental 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 can 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-size 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:

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

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

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 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 alone, and allows for the estimation of γ consistently.

The following two assumptions are made:

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[4], 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 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 (δ = 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 ($\delta = 0$

[4] 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.

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.

3. Econometric Strategy

3.1: The Main Approach to Estimating the Social Multipliers

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

$$\mathrm{A}_{igt} = \frac{\alpha}{1-\beta} + X_{igt}\gamma + \overline{X}_{gt}\left(\frac{\beta\gamma+\delta}{1-\beta}\right) + \frac{v_g}{1-\beta} + \frac{v_t}{1-\beta} + \varepsilon_{igt}$$, 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). Unbiased and efficient estimates are obtained by using Ordinary Least Squares (OLS) with White robust standard errors clustered by geographical clusters. In addition, I assume 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 in the individual decision to undergo screening, I include dummy variables for state or county (depending on which one is considered as a peer group) and the year of the interview. It is important to note that including state or county dummy variables, however, will not allow estimating the impact of $\overline{X}_{gt}$, because they are invariant to time-specific group effects and will be cancelled out.

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

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

Including the state or county and year dummy variables allow to control for the correlated effects incorporated in v_{gt} and to minimize the omitted variable bias. Year dummy variables will capture time variant effects that were affected all group in the same way. Such affects can account for changes in technology that would make people more/less likely to undergo screening (e.g. the introduction of digital mammography in early 2000s), and control for any time-specific national public health interventions and breast cancer screening campaigns. State or county dummies will control for in the unobserved factors that influence breast cancer prevention that are 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 public health interventions.

Next, I calculate 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 use 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 test the hypothesis that the obtained ratios are significantly greater than unity.

Each year of the surveys comes with the weights that could be used to account for the different sampling probabilities of each woman in the population. I use 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).

3.2: Empirical Specification

Peer Groups: Peer groups consisted of women of the same age in the county or state. First, I allowed all women over age 40 in the county or state to be affected by all other women over age 40 in the same county or state. Then I stratified the analysis by age-groups, where only age-specific peers could influence individual woman's screening decision: for example, the peer group for women ages 40-49 consists of other women ages 40-49 in the same county or state, and so.

Dependent Variable: I considered annual (as opposed to biennial or triennial) mammography visits to be the dependent variable, since recommendations of an annual mammography were 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 in terms of 2008 purchasing power 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 characteristic.

3.3: 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 (general equilibrium effects, for instance). 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.

3.4: 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 sub-means 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.

4: Data and Summary Statistics

4.1 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 for inflation.

4.2: 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. In view of the 2009 changes in the USPSTF recommendations regarding the frequency of routine breast cancer screening, 2008 was the last year 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.

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 (Table 1). 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).

4.3 Descriptive Statistics

The d*ependent variable:* For 1993-2008, the mean use of a mammogram in the 12 months prior to the interview for all 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 month of the survey.

Explanatory variables summary: 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 ethnicity.

In comparison to women in the other age groups, women ages 40-49 had the highest proportion of uninsured (12.1%), but also healthy individuals (96.6%). In addition, women in this age group had the highest rates of being married (63.4%), at least a high school level of education completion (94.1%), being employed (77.6%), and the highest mean household income ($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).

The oldest group of women, women age 75 and older, had the highest proportion of individuals with health insurance (98.6%), but also persons 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 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.

The means at the county and state levels are rather similar to the means at the individual level (Tables 2 & 3). Note that 598,489 individual level observations aggregate into 9,944 county level observations and 575 state level observations.

4.4: Geographic Variation in Mammography Use.

Figure 1 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.

For 1993-2008, the average mammogram rate varied significantly between different states (Table A.1). For example, in 2008, the rate of mammography use within twelve months of the interview ranged from 50.36% (Utah) to 72.95% (Massachusetts). 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 (Miller, King, Joseph, & Richardson, 2012).

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).

5: Results

5.1: Determinants of Individual Mammography Receipt

Results of the individual level regressions of mammography use in the past 12 months are reported in Table 4. Column (1) presents results for all women over age 40, whereas column (2), (3), and (4) contain the results for women ages 40-49, ages 50-75, and age 75 and older. The effects of explanatory variables on the receipt of a mammogram in the past 12 month is differed between the age groups, suggesting that multipliers may not be associated with the same explanatory variables among 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 individual woman’s probability of screening 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 in this age group (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 seeking a mammogram.

