Estimates of Crowd-Out from a Public Health Insurance Expansion Using Administrative Data[1]

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Abstract

We use administrative data from Wisconsin to estimate the percent of individuals newly enrolled in public health coverage that had access to private, employer-sponsored health insurance at the time of their enrollment and the percent that was uninsured. We also estimate the percent of new enrollees that dropped private coverage in the six months prior to or following enrollment. We estimate that, among all new enrollees and after expansion of eligibility for public coverage, approximately 21% had access to private health insurance at the time of enrollment and that only 10% dropped this coverage. We also estimate strict bounds for these percentages and find that the percentage of new enrollees with private insurance coverage at the time of enrollment lies between 16% and 29% and the percentage that dropped private coverage in favor of public insurance lies between 4% and 18%. These estimates of crowd-out are relatively low compared with estimates from the literature based on Medicaid and Children's Health Insurance Program expansions, although based both on different data and on a different method. In order to facilitate comparison of our method with previous studies, we develop a conceptual method for understanding the various types of crowd-out measures.

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1. Introduction

The 2010 Patient Protection and Affordable Care Act (ACA) is expected to increase health insurance coverage largely through expansions to Medicaid (Congressional Budget Office, 2009). The extent of declines in uninsurance rates depends on the target efficiency of the Medicaid expansions —that is, the percentage of individuals that are newly enrolled into public insurance programs that previously had private insurance. Reductions in the number of uninsured individuals are not the only objective of expansions in public insurance, as these expansions may also seek to improve the quality of benefits received, increase affordability, and reduce financial uncertainty. However, the policy debate continues to focus on the degree to which expansions efficiently reach the uninsured by not promoting the substitution of public coverage for private coverage.

To date, a large number of studies in the economics and policy literature have provided estimates of the extent of substitution between public and private health insurance. These estimates vary widely, in part, because of differing methods, data, and time periods or programs that have been examined. A summary of the literature produced the oft-cited assertion that the crowd-out rate associated with previous public health insurance program expansions in the U.S. lies between 25% and 50% (CBO, 2007).

Our paper contributes to this literature on the crowd-out of private coverage from public health insurance program expansions in two ways. First, we are, to our knowledge, the first paper to use administrative data to estimate the movement between private and public insurance programs. The administrative data we use are from Wisconsin's BadgerCare Plus (BC+) program, which is a combined Medicaid/Children's Health Insurance Program. The data allow us to observe the universe of enrollees in the state's public insurance program as well as their family members. The size of our administrative sample also allows us to examine crowd-out

rates by subgroup, including age, income, and geographic location. We can link these data to a number of additional administrative data sources in order to accurately capture movements between private and public coverage for individuals who enroll in public coverage, which has not been previously possible, and to observe work transitions that may be associated with losses of coverage.

Second, the expansion in public coverage we examine is to populations that are not typically covered by Medicaid or the Children's Health Insurance Program (CHIP). Specifically, we study Wisconsin's 2008 expansions to two populations: first, to all children without access to insurance without income limits; and second, to parents and caretaker relatives with family incomes below 200% of the Federal Poverty Level. Thus, the estimates we provide will be informative as Medicaid expansions move forward under the ACA.

Our results show that among all enrollees in the post-expansion period (April 2008 through November 2009), 21.2% had private coverage at the time of enrollment. They also show that another 9.9% dropped coverage in the 6 months following enrollment. These percentages are lower than most estimates of crowd-out in the literature, however, as we discuss below, they are not directly comparable due to differences in method and approach. We develop a conceptual method for understanding various types of crowd-out measures in order to fit our estimates within the literature.

Our results also show that 16% of enrollees into public insurance programs simultaneously hold private policies. This phenomenon of dual-coverage is under-researched to date, with the exception of a 2006 Government Accountability Office report concerned with ensuring that Medicaid is the payer of last resort in such cases, but is consistent with survey data sources such as the Current Population Survey in which a similar proportion of survey

respondents indicate having both private insurance coverage and Medicaid. We find that higher-income individuals are more likely to have private insurance at the time of enrollment and are more likely to have dropped private coverage.

The paper proceeds as follows. Section 2 discusses our conceptual approach to measuring crowd-out and contrasts it with previous approaches. Section 3 gives a brief overview of how we constructed the linked administrative dataset used in the analysis. Section 4 specifies the methods we use to measure the percentage of enrollees with private insurance coverage at the time of enrollment, the percentage of enrollees who dropped private coverage in the 6 months following enrollment, and the percentage who dropped private coverage in the 6 months preceding enrollment. Section 5 reports our results and Section 6 discusses the implications of our results for policy and presents our conclusions.

2. Conceptual Approaches to Measuring Crowd-Out

Interest in the potential displacement of private insurance coverage by public health programs increased with the expansions of state Medicaid programs in the late 1980s and early 1990s. Traditionally, Medicaid coverage had been tied to eligibility for AFDC cash assistance, but expansions in Medicaid eligibility as well as the 1996 welfare reform severed this link and allowed new family types and income categories to gain public health insurance coverage. Enrollment in public health insurance programs grew significantly with these changes, raising concerns among some policy-makers about the extent to which new enrollees into public coverage came from the uninsured population as opposed to from the privately insured population, or the extent to which the program was effectively targeting the uninsured. This measure, as we discuss below, is closely related to the concept of crowd-out as usually defined.

The approach we take in this paper is to directly measure the percentage of new enrollees that were previously uninsured. Consider an individual *i* who enrolls into public insurance at time *t*. We would consider this person to be coming from the uninsured population if they either had no insurance coverage at all in the period between *t-s* and *t* or if they had private insurance during that period but lost that coverage for reasons unrelated to the existence of the public insurance program (e.g., a job change or loss). Enrollees coming from the privately insured population are those with some private insurance coverage in the *t-s* to *t* period who did not lose that coverage as a result of the existence of the public insurance program.