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5.2: Evidence of Social Spillover in Breast Cancer Screening

Table 5 presents the individual and group level regression results side by side for all women age 40 and older. Column (1) reports individual-level regression coefficients with dummy control variables for county and year of the interview, whereas column (2) report respective coefficients from county level regressions. Note that the number of observations decreases sharply as we move from column (1) to column (2): there are 598,489 women in column (1), but they are aggregated into 9,944 county level observations in column (2). Column (3) contains regression coefficients with dummy control variables for the state and year of the interview, and column (4) report respective coefficients from state level regressions. Tables 6, 7, and 8 present results for women ages 40-49, age 50-74, and age 75 and older in the same way.

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 individual effect when state is considered as a peer group (0.20). 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.

Similarly to the results obtained for all women age 40 and older, the analysis stratified by 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.

Although not evident from the regressions result for all women over age 40, there appears to be an increase in the coefficients associated with being employed for women across all age groups in the stratified analysis. To illustrate, for women ages 40-49, the coefficient increases from the individual- level (0.02) to county (0.04) and state (0.09) levels, whereas for women ages 50-75 the employment coefficient becomes progressively negative from -0.02 at the individual level to -0.04 at both county and state levels. Since in both cases the ratio of the coefficients will produce a positive ration, one needs to be mindful of the direction of the spillover when interpreting social interactions as measured by the social multiplier.

Specific to women ages 40-49, in addition to evidence of spillover associated with education, there was a modest increase in the coefficient on having a health plan from the individual- level (0.22) to county (0.25) and state (0.26) levels.

For women over age 75, in addition to education, employment, and select ethnicities, unique to this group were the spillovers associated with being married and age. Turning one year older decreased the likelihood of a mammogram by 1.67 percentage points for women age 75 and older. 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. Finally, the effect of being married or living as a couple increased in magnitude from 3.6 percentage points at the individual level to 5.1 percentage points at the county level and 16 percentage points at the state level. This suggests that the proportion of same-aged married individuals may have a positive effect on the probability of screening for a woman age 75 and older. Among all age groups considered, the number of coefficients indicating existence of social influences in mammogram was the largest for women over age 75 with state considered as a peer group.

5.3: The Social Multipliers in Mammography Use

The social multipliers in breast cancer screening are presented in Table 9. The vectors of social multipliers were computed by dividing the coefficients from the group-level regressions in columns (2) and (4) by the coefficients of the same explanatory variable from the individual-level regression in columns (1) and (3). In the presence of social spillovers, this ratio should be significantly 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.

Education multiplier: in regards to breast cancer, the biggest multiplier was associated with a woman's education. With the exception of the ratio for women 50-75 when county is considered as a group, the multipliers associated with education were statistically significant and greater than unity across all age groups. For all women over age 40, I found a county-level multiplier in education of 1.80 and a state-level multiplier of 3.29. The multiplier associated with education was the largest-in-magnitude for women ages 40-49, in comparison to women of other age groups: equaled 3.12 at the county level and 8.94 at the state level. This suggests that education plays an especially important role in the decision to undergo mammography for women ages 40-49. For women age 50-75, the multiplier in education was statistically significantly greater than unity at the county (1.76) and state (3.11) levels. Finally, for women over age 75, the effect of education on breast cancer screening was 2.8 times larger at the state-level than the individual-level effect.

Multiplier associated with education 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. This multiplier 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.

Select ethnicities multiplier: in addition, I found significant evidence of peer effects in mammography among black (1.31 county- and 1.55 state-level) and other race/ethnicity (5.94 county and 17.46 state-level) women age 40 and older. These multipliers may indicate 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). However, since these multipliers did not always appear in the age-stratified analysis, the results should be interpreted with some caution.

Workplace multiplier: the analysis stratified by age-group revealed group-specific multipliers associated with being employed. One possible explanation for this employment multiplier is that turning 40, 50, and 75 years old is a significant milestone in every woman's life that is usually observable to others, including co-workers. In particular, 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 colleague's preventive behavior increased the effect of employment by 2.6 and 6.0 times at the county and state levels for women age 40-49 in comparison to the individual-level effect of employment. In contrast, women over age 75 might be subject to social pressure to gradually discontinue screening through her place of employment.

Uniquely for women 40-49 years old, there was a modest, statistically significantly greater-than-unity multiplier associated with having health insurance at the county (1.20) and state (1.17) 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.

The strongest evidence of social interactions was found for women age 75 and older when state was used as a peer group, where nearly two thirds of the ratios were significantly greater than unity. Specifically, in addition to multipliers associated with education, select ethnicities, being employed, and health plan, I found multipliers associated with age and being married.

The county-level age multiplier equaled 1.19 and the state-level age multiplier equaled 1.69. 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 1.44 at the county-level and 4.74 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.

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.

5.4: Falsification Test Results

Table 10 reports ratios of group level effects to individual level effects when using height as a new dependent variable. For the most part, the results indicate that there are no social spillovers associated with individual's height. The negative ratios provide evidence against the existence of a multiplier in height, since they violate the assumption that γ and δ have the same sign. The positive ratios at the county and state levels are either less than one, insignificant, or not statistically different from one. The only two exceptions where coefficients are greater than unity are the coefficients on the dummy variable for Hispanic in the first two columns; luckily, in breast cancer screening application these exact coefficients were not predicted to be greater than unity, and therefore the two ratios do not undermine my main results.

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 some additional credibility to the main approach to estimating social multipliers in the breast cancer at both the county and the state levels.

5.5: Split-Sample Instrumental Variable Results

Table 11 contains the results of the split sample instrumental variable (SSIV) method that corrects for measurement error in $\overline{X}_{gt}$ and $\overline{A}_{gt}$ in the group level regressions. Column (1) reports the coefficients obtained from state level OLS fixed effects regression (from Tables 7-10), whereas column (2) shows coefficients from state level regressions using SSIV method with fixed effects.

The coefficients in the group level regressions for all the dependent variables associated with social spillover are 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 are in general a bit larger than those obtained by OLS, which implies a downward bias in the original estimates of the social multipliers.

6: Concluding Remarks

6.1: Conclusion

Breast cancer screening rates are below the current public policy goal. In this paper, 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, select ethnicities, and a woman's place of employment 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 all women over age 40, 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. As evidenced by the spillover through the place of employment, on-site employer sponsored programs may be an effective way to prompt women ages 40-49 to participate in screening, while at the same time, such programs may reduce the participation among women over age 75.

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 the ownership of health insurance, while for women age 75 and older, social influence in regards to mammography is significantly related to aging and being married. Furthermore, for women over age 75 when state was used as a peer group, I found that social interactions in regards to mammograms were the strongest. From the public policy perspective, this is a thought-provoking finding since screening guidelines are not clear for this age group, and the decision to have a routine mammograms is an individual womna's choice.

The overarching finding that what other women do may matter 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.

6.2: 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 annual mammography being perceived as a socially desirable behavior: not only telephone respondents are more likely to present themselves in socially desirable ways than face-to-face interview respondents (Holbrook et al., 2003), but women, especially Non-Hispanic and non-white women, also 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.

6.3: 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.

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Table 1: 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 (0.490)	0.520 (0.500)	0.655 (0.475)	0.559 (0.497)
Age	58.22 (12.79)	44.43 (2.864)	60.45 (7.116)	80.54 (4.493)
Health Plan	0.916 (0.277)	0.879 (0.326)	0.920 (0.271)	0.986 (0.116)
Married	0.520 (0.500)	0.634 (0.482)	0.530 (0.499)	0.222 (0.415)
Education	0.896 (0.305)	0.941 (0.236)	0.895 (0.306)	0.799 (0.401)
Hispanic	0.0466 (0.211)	0.0638 (0.244)	0.0424 (0.201)	0.0245 (0.155)
Black	0.0801 (0.271)	0.0942 (0.292)	0.0796 (0.271)	0.0501 (0.218)
Asian/Pacific Islander	0.0170 (0.129)	0.0223 (0.148)	0.0151 (0.122)	0.0127 (0.112)
American Indian / Alaskan Native	0.00784 (0.0882)	0.00889 (0.0939)	0.00813 (0.0898)	0.00432 (0.0656)
Other	0.0153 (0.123)	0.0155 (0.124)	0.0158 (0.125)	0.0127 (0.112)
Employ	0.514 (0.500)	0.776 (0.417)	0.483 (0.500)	0.0444 (0.206)
Poor Health	0.0619 (0.241)	0.0342 (0.182)	0.0676 (0.251)	0.102 (0.303)
Income ($10,000)	4.856 (2.957)	5.904 (2.977)	4.742 (2.867)	2.939 (2.090)
Observations	598,489	186,502	329,781	82,206

Notes. Mean coefficients. Standard deviations in parenthesis.

Table 2: 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 3: 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.