To measure the percentage of enrollees who dropped private coverage, we first consider those with some private insurance coverage in the *t-s* to *t-1* period but no private coverage in *t*. We also consider those enrollees with private insurance coverage in *t*, who did not have that coverage in period *t+s* while remaining enrolled in public insurance in period *t+s*. The percentage of enrollees who dropped private coverage (either prior to or following enrollment) is our measure of the extent to which public insurance displaced private insurance.

Crowd-out has been defined slightly differently in other studies. The broadest concept of crowd-out, when applied to public insurance, would be to compare the number of privately insured individuals in the state of world with a public insurance program with the number in the unobserved counterfactual state of the world with no public insurance program. A related concept is crowd-out associated with incremental expansions of an existing public health insurance program. In this case, one would compare the number of the number of privately insured individuals in the state of world with a less-generous public insurance program with the number in the unobserved counterfactual state of the world with a more generous public insurance program.

Many of the most influential studies in the crowd-out literature adopt this latter conceptual approach. Seminal work by Cutler and Gruber (1996) measures the extent to which crowd-out occurred in response to the expansions in Medicaid income-eligibility thresholds targeting poor younger children during the years 1987 and 1992. To identify crowd-out from these incremental expansions, they use state variation in eligibility (due to variation in policy implementation), cross-sectional data from the Current Population Survey (CPS), and an instrumental variable framework (where simulated eligibility based on the state-level eligibility rates using a national sample serves as the instrument for actual eligibility), and estimate rates of crowd-out rate of approximately 50%.

This paper spurred a large literature on crowd-out in public health insurance programs, much of which found considerably lower crowd-out rates (examples include Dubay and Kenney 1996; Shore-Sheppard 1996; Blumberg, Dubay, and Norton 2000; Yazici and Kaestner 2000; and Shore-Sheppard 2008). Gruber and Simon (2008) trace the evolution of the crowd-out literature in the decade following Cutler and Gruber (1996), noting the large range of crowd-out estimates. They explain this range as due to wide variation in estimation methodologies, data types and even the particular computation of the crowd-out measure. CBO (2007) reviewed the literature on crowd-out from CHIP-era (generally defined as 1997-2002) expansions, which targeted near-poor children of all ages, and concluded that the crowd-out rate from these later expansions was between 25% and 50%.

In order to facilitate comparison of our method with previous studies, we develop a conceptual method for understanding the various types of crowd-out measures. When measuring the crowd-out in response to an expansion in the income eligibility threshold from I_0 to I_1 that occurs in year *t*, crowd-out is defined as the net change in private insurance coverage between *t*

and *t+1* as a proportion of the net change in public insurance coverage between *t* and *t+1* among the population with incomes between I_0 and I_1. Because private coverage may change for reasons unrelated to the public insurance expansion, we would subtract off that change in private coverage that would have occurred in the counterfactual world of no public insurance expansion (in practice, states that did not expand coverage are used as controls). Thus, the crowd-out rate resulting from an incremental expansion is given by:

$$CO = \frac{\Delta \text{Private}_T - \Delta \text{Private}_C}{\Delta \text{Public}_T - \Delta \text{Public}_C} = \frac{\Delta \text{Private}_T - \Delta \text{Private}_C}{\Delta \text{Public}_T} \tag{1}$$

where: $\Delta \text{Private}_T$ is the net change in number of individuals with private health insurance in the expansion population between *t* and *t+1*;

$\Delta \text{Private}_C$ is the counterfactual net change in number of individuals with private health insurance in the expansion population between *t* and *t+1*;

ΔPublic_T is the net change in number of individuals with public health insurance in the expansion population between *t* and *t+1*; and

ΔPublic_C is the counterfactual net change in number of individuals with public health insurance in the expansion population between *t* and *t+1*, which by definition is equal to zero.

The numerator of the crowd-out rate is the net decrease in private insurance coverage and can be further decomposed into the gross flows between insurance states:

$$\Delta \text{Private} = (\text{Private} \to \text{Public}) + (\text{Private} \to \text{Uninsured}) - (\text{Uninsured} \to \text{Private}). \tag{2}$$

Thus, the numerator of the crowd-out rate as defined in equation (1) is given by:

$$\begin{aligned} \Delta \text{Private}_T - \Delta \text{Private}_C &= (\text{Private} \to \text{Public})_T \\ &+ \left[(\text{Private} \to \text{Uninsured})_T - (\text{Private} \to \text{Uninsured})_C \right] \\ &- \left[(\text{Uninsured} \to \text{Private})_T - (\text{Uninsured} \to \text{Private})_C \right] \end{aligned} \tag{3}$$

where: $(\text{Private} \rightarrow \text{Public})_T$ is the number of individuals in the expansion population who transition from private to public insurance between *t* and *t+1*;

$(\text{Private} \rightarrow \text{Uninsured})_T$ is the number of individuals in the expansion population who transition from private insurance to being uninsured between *t* and *t+1*;

$(\text{Private} \rightarrow \text{Uninsured})_C$ is the counterfactual number of individuals in the expansion population who transition from private insurance to being uninsured between *t* and *t+1*;

$(\text{Uninsured} \rightarrow \text{Private})_T$ is the number of individuals in the expansion population who transition from being uninsured to having private insurance between *t* and *t+1*;

$(\text{Uninsured} \rightarrow \text{Private})_C$ is the counterfactual number of individuals in the expansion population who transition from being uninsured to private insurance between *t* and *t+1*.

The first term on the right-hand side of equation (2) – the number who transition from private insurance to public insurance -- is something that can be measured directly, as we suggest doing above.

The second term on the right-hand side of equation (2) – the difference between the number who transition from private insurance to uninsured in the expansion and counterfactual states – is of ambiguous sign, though it is probably negative. On the one hand, some people who would have moved from private to uninsured will now be able to move from private to public, which would tend to make this term negative. On the other hand, the expansion may lead some employers to drop coverage for eligible employees, who then may chose not to enroll in public insurance, which would tend to make this term positive. We believe that this latter effect is likely smaller than the former effect. Importantly, neither of these terms can be measured directly using administrative data on enrollment, as they do not involve enrollees in public insurance programs.