Table 4: Determinants of Individual Mammography Receipt within Twelve Months of Interview by Age Group, U.S. Women 1993-2008 (OLS FE)

	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 robust standard errors in parentheses

Table 5: 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, County FE (1)	County-Level OLS-FE (2)	Individual- Level OLS, State FE (3)	State-Level OLS-FE (4)
Age	0.0034***	0.0034***	0.0035***	0.0007
	(0.0001)	(0.0008)	(0.0002)	(0.0042)
Health Plan	0.2206***	0.2127***	0.2225***	0.0879
	(0.0027)	(0.0319)	(0.0044)	(0.1611)
Married	0.0358***	0.0236	0.0336***	-0.0493
	(0.0015)	(0.0196)	(0.0017)	(0.0755)
Education	0.0601***	0.1087***	0.0611***	0.2010**
	(0.0025)	(0.0291)	(0.0037)	(0.0956)
Hispanic	0.0653***	0.0456	0.0674***	-0.0209
	(0.0047)	(0.0436)	(0.0068)	(0.1405)
Black	0.0811***	0.1063***	0.0864***	0.1336*
	(0.0030)	(0.0264)	(0.0047)	(0.0757)
Asian/Pacific	-0.0116	-0.1875	-0.0081	-0.2739*
	(0.0130)	(0.1867)	(0.0221)	(0.1434)
Indian/Alaskan	0.0125	-0.0726	0.0049	-0.2097*
	(0.0105)	(0.1008)	(0.0158)	(0.1185)
Other	-0.0257***	-0.1524**	-0.0251***	-0.4385***
	(0.0051)	(0.0692)	(0.0055)	(0.1056)
Employed	-0.0024	0.0252	-0.0027	0.1276
	(0.0017)	(0.0214)	(0.0023)	(0.1057)
Poor Health	-0.0400***	-0.0155	-0.0406***	0.1270
	(0.0028)	(0.0350)	(0.0026)	(0.1794)
Income	0.0172***	0.0127***	0.0176***	0.0130*
	(0.0003)	(0.0034)	(0.0007)	(0.0073)
Constant	-0.0972***	-0.0743	-0.0285**	0.1321
	(0.0008)	(0.0638)	(0.0117)	(0.3681)
Observations	598,489	9,944	598,489	575
R-squared	0.0602	0.6051	0.0537	0.7642
Groups	n/a	2,413	n/a	48
County FE	Yes	Yes		
State FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Robust standard errors clustered by county (1), (2) and state (3), (4) are reported in parentheses.

Table 6: Individual- and Group-Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Ages 40-49, 1993-2008 (OLS-FE)

	Individual-Level OLS, County FE (1)	County-Level OLS-FE (2)	Individual- Level OLS, State FE (3)	State-Level OLS-FE (4)
Age	0.0189***	0.0182***	0.0188***	0.0046
	(0.0004)	(0.0031)	(0.0005)	(0.0116)
Health Plan	0.2163***	0.2597***	0.2184***	0.2560**
	(0.0034)	(0.0270)	(0.0037)	(0.0967)
Married	0.0030	-0.0085	-0.0000	-0.1391**
	(0.0029)	(0.0210)	(0.0034)	(0.0566)
Education	0.0205***	0.0661*	0.0197***	0.1764*
	(0.0053)	(0.0377)	(0.0061)	(0.1038)
Hispanic	0.0736***	0.0488	0.0801***	0.0059
	(0.0062)	(0.0426)	(0.0074)	(0.1261)
Black	0.0789***	0.0550	0.0850***	0.0388
	(0.0047)	(0.0382)	(0.0051)	(0.0837)
Asian/Pacific	-0.0186	-0.0125	-0.0150	-0.3273***
	(0.0130)	(0.0830)	(0.0151)	(0.1126)
Indian/Alaskan	0. 0026	0.0879	0.0008	-0.3986***
	(0.0153)	(0.1219)	(0.0201)	(0.0819)
Other	-0.0096	0.0435	-0.0087	-0.3422***
	(0.0089)	(0.0867)	(0.0102)	(0.0736)
Employed	0.0166***	0.0428**	0.0163***	0.0977
	(0.0028)	(0.0218)	(0.0031)	(0.0663)
Poor Health	0.0049	0.0614	0.0028	-0.2212
	(0.0064)	(0.0527)	(0.0055)	(0.1494)
Income	0.0165***	0.0133***	0.0169***	0.0182***
	(0.0006)	(0.0037)	(0.0010)	(0.0065)
Constant	-0.7035***	-0.7425***	-0.6562***	-0.2015
	(0.0206)	(0.1436)	(0.0232)	(0.5380)
Observations	186,502	9,761	186,502	575
R-squared	0. 0786	0.5135	0.0649	0.6767
Groups	n/a	2,251	n/a	48
County FE	Yes	Yes		
Group FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Robust standard errors clustered by county (1), (2) and state (3), (4) are reported in parentheses.