The final term on the right-hand side of equation (2) – the difference between the number who transition from uninsured to private insurance in the expansion and counterfactual states – is if anything negative but probably small. Some employers might have added health insurance coverage (reducing the number of uninsured) but choose not to do so once public health insurance is expanded.

Thus, the direct measure of the number of people who transition from private to public insurance in response to the public insurance (which is what we measure in our approach) is closely related to what would appear in the numerator of an incremental crowd-out rate. It is exactly equal to the numerator of the incremental crowd-out rate if the rates of transition between private insurance coverage and being uninsured are largely unaffected by the public insurance expansion.

The denominator of the crowd-out rate is the net increase in public insurance coverage. This too can be decomposed into flows into and out of public insurance.

$$\begin{aligned}\Delta\text{Public}_T = &\left(\text{Private} \rightarrow \text{Public}\right)_T + \left(\text{Uninsured} \rightarrow \text{Public}\right)_T \\ &- \left(\text{Public} \rightarrow \text{Uninsured}\right)_T - \left(\text{Public} \rightarrow \text{Private}\right)_T\end{aligned} \tag{3}$$

In our approach, we measure the gross flows into public insurance coverage from being uninsured and from having private insurance coverage: $\left(\text{Private} \rightarrow \text{Public}\right)_T$ and $\left(\text{Uninsured} \rightarrow \text{Public}\right)_T$. Thus, the difference between the sum of the two quantities that we measure and the denominator of the crowd-out rate is the difference between gross enrollment and net enrollment into public insurance.

To summarize, our approach is to measure the fractions of new enrollees that enter public insurance from the state of having private insurance and from the state of being uninsured. In terms of the notation above, these fractions are:

(4) $$\frac{(\text{Private} \rightarrow \text{Public})}{(\text{Private} \rightarrow \text{Public}) + (\text{Uninsured} \rightarrow \text{Public})}, \text{ and}$$

(5) $$\frac{(\text{Uninsured} \rightarrow \text{Public})}{(\text{Private} \rightarrow \text{Public}) + (\text{Uninsured} \rightarrow \text{Public})}.$$

The denominator in both equations (4) and (5) is the total (gross) enrollment into public insurance while the numerator is the enrollment from private insurance and uninsured states respectively.

These quantities are well defined for all enrollees and for subgroups of enrollees. One interesting subgroup is comprised of enrollees in the income expansion population, which would be:

(6) $$\frac{(\text{Private} \rightarrow \text{Public})_T}{(\text{Private} \rightarrow \text{Public})_T + (\text{Uninsured} \rightarrow \text{Public})_T}, \text{ and}$$

(7) $$\frac{(\text{Uninsured} \rightarrow \text{Public})_T}{(\text{Private} \rightarrow \text{Public})_T + (\text{Uninsured} \rightarrow \text{Public})_T}.$$

The measures in equations (6) and (7) are not directly comparable to estimates of crowd-out for the expansion population. However, if public insurance expansions have a negligible effect on the transition rates between private insurance and uninsurance and if we replace the denominator of equations (6) and (7) with estimates of total net enrollment into public insurance, we should be able to construct estimates of the crowd-out rate that are comparable to those in the literature:

(8) $$\frac{(\text{Private} \rightarrow \text{Public})_T}{(\text{Net Public Enrollment})_T}.$$

One small issue to consider is how to treat those with both private and public coverage. Some individuals with private insurance coverage will enroll in public insurance but not drop

their private coverage. We, therefore, construct estimates both of the fraction of enrollees with private coverage and of the fraction of enrollees who dropped private coverage. We do not consider individuals who do not drop their private coverage to be crowded-out by public insurance.

Estimates of the incremental crowd-out rate are sensitive to the treatment of those with both private and public coverage. For example, Cutler and Gruber (1996) identified two approaches to computing it: the ratio of the marginal change in private coverage to the marginal change in public coverage, or one minus the ratio of the marginal change in the uninsured to the marginal change in public coverage. The two measures differ because of the fact that some people report having both private and public coverage. The treatment of this overlap is an important source of differences in estimates.[2] The overlap is sometimes thought of as a measurement issue: either a reporting error on the part of survey recipients or an issue of timing (those who moved from one source of coverage to the other report having both). We have an alternative explanation: we observe that 11.7% of BadgerCare Plus enrollees in fact maintain some form of private insurance coverage for at least six months of their enrollment period.[3]

3. Data

We use a variety of administrative data sources, which we link together, to construct the estimates. Our administrative enrollment records cover the universe of Medicaid enrollees in Wisconsin. We supplement these records with two sources of cross-sectional survey data representative of the Wisconsin population. We link the enrollment records to a database containing lists of all individuals insured by privately held policies by Social Security Number

[2] For example, Lee et al. (2008) find no crowd-out using the first approach, but 40% using the second.
[3] GAO (2006) also found that a substantial amount of Medicaid enrollees also had private coverage.

(SSN). We also link these enrollment records, which include not only information on enrollees but on all household members of enrollees, to Unemployment Insurance (UI) earnings records using SSN. Finally, we link a Department of Labor list of self-insured firms to enrollees and their household members using Federal Employer Identification Numbers (FEINs), which are also available in the UI records. Thus, for our analysis, we construct a longitudinal administrative dataset from four administrative databases:

- CARES: Wisconsin's program eligibility database;
- TPL: Wisconsin's Third Party Liability database;
- UI: Unemployment Insurance and quarterly wage records; and
- DOL: a U.S. Department of Labor database of all self-insured firms.

Here, we describe each of the data sources and the matching process in further detail.

A. *Administrative Enrollment Data*

The main data source is an administrative enrollment database, CARES, from the state of Wisconsin's Medicaid and CHIP programs, which were provided to us by agreement with the Wisconsin Department of Health Services. The unit of observation in this dataset is an individual-month beginning in the first month that individual enrolled in BC+ between January 2006 and May 2009.[4] For some of the analysis, we use data from other case members; a case includes all individuals associated with eligibility determination (generally, everyone in the applicant's household). Over this time period, we have monthly enrollment data for a total of 1,392,185 enrollees in 433,525 unique cases. CARES also contains demographic and income information, including age, sex, ethnicity, citizenship, educational attainment, and sources as well as amount of household income. From the income data, we are able to observe whether the main source of income for a case is self-employment.

[4] We include only new enrollees; all of the enrollees in January 2006 are left-censored, so we cannot observe the start-date of their spells. We exclude these censored observations from our analysis. We use the panel nature of the data to look six months ahead at private status, so although the data go through November 2009, the last new spells we include are those beginning in May 2009.

Individuals are matched to the TPL database using their SSNs. TPL is an individual-level database that contains all enrollees in state health insurance programs who are covered by a private fully-insured health insurance plan. This database, while an excellent resource for our study on crowd-out, is limited in two ways. First, the database does not contain individuals who are covered by health insurance provided by a self-funded employer (whose policies are not subject to state regulation). Second, these data are available for each month in which an individual is enrolled in BC+, but do not contain information on the health insurance coverage of individuals in months prior to enrollment or following disenrollment. Those enrollees who do not have insurance according to the TPL database either do not have private insurance or have health insurance through a self-funded employer.

To assess whether enrollees may have access to health insurance coverage through a self-funded employer, we connect each BC+ case to the set of employers for workers in the case by linking CARES through SSNs to a database of quarterly earnings records from Wisconsin's unemployment insurance (UI) system. Employers are required to file quarterly wage reports for each employee on the payroll in case of later unemployment claims. The wage reports include the employee's SSN and quarterly wages and the employer's FEIN and industry classification code. Only employers not subject to unemployment insurance laws are exempt from reporting.[5] Employers who are exempt from UI reporting (such as independent contractors) are highly unlikely to provide a self-funded health insurance plan. Since our enrollment data are monthly, we assign enrollees to a firm in each month within the quarter in which we observe them in UI. Those who work at multiple firms are assigned the FEIN of the employer from which they earned the most in wages. The UI data are available for all workers in CARES both prior to and

[5] In general, WI employers are subject to UI liability if they pay $1,500 or more in wages in any calendar quarter or have full or part-time employees working for them in 20 weeks or more during a calendar year. Special rules apply for agriculture, non-profit firms, and employers of domestic service workers.

post enrollment, enabling us to identify workers who had a job loss around the time of enrollment. Of the 433,525 cases in our sample, 286,352 cases have a member that also appears in the UI database. That is, 66% of our cases have a member who was employed by a UI reporting firm.

The longitudinal aspect of the UI data allows us to observe job loss and change among employees. Newly enrolled cases with access to private coverage prior to BC+ enrollment, but who simultaneously lose their jobs likely should not be counted as having been crowded-out.[6] We identify workers who experienced a job loss, defined as going from having a UI job match in the quarter of enrollment in BC+ to having no job match in the following quarter. We then assign these workers as not having dropped health insurance for the purposes of all of the estimates reported below.

Next, for those who do not have a TPL match, we use FEINs (obtained from UI) to link to data from the U.S. Department of Labor (DOL), in order to see if a BC+ case member's employer offers a self-funded plan.[7] We obtained these data through a Freedom of Information Act request. The data represent the universe of employers within the United States from 2003-

[6] We recognize the possibility that obtaining public coverage could in theory induce individuals to reduce their labor supply, which would result in our classifying intentional exits as job losses. Existing literature suggests that this is not a prevalent phenomenon (see, for example, Strumpf 2011). A more likely potential phenomenon is a switch to self-employment induced by receiving public coverage that results in the lack of a longitudinal match to the UI data. This phenomenon would suggest that we are misclassifying some intentional switches to self-employment as job losses. However, it is debatable whether these switches should be counted in the crowd-out figures, given that being "job locked" in a position with health insurance coverage when one prefers to be self-employed is widely considered to be welfare reducing (see, for example, Madrian 1994 and Monheit and Cooper 1994).

[7] A minor issue involves the usage of FEINs to link data from different sources. FEINs are issued by the Internal Revenue Service for payroll tax reporting. Although a FEIN is unique to a firm, firms can have more than one FEIN if they have more than one location or operate under different names. For single-unit firms (which have only one establishment), there is a one-to-one relationship between the firm and the FEIN. However, multi-unit firms, such as chain stores, can have more than one FEIN, although each establishment can be associated with only one FEIN. Because the UI system sometimes cross-verifies data with the IRS, we are confident that FEINs used in the DOL and UI data are correctly matched. Additionally, for a small sample of employers (including one retail chain, one company that owned several chains in the same industry, and one major manufacturer), we were able to directly verify that the FEINs that were submitted to UI and DOL were identical and accurately represented who owned the responsibility for the insurance offer.

2007 that are self-insured for health, life, and disability and related insurance plans. These data are used to administer the Employee Retirement Income Security Act (ERISA), and are acquired as part of the required reporting of self-insured firms to the Internal Revenue Service. Because we are unable to directly observe which if any members of a case in which someone works for a self-insured firm obtain their health insurance from the self-insured firm, we alternatively compute strict lower and upper bounds on and impute the percentage of enrollees who receive their coverage in this manner. We describe our method in more detail in Section 4. In the data, we match roughly 10% of enrollees to a DOL firm, meaning that 10% of enrollees have a family member who is employed by a self-insured firm.

For much of the analysis, we separate the data into three time periods: pre-reform (January 2006 to January 2008), transitional (February and March 2008), and post-reform (April 2008 to November 2009). We do this for several reasons. First, it allows us to compare pre and post reform, although the economic recession that began in December 2007 and ended in June 2009 confounds this comparison. Second, we separate the transitional period because we are concerned that these initial enrollees are different. We know that a group of nearly 50,000 eligible parents and siblings of current program enrollees were automatically enrolled in the program in February 2008, many of whom already had private health insurance. We can identify these in the data and examine them separately below. Another concern is the possibility that initial program enrollees behaved strategically in waiting to enroll on Medicaid until after the reform had been implemented (because of different cost-sharing provisions, for example). Third, it is important to separate the analysis by time period when analyzing crowd-out by income group because some income groups became newly eligible.