Table 7: Individual and Group Level Regressions of Mammography Receipt within Twelve Months of Interview, Women Ages 50-74, 1993-2008 (OLS-FE)

	Individual-Level OLS, County FE (1)	County-Level OLS-FE (2)	Individual-Level OLS, State FE (3)	State-Level OLS-FE (4)
Age	0.0028***	0.0007	0.0028***	-0.0043
	(0.0001)	(0.0014)	(0.0002)	(0.0042)
Health Plan	0.2383***	0.2077***	0.2405***	0.1715
	(0.0037)	(0.0299)	(0.0058)	(0.1153)
Married	0.0309***	0.0157	0.0282***	-0.1351***
	(0.0019)	(0.0192)	(0.0018)	(0.0492)
Education	0.0511***	0.0900***	0.0521***	0.1620*
	(0.0030)	(0.0260)	(0.0038)	(0.0831)
Hispanic	0.0671***	0.0800	0.0689***	0.0283
	(0.0055)	(0.0525)	(0.0075)	(0.1210)
Black	0.0813***	0.1208***	0.0856***	0.1372*
	(0.0037)	(0.0291)	(0.0059)	(0.0785)
Asian/Pacific	0.0002	-0.2474*	0.0051	-0.1885*
	(0.0099)	(0.1502)	(0.0132)	(0.1120)
Indian/Alaskan	0.0086	-0.1215	0.0011	-0.2044*
	(0.0125)	(0.0831)	(0.0164)	(0.1199)
Other	-0.0338***	-0.1462**	-0.0336***	-0.4765***
	(0.0069)	(0.0633)	(0.0066)	(0.1271)
Employed	-0.0174***	-0.0411*	-0.0178***	-0.0401
	(0.0020)	(0.0220)	(0.0022)	(0.0609)
Poor Health	-0.0493***	-0.0765**	-0.0497***	0.0212
	(0.0036)	(0.0349)	(0.0035)	(0.1037)
Income	0.0187***	0.0205***	0.0193***	0.0177**
	(0.0004)	(0.0032)	(0.0007)	(0.0086)
Constant	0. 0014	0.1620	0.0326**	0.5460
	(0. 0118)	(0.0991)	(0.0140)	(0.3377)
Observations	329,781	9,921	329,781	575
R-squared	0. 0667	0.5254	0.0570	0.6913
Groups	n/a	2,393	n/a	48
County FE	Yes	Yes		
Group FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Robust standard errors clustered by county (1), (2) and state (3), (4) are reported in parentheses.

Table 8: 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, County FE (1)	County-Level OLS-FE (2)	Individual-Level OLS, State FE (3)	State OLS-FE (4)
Age	-0.0168***	-0.0201***	-0.0167***	-0.0282***
	(0.0003)	(0.0021)	(0.0005)	(0.0079)
Health Plan	0.0857***	0.0491	0.0906***	0.6022***
	(0.0143)	(0.0805)	(0.0127)	(0.2163)
Married	0.0356***	0.0510**	0.0337***	0.1599*
	(0.0043)	(0.0219)	(0.0036)	(0.0823)
Education	0.0726***	0.0569***	0.0752***	0.2116***
	(0.0048)	(0.0213)	(0.0058)	(0.0693)
Hispanic	0.0167	-0.0849	0.0152	0.2398
	(0.0128)	(0.0618)	(0.0121)	(0.1689)
Black	0.0376***	0.0297	0.0445***	0.3734***
	(0.0098)	(0.0410)	(0.0090)	(0.0844)
Asian/Pacific	0.0828***	-0.0196	0.0797	0.1674
	(0.0361)	(0.1481)	(0.0665)	(0.5725)
Indian/Alaskan	0.0348	0.0504	0.0159	-0.5394*
	(0.0303)	(0.1267)	(0.0359)	(0.2916)
Other	-0.0187	0.0274	-0.0223	0.1721
	(0.0144)	(0.0844)	(0.0162)	(0.2445)
Employed	-0.0334***	0.0025	-0.0340***	-0.1599
	(0.0087)	(0.0490)	(0.0092)	(0.1484)
Poor Health	-0.0680***	-0.0394	-0.0672***	0.0252
	(0.0058)	(0.0270)	(0.0063)	(0.1247)
Income	0.0175***	0.0173***	0.0184***	0.0182**
	(0. 0010)	(0.0046)	(0.0011)	(0.0084)
Constant	0.9200***	1.8525***	1.6097***	1.8310**
	(0.03670)	(0.1915)	(0.0435)	(0.7694)
Observations	82,206	9,317	82,206	575
R-squared	0.0921	0.3966	0.0617	0.6333
Groups	n/a	2,183	n/a	48
County	Yes	Yes		
Group FE			Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. *** denotes significance at 1% level. ** denotes significance at 5% level.*denotes significance at 10% level. Robust standard errors clustered by county (1), (2) and state (3), (4) are reported in parentheses.