Means of the characteristics of the enrollees are reported in Table 1. Most notably, the youngest child in the family is under 5 for nearly half of our sample. Almost the entire sample consists of cases under 150% FPL; as discussed in Leininger et al. (2011), much of the new enrollment in this expansion occurred in populations that were income-eligible even prior to reform. Very few households earn a majority of their income from self-employment (the definition we use for self-employed), although many appear to be full-time workers. We define full- or part-time status by imputation: we compare a worker's quarterly UI-reported earnings with what they could expect to earn working full-time (35 hours) at minimum wage; workers below that level were considered part-time.[8]

B. *Survey Data*

We use two sources of survey data in this paper: the Wisconsin Family Health Survey (FHS) and the Current Population Survey Annual Social and Economic Supplement (CPS). We use both the FHS and the CPS to predict the probability of having private health insurance for enrollees with a family member employed by a firm with a self-funded plan.

The 2007-2009 March CPS data have 11,418 Wisconsin respondents in total. Our analytical sample consists of employed men and women who are 18 to 65 years old. We further limit our sample to those living with at least one child under the age of 18 in the family in order to mimic the Medicaid eligibility criteria in Wisconsin, yielding an analytical sample of 2,685 men and women.[9] The health insurance question in the CPS asks about coverage sources in the previous year.

[8] Previous work found that wage and hours worked information from CARES to be of low quality relative to UI information. See Wolfe et al. (2006).

[9] We only consider those workers who were living in a family (defined by CPS) in which at least one relative child (that is, under 18 years old) was present. Workers who were in families without any related child or who were living alone with unrelated children were excluded from our analysis. For multiple-family households, the workers

The FHS is a yearly phone survey of households in Wisconsin that includes questions about health status, behaviors, health services, and insurance. It also contains information on demographics and income. We use a question in the FHS that asks about current health insurance coverage to construct the dependent variable. The 2007 and 2008 FHS data have 5,161 respondents in total. We restrict the sample to households headed by workers aged 18-65 and that have one or more children, leaving us with 2,016 observations. Appendix Table A1 contains descriptive statistics of the sample populations from the CPS and the FHS.

4. Methods

The following section outlines our approach to answering our research questions:

(1) What percentage of new enrollees in public insurance had private insurance coverage at the time of enrollment?

(2) What percentage of new enrollees dropped their private coverage prior to or after enrolling?

In particular, we discuss our methods for obtaining point estimates of and strict bounds for these percentages.

A. *Estimates of the Percentage of Enrollees with Private Health Insurance Coverage*

We begin by estimating the percentage of individuals that are covered by private, employer sponsored health insurance (ESI) at the time of enrollment. We will refer to this quantity as P(ESI | enroll) or more simply, P(ESI). We break this probability into two pieces: the probability that the enrollee had ESI from a fully-insured firm and the probability that the individual has ESI from a self-insured firm.

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who were in unrelated sub-families but had no related child in his/her own family would not be included in our sample.

P(ESI) = P(ESI at fully-insured firm) + P(ESI at self-insured firm)

The probability of having ESI at a self-insured firm is given by the probability of having health insurance given that a member of the case is employed at a self-insured firm multiplied by the probability of employment at such a firm:

P(ESI at self-funded firm) = P(ESI at self-insured firm| Employed at self-insured firm)

x P(Employed at self-insured firm)

We assume that the probability of having ESI at a self-insured firm is zero for those without a case member who is employed at a self-insured firm:

P(ESI at self-insured firm | Not employed at self-insured firm) = 0

While this is not literally true because of the availability of retiree health insurance and COBRA, estimates from the CPS suggest that the number of people who obtain such coverage is very low.

Thus, the probability of having ESI is given by:

(1) *P(ESI) = P(ESI at fully-insured firm)*

+ P(ESI at self-insured firm| Employed at self-insured firm)

x P(Employed at self-insured firm).

Our strategy is to estimate each piece of equation (1) to estimate the probability that a new enrollee in BC+ was covered by ESI at the time of enrollment. We do this by first calculating whether an enrollee was covered by an insurance plan in TPL in the month of enrollment. We then determine the percentage of enrollees with case members who are employed at firms with self-funded plans. Finally, we estimate the probability of having ESI conditional on having a case member employed at a firm with a self-funded plan using survey data.

In order to measure *P(ESI at self-insured firm| Employed at self-insured firm),* we first calculate a point estimate of the percentage of BC+ enrollees with a case member employed by a firm with a self-funded plan that were covered by that plan. We do this by using the DOL administrative data files to determine whether a case member is employed at a self-insured firm. We then estimate the probability of their being offered health insurance using survey data. To do this, we estimate probit models where the dependent variable is an indicator for employment-based health insurance coverage of the highest-earning worker and the independent variables are various individual and family characteristics. We use the 2007-2009 March CPS and 2007-2008 Wisconsin FHS to estimate the probit models and calculate the predicted probabilities that the relevant case member(s) will have ESI. We use the probit models to predict these probabilities for each new enrollee with a case member who is employed at a self-funded firm and take the average predicted probability for each group as the conditional probability. Details of these models and their results are reported in the Appendix.

We also employ a "strict bounds" approach that makes more conservative assumptions (Manksi, 1997). In it, we obtain strict upper bounds by assuming that any enrollee with a case member employed at a large, self-funded firm has ESI coverage. That is, we assume:

(2) *P(ESI at self-insured firm| Employed at self-insured firm) = 1.*

We then obtain strict lower bounds by assuming that none of these enrollees have ESI coverage.

(3) *P(ESI at self-insured firm| Employed at self-insured firm) = 0.*

We consider this method as providing strict bounds because it represents both the minimum and the maximum possible take-up of coverage by workers at self-insured firms. Some employees at firms that offer health insurance are themselves not eligible for health insurance either because they work part-time, are in occupations that are not covered, or have not been at the firm for a

sufficient period of time. For example, Farber and Levy (1998) report that in 1997, only 91 percent of workers in firms that offered health insurance were eligible for coverage. The bulk of those workers who were ineligible for health insurance were part-time workers.

B. *Estimates of the Percentage of New Enrollees who Dropped Private Coverage*

Not every person with private health insurance at the time of enrollment in public programs will drop that coverage. In addition, some people who are uninsured at the time of enrollment will have recently dropped that coverage. As discussed in Section 2 above, it is the rate of transition from private insurance coverage to public insurance coverage that is most closely related to the concept of crowd-out.

Many BC+ enrollees who have private insurance at the time of enrollment are permitted or required to maintain their private coverage. In such cases of dual coverage, BC+ is the payer of last resort.[10] Since these individuals do not drop their private insurance coverage in favor of public coverage, we do not consider them as having been crowded out in our estimates (although they may be making intensive margin adjustments by choosing less comprehensive coverage).

The percentage of enrollees who dropped their private coverage is the sum of those who dropped coverage prior to enrollment (and appear uninsured at the time of enrollment) and those who dropped coverage after enrollment (and appear privately insured at the time of enrollment).

[10] This provision is not specific to Wisconsin. We reviewed the websites for each state program to determine which states allow their family and child program applicants to have dual coverage. Most states' websites provided sufficient evidence to determine their dual coverage policy. When this was not the case, we called the state's CHIP program office directly for further information. Nine states allow some sort of dual coverage with their CHIP program: Alaska, Idaho, Indiana, Kansas, Maryland, Michigan, Oregon, South Dakota, and Wisconsin. These dual coverage programs range in breadth from allowing children/families with private insurance to be dually covered, with income restrictions (Alaska, Idaho, Indiana, Kansas, Maryland, South Dakota, and Wisconsin), to only allowing dual coverage in cases of underinsurance, again with income restrictions (Michigan and Oregon). Conclusive evidence is lacking for seven states (D.C., Hawaii, Maine, Minnesota, Montana, North Carolina, and Washington). These states' websites are unclear on the subject of dual coverage and phone calls to get more information were unsuccessful. Thirty-four states do not allow any sort of dual coverage. That is, individuals must not have private coverage under any circumstances to be eligible for these programs.

We can use our merged administrative data to directly observe the latter piece and the former piece.

To determine the percentage of enrollees that had private coverage at the time of enrollment but subsequently dropped that coverage, we once again use the TPL database that collects information on all individuals with a private source of insurance in the state who are also enrolled in BC+. We look forward six months post-enrollment. Those individuals who had coverage at the time of enrollment (month 1), but did not have it in any of the following six months (months 2 through 7) and were still enrolled in BC+ were considered as having dropped their private coverage. In the case of spells shorter than 7 months, those that keep their private coverage for the entire spell are considered to not have dropped private coverage and those who drop private coverage prior to disenrollment are counted as such.

We cannot directly observe the dropping of insurance coverage among those enrollees who we imputed as having private insurance coverage from a self-insured firm. We alternatively can assume that all of these enrollees or that none of these enrollees drop this coverage, as in our description of the upper and lower bounds above.

To estimate the percentage of enrollees that intentionally dropped coverage (and thus experiencing a spell of being uninsured) prior to enrollment, we do the following. First, note that under program rules, children and parents with family incomes of less than 150% FPL are eligible to enroll into BC+ regardless of whether they are enrolled in or have access to private health insurance through an employer. These individuals have no incentive to drop their private insurance coverage in favor of public coverage *prior to* enrolling in the public insurance program and, therefore, we assume that no enrollee who appears uninsured at the time of enrollment with family income less that 150% FPL dropped private coverage prior to enrollment.

We do, however, consider the possibility that enrollees with incomes greater that 150% FPL dropped private coverage in the months prior to enrollment. They have an incentive to do so because program rules prohibit them from enrolling if they are currently enrolled in ESI.[11] To estimate the percentage that may have dropped their ESI coverage in anticipation of enrolling, we first use UI records matched to the TPL data to calculate for each firm the number of BC+ enrollees plus family members employed at that firm and the fraction of these who are covered by an insurance policy according to the TPL database. We use this fraction as an estimate of the probability that that a firm offers health insurance to a worker with a family member eligible for BC+. Second, for each enrollee with family income greater that 150% FPL, we use UI data to determine all of the firms that they themselves or their family members worked for in the 6 months prior to enrollment into BC+ and apply the firm-level estimates of health insurance provision to these families. We calculate this only for those who appear otherwise uninsured at the time of enrollment according to the TPL data and have no estimated insurance from the DOL database match. This method will accurately capture those who dropped in anticipation under the assumption that the distribution of ESI coverage and employers is consistent for enrollees above and below 150% FPL.

C. *Estimates by Subgroup*

We estimate the percentages of enrollees who were covered by ESI at the time of enrollment and those who subsequently dropped this coverage for a variety of sub-groups and time periods. This is generally not possible in typical studies due to limited sample sizes in subgroups, but is possible using our administrative data. We examine three time periods – a pre-expansion period (January 2006-January 2008), an initial post-expansion period (February and

11 There are many nuances to the rules about access to employer-provided health insurance coverage, but these rules only apply to those above 150% FPL. The rules are described in Section 7 of the BadgerCare Plus Eligibility Handbook, available at http://www.emhandbooks.wisconsin.gov/bcplus/bcplus.htm

March 2008), and a post-expansion period (April 2008- November 2009) – and multiple income categories – above and below 150% FPL, 150-200% FPL, 200%-300% FPL, and above 300% FPL. We also separately examined child and adult enrollees and residents of rural and urban counties. We do not report separate results for parents and children here, as they differed little from one another.