Table 9: Social Multipliers in Breast Cancer Screening among US Women

	County/ Individual Ratios				**State/Individual Ratios**			
	40 and Older	Ages 40-49	Ages 50-74	75 and Older	40 and Older	Ages 40-49	Ages 50-75	75 and Older
Age	0.990 (0.033) [0.925-1.055]	0.964 (0.051) [0.864- 1.064]	0.250 (0.108) [0.037-0.462]	**1.194***** (0.054) [1.089-1.299]	0.216 (0.004) [0.208-0.224]	0.246 (0.005) [0.236-0.256]	(+)/(-)	**1.687***** (0.048) [1.593-1.782]
Health Plan	0.964 (0.022) [0.921-1.007]	**1.201***** (0.040) [1.122-1.279]	0.872 (0.019) [0.834-0.910]	0.5725 (0.467) [-0.344-1.489]	0.395 (0.004) [0.387-0.403]	**1.172**** (0.019) [1.135-1.209]	0.713 (0.010) [0.694-0.732]	**6.646***** (1.185) [4.322-8.969]
Married	0.659 (0.110) [0.446-0.872]	(+)/(-)	0.510 (0.111) [0.291-0.728]	**1.437***** (0.213) [1.023-2.250]	(+)/(-)	**13,748***** (1,114) [11,563-15,932]	(+)/(-)	**4.744***** (0.654) [3.462-6.027]
Education	**1.808***** (0.103) [1.606-2.009]	**3.232***** (0.996) [1.280-5.184]	**1.760***** (0.168) [1.431-2.089]	0.784 (0.133) [0.523-1.045]	**3.291***** (0.122) [3.052 - 3.529]	**8.935***** (2.969) [3.115-14.754]	**3.110***** (0.175) [2.767-3.452]	**2.815***** (0.185) [2.451-3.178]
Hispanic	0.699 (0.045) [0.610-0.787]	0.664 (0.156) [0.358-0.970]	**1.193*** (0.121) [1.173-1.213]	(+)/(-)	(+)/(-)	0.074 (0.005) [0.064-0.083]	0.410 (0.027) [0.358-0.464]	**15.744***** (7.196) [1.640-29.848]
Black	**1.309***** (0.045) [1.221-1.398]	0.697 (0.156) [0.387-1.007]	**1.485***** (0.093) [0.956-1.430]	0.789 (0.889) [-0.953-2.531]	**1.545***** (0.044) [1.460-1.631]	0.457 (0.022) [0.413-0.500]	**1.603***** (0.060) [1.485-1.720]	**8.390***** (1.823) [4.816-11.965]
Asian/Pacific	16.162 (69.999) [-121.034- 153.358]	0.672 (1.976) [3.200-4.544]	(+)/(-)	(+)/(-)	33.625 (60.680) [-87.735- 154.990]	21.895 (100.187) [-174.467- 218.257]	(+)/(-)	2.100 (1.376) [-0.597- 4.797]
Indian/Alaskan	(+)/(-)	33.767 (247.559) [-451.440- 518.974]	(+)/(-)	1.445 (13.691) [-25.388-28.279]	(-)/(+)	(+)/(-)	(+)/(-)	(+)/(-)

Table 9 (Continued): Social Multipliers in Breast Cancer Screening among US Women

Other	**5.941***** (1.227) [3.536-8.346]	(-)/(+)	**4.329***** (1.155) [2.065-6.593]	(-)/(+)	**17.463***** (4.484) [8.675 - 26.251]	39.425 (65.320) [-91.215-170.065]	**14.193***** (3.691) [6.959-21.427]	(-)/(+)
Employed	(-)/(+)	**2.589***** (0.683) [1.243- 3.919]	**2.359***** (0.370) [1.634-3.084]	(-)/(+)	(-)/(+)	**6.012***** (1.307) [3.449-8.574]	**2.258***** (0.248) [1.772-2.745]	**4.701***** 1.505 [1.750-7.652]
Poor Health	0.386 (0.119) [0.152-0.620]	12.527 (35.084) [-56.237-81.291]	**1.552***** (0.151) [1.255-1.848]	0.579 (0.182) [0.222-0.937]	(-)/(+)	(+)/(-)	(-)/(+)	(-)/(+)
Income	0.737 (0.032) [0.674-0.799]	0.808 (0.068) [0.674-0.942]	**1.095 ***** (0.042) [1.013-1.178]	0.986 (0.130) [0.731-1.241]	0.740 (0.012) [0.716-0.764]	**1.077***** (0.028) [1.021-1.132]	**0.915** (0.018) [0.881-0.949]	0.989 (0.046) [0.898-1.080]

Notes: *** denotes significance at 1% level. ** denotes significance at 5% level. * denotes significance at 10% level. Significance levels with regards to ratios mean significantly greater than 1. Standard errors are reported in parentheses. […] denotes 95% confidence intervals. Standard errors and confidence intervals for the ratios are bootstrapped, applying a panel bootstrap using 1,000 replications. Ratios where the individual and group-level coefficients didn't have the same signs ((-)/(+) and (+)/(-)) violate the assumption of δ and γ having the same sign, and therefore were not bootstrapped.