5. Results

We report the results of our analysis in this section. First, we show our upper bound, lower bound, and point estimates of the percentage of enrollees with ESI coverage at the time of enrollment, obtained from the administrative data. Second, we present our estimates of the percentage of enrollees who dropped private coverage.

A. *Administrative Data Estimates of the Percentage with Private Insurance Coverage at the Time of Enrollment*

Overall, for all enrollees, we estimate that in the post-BadgerCare Plus expansion period (April 2008-November 2009), 21.2% of enrollees had private insurance coverage at the time of enrollment. The 95% confidence interval for this estimate is 20.0% to 22.3%.[12] As described above, we also compute upper and lower bound estimates that make different assumptions about the insurance status of those at self-insured firms, which we do not directly observe. The upper bound estimate suggests that the percentage of new enrollees with private health insurance at the time of enrollment was at most 28.1% during the April 2008-November 2009 period, while the lower bound on the percentage of new enrollees with private health insurance is at least 16.0%. These results are presented in Table 2.

[12] All reported confidence intervals for point estimates are 95% normal bootstrap confidence intervals from at least 300 replications. Percentile and bias-corrected confidence intervals are very similar and not reported here.

We separately consider the "initial" post-expansion period (February and March 2008) because of the auto-enrollment and initial large jump in enrollment that occurred with program launch. The percentage of new enrollees in those two months that had private health insurance at the time of enrollment was substantially higher – we estimate that percentage to be 34.4% (95% CI [33.1%, 35.7%]). This jump is mostly due to the autoenrollees, although we also estimate a slightly higher than average number with private health insurance among other enrollees in February and March 2008.

The percentage of enrollees with private health insurance at the time of enrollment was lower prior to the program expansion (January 2006-January 2008). We estimate this percentage to be 19.3%, (95% CI, [18.0%, 20.1%]). The increase in crowd-out could be partly due to the effects of the recession, which began in December 2007, or increased awareness associated with the expansion.

Table 2 also presents these results stratified by poverty level and by whether the county of residence was urban (defined as Milwaukee, Waukesha, or Dane counties) or rural (all other counties). The time patterns discussed above hold generally for the subgroups as well. Higher percentages of enrollees living in families with higher incomes as a percentage of the federal poverty level had access to private insurance at the time of enrollment. Enrollees living in urban as opposed to rural counties were slightly more likely to have access to private insurance. Table 4 presents sample sizes for each cell.

In order to compute the estimates of ESI coverage for those with a case member employed at a DOL firm, we use the estimates from the health insurance model, described above, to predict the probability of a worker having private health insurance conditional upon his or her employment status. This model is described in the Appendix and its results are reported in

Appendix Table A2. Overall, and despite slightly different models, we estimate very similar ESI offerings using both the FHS data and the CPS data. Both the CPS and the FHS estimates suggest that 42% of enrollees with a case member who worked for a firm with a self-funded plan have ESI. Results reported here were calculated using the CPS.

Because our estimates rely on two very different sources of data – the TPL data for those with coverage through non-self-funded insurance plans and the DOL data and survey data from the CPS for those with coverage through self-funded plans, we separate the sources of the estimates into these two components in Table 3. For example, of the 21.2% of new enrollees between April 2008 and May 2009 that we estimate to have access to private health insurance, 16.0 percentage points had access via a non-self-funded plan (TPL) while we estimate 5.2 percentage points had access through a self-funded plan.

We also calculated all results separately for children and adults, although we do not report them here because they did not appreciably differ from one another. This is perhaps not surprising because the adults in this study are parents (or caretaker relatives), and children tend to have the same sources of private coverage as their parents. Gruber and Simon (2008) conclude that the crowd-out rate is close to 60% if the estimate is computed at the family level, and is roughly 30% when computed at the individual level. We have also performed this estimation at the case level rather than the individual level, using the first month that anyone the in the case was enrolled and the employment status of the highest earner on the case and did not find any important differences. We think this is because we observe directly the insurance liability of the enrollee, and not just information on the policies held as one would typically find in survey data. However, we are measuring crowd-out conditional on enrolling in public insurance, so we do not

consider those situations in which, for example, a father drops his own insurance coverage and goes uninsured once Medicaid covers his dependents.

In order to estimate the upper bounds for the percentage of newly enrolled cases with access to employer sponsored health insurance at the time they enrolled in BC+, we assume that all enrollees with a case member working at self-funded firms have ESI coverage. The proportion of new enrollees with coverage indicated in the TPL is calculated as before. This yields an "upper bound" estimate of 28.7% for all new enrollees in the post-expansion period. That is, we are highly confident that the percent of cases with ESI at the time of enrollment is lower than 28.7%.

This is calculated under the assumption that all persons employed at self-funded firms do actually have access. This is a strong assumption, given that we are unsure of a worker's part-time or full-time status at these firms or whether the firms offer insurance to all workers or just to management. However, obtaining this number from such strong assumptions makes us confident that it is indeed an upper bound. In particular, our upper bound rules out many of the larger estimates in the literature. Calculated by time period, we find that a maximum of 26.1%, 41.7%, and 28.7% had ESI coverage for the pre-, reform, and post-periods, respectively.

Similarly, the calculation of the lower bounds relies on the assumption that none of the enrollees with a case member working at a self-funded firm have ESI coverage. The lower bound resulting from this assumption in the post-expansion period is 16.0%, and uses only the private insurance liability data from those who are directly observed to have private insurance at the time of enrollment. This lower bound would seem to rule out many of the lower estimates of crowd-out in the literature, but a significant portion of enrollees maintain their private coverage

for at least six months following initial enrollment, so the number that we would consider crowded-out is likely to be smaller. This issue is described in further detail in the next section.

B. Percentage of Enrollees that Dropped Private Coverage

Not all enrollees who have private coverage at the time of enrollment drop this coverage immediately. We identify We estimate that overall, only 9.9% (95% CI, [8.8%, 11.1%]) of enrollees in the April 2008-November 2009 period dropped private coverage within seven months of enrollment. Moreover, the upper-bound estimate suggests that this percentage was less than 17.4%. This percentage was only slightly higher in the transitional period – 10.6% (95% CI, [9.7%, 11.8%]) – and was lower in the pre- period – 8.9% (95% CI, [7.6%, 10.2%]). These estimates are reported in Table 4.