Table 10: Results of the Falsification Test: Social Multipliers in Height

	County/ Individual Ratios				**State/Individual Ratios**			
	40 and Older	Ages 40-49	Ages 50-74	75 and Older	40 and Older	Ages 40-49	Ages 50-75	75 and Older
Age	18.721 (140.374) [-256.408- 293.850]	0.388 (0.404) [-0.403-1.180]	3.586 (12.767) [-21.436-8.609]	0.558 (0.286) [-0.003-1.120]	15.897 (136.667) [-251.967-283.761]	2.322 (2.736) [-3.041-7.684]	(+)/(-)	(+)/(-)
Health Plan	0.427 (0.128) [0.176-0.679]	1.163 (0.208) [0.756-1.571]	0.022 (0.221) [-0.411-0.456]	2.009 (19.851) [-36.899-40.916]	0.483 (0.040) [0.405-0.560]	0.760 (0.076) [0.611-0.909]	0.452 (0.062) [0.331-0.573]	0.380 (0.215) [-0.05-0.81]
Married	0.129 (0.057) [0.017-0.242]	0.711 (0.240) [0.241-1.182]	(+)/(-)	(+)/(-)	0.950 (0.227) [0.496-1.404]	0.129 (0.014) [1.101-0.157]	(+)/(-)	0.637 (0.105) [0.427-0.874]
Education	0.961 (0.084) [0.795-1.127]	0.546 (0.205) [0.145-0.947]	0.507 (0.086) [0.337-0.676]	0.372 (0.092) [0.191-0.553]	(+)/(-)	(+)/(-)	0.345 (0.022) [0.301-0.389]	0.334 (0.047) [0.242-0.426]
Hispanic	**1.770***** (0.072) [1.627-1.912]	**1.238***** (0.084) [1.073-1.403]	0.736 (0.043) [0.652-0.818]	0.224 (0.076) [0.076-0.372]	0.882 (0.027) [0.827-0.937]	0.865 (0.040) [0.786-0.944]	0.555 (0.027) [0.503-0.607]	0.216 (0.026) [0.158-0.274]
Black	0.544 (0.515) [-0.465-1.553]	5.482 (47.415) [-87.450-98.414]	1.097 (1.631) [-2.099-4.294]	0.560 (0.159) [0.248-0.872]	0.851 (0.505) [-1.011-1.861]	(+)/(-)	(+)/(-)	0.552 (0.107) [0.341-0.762]
Asian/Pacific	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	2.597 (9.107) [-15.251-20.446]
Indian/Alaskan	6.525 (90.112) [-170.091-183.141]	15.687 (352.008) [-674.236-705.609]	7.895 (66.620) [-122.678-138.468]	52.802 (261.299) [-459.334-564.939]	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)

Table 10 (Continued): Results of the Falsification Test: Social Multipliers in Height

Other	(+)/(-)	7.504 (40.751) [-72.367-87.376]	(+)/(-)	5.459 (16.709) [-27.290-38.208]	(+)/(-)	3.538 (7.239) [-10.650-17.726]	(+)/(-)	5.279 (43.309) [-79.606-90.166]
Employed	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)	0.461 (0.176) [0.116-0.806]	0.375 (0.125) [0.129-0.621]	(+)/(-)
Poor Health	105.148 (716.104) [-1,298.389-1,508.685]	2.410 (9.606) [-16.418-21.237]	(+)/(-)	(+)/(-)	(+)/(-)	0.792 (0.445) [-0.081-1.666]	1.554 (11.56841) [-21.120-24.228]	0.975 (4.089) [-7.039-8.990]
Income	0.911 (0.087) [0.739-1.082]	0.098 (0.155) [-0.206-0.402]	1.364 (0.414) [0.743-1.985]	0.716 (0.320) [0.090-1.342]	1.176 (0.205) [0.771-1.582]	0.610 (0.059) [0.495-0.727]	0.237 (0.035) [0.167-0.307]	0.705 (0.198) [0.315-1.0940]

Notes. Height is the new dependent variable. Significance levels of ratios tests whether ratios are significantly larger than unity. Standard errors in parenthesis I bootstrap the standard errors of the social multipliers, applying a panel bootstrap using 1,000 replications. . Ratios where the individual and group-level coefficients didn't have the same signs ((-)/(+) and (+)/(-)) violate the assumption of δ and γ having the same sign, and therefore were not bootstrapped

~~Table 11: Group Level Regressions for Breast Cancer Screening for US Women (OLS and Split-Sample IV)~~

	~~State OLS-FE (1)~~	~~State SSIV-FE (2)~~
~~**THIS TABLE IS TO BE REDONE**~~		
~~**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~~

~~**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. For county and State level estimation I use group averages of the variables constructed from only half of the data. The averages of the remaining half of the data are used as instruments.

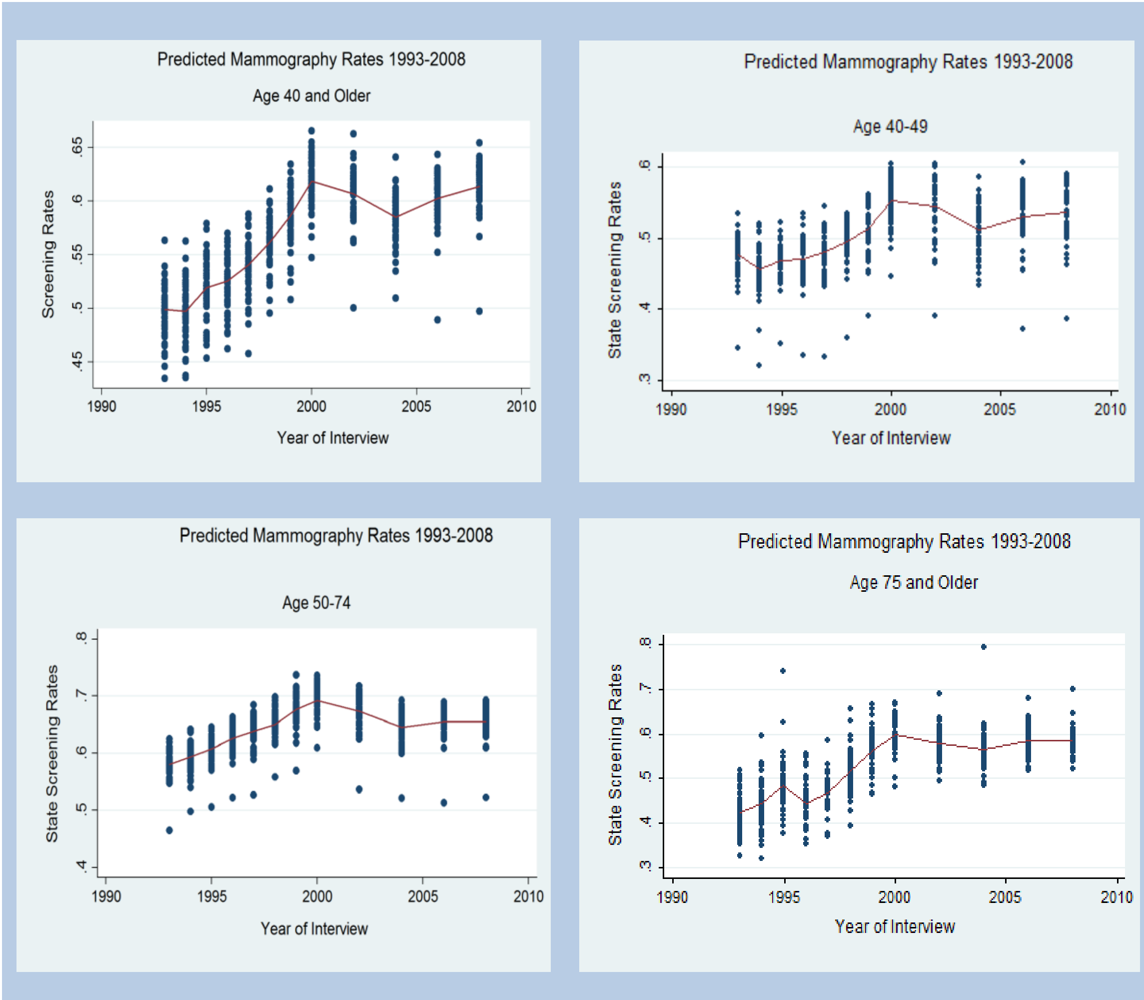

Figure 1: Geographic Variation in Mammotraphy Rates by Age Group, 1993-2008. State mammography rates adjusted for age, race, marrital status, health insurance, education, health status, employment, and income.

Appendix

Table A.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

Table A.2: State Level Means of Self-Reported Mammography Receipt within 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.2: (Continued): State Level Means of Self-Reported Mammography Use in the Past 12 Months on BRFSS Interview

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%

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:

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

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

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

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

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