These estimates of the percentage of enrollees who dropped their private coverage are low compared with estimates from the previous literature. As with the estimates of the percentage of enrollees with access to private coverage at the time of enrollment, the estimates of the percentage that dropped private coverage are higher for those individuals in families with higher incomes as a percentage of FPL and are slightly higher for those enrollees who reside in urban counties. The estimates are also very similar when estimated separately for children and for parents, although we do not report these results here.

Finally, we report estimates of the proportion of enrollees who dropped private coverage in anticipation of enrollment in Table 5. For this measure, only those enrollees above 150% FPL who were employed at the time of enrollment, but were neither TPL nor DOL matches are considered, so they are not represented in the measures reported in Table 2, Table 3, or Table 4. Approximately 2.3% of enrollees above 150% FPL are captured by this additional measure.

6. Conclusion

Our estimates, based primarily on administrative data, suggest that the expansions in Wisconsin's BC+ program that took place in February 2008 did not lead to a substantial reduction in private insurance coverage. We estimate that between April 2008 and May 2009, 21.2% of enrollees had coverage from private health insurance at or around the time they entered BC+. Of these, 11.3 percentage points represent cases that we estimate kept private insurance coverage while on BC+ while the remaining 9.9 percent dropped this private coverage within 6 months. To obtain these estimates, we used a combination of administrative data sources along with survey data from the FHS and the CPS. These estimates are more precise and credible than what one could obtain using survey data alone.

Our estimates are low compared with estimates from both Medicaid and CHIP expansions, which tend to be in the 25% to 50% range (CBO, 2007). Moreover, they are low given that current state policy stipulates that all families below 150% FPL are eligible for BC+ regardless of whether they have access to ESI, and all families are eligible if they were required to pay more than 20% of the total premium associated with an employer's plan. The large increase in public coverage in response to the BC+ expansion, therefore, reduced the ranks of the uninsured or added secondary coverage to families with weak private coverage that elected to enroll.

It should be noted that these estimates are low compared to those in the literature in part because they are based on panel data and do not include as crowd-out those uninsured individuals who move to public coverage but who, in the absence of the BC+ expansion, might have later moved to the "privately insured" state. This is a limitation of using administrative panel data to construct these estimates.

If the number of people on private insurance is reduced with increased public program eligibility, there are two possible mechanisms: a decrease in the take-up of insurance by individuals, or a decrease in the offering of insurance by employers. Cutler and Gruber (1996) find that only the employee take-up margin is important, consistent with the negative results on firm offer rates of Shore-Sheppard et al. (2000) and Marquis and Long (2003). We are unable to observe directly whether the individuals in our sample discontinue coverage voluntarily - take up public coverage in favor of an offer of private ESI- or because their employers cease to offer it. This is a general weakness of this literature.

We do not claim to capture all dimensions of crowd-out. Specifically, we focus on those individuals who actually enroll in Medicaid and had private insurance at the time of enrollment. If potential enrollees are able to use Medicaid as an implicit insurance plan, available when needed but not necessary to maintain active enrollment in, then we will understate the degree of crowd-out. In this sense, our estimates provide more of a lower bound. We are also unable to account for anticipatory behavior, although much of our sample (all of those under 150% FPL in the post period) would have no eligibility incentive to drop private coverage and go uninsured prior to taking up Medicaid, as they face no premium cost for public program coverage. Despite these limits, this study has captured the actual number of Medicaid enrollees who substitute public coverage for private insurance and the number of those newly enrolled in the expanded public program that come from the uninsured - a dimension that has not been previously understood.

This analysis suggests that using administrative data can yield credible estimates of the fraction of public health insurance program enrollees that have access to private health insurance.

Moreover, it suggests that, in contrast to some expectations, increases in public coverage in the post-CHIP era do not necessarily incur widespread substitution for private health insurance.

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Appendix: CPS and FHS Samples and Health Insurance Models

We report summary statistics or our FHS and CPS samples in Table A1. We also use both data sets to estimate probit models of health insurance coverage. The predictors in the probit models include sex, age, geographic location, age of the youngest child in the family, educational level, self-employment status, occupational industry, firm size, earnings, and federal poverty level (FPL). The FHS has fewer available covariates than the CPS. See table A1 in appendix A for descriptive statistics on the CPS and FHS samples. Except for FPL and age of the youngest child, all variables are employment or demographic characteristics of either the highest earner in a family (CPS) or the reference individual (FHS). These variables were selected and constructed to match with the available information in administrative data. The age of the highest earner is coded into 18-34, 35-54, and older than 54 years old (reference). The educational level of the highest earner is coded into less than high school (reference), high school graduation or GED but no college education, and at least one year of college education. The size of the employer is coded into a dichotomous variable, with less than 100 as the reference group. The yearly earnings of the highest earner are coded into less than $10,000, $10,000-$14,999, $15,000-19,999, $20,000-$29,999, and more than $30,000 (reference). Earnings are inflated to 2009 dollars using the CPI-U. FPL is divided into 150% and less (reference), 151-200%, 201-300%, and greater than 300%. We use two indicators to identify the residential counties that are more diverse and highly urbanized: living in Dane county (mainly Madison) and living in Milwaukee or Waukesha counties.[13] We create a dichotomous indicator for the goods-producing industries, including agriculture/forestry, mining, construction and manufacturing industries in

[13] We first intended to separate urban and rural residential areas. Though CPS contains geographic information sufficient for our purpose, the administrative data only have residential county. We thus created two indicators of urban counties in order to match both data sets. We cannot separate Milwaukee from Waukesha in the CPS data.

the major industry code. Age of the youngest child is categorized into being younger than 6, 6-12 (reference), and older than 12. We also control for the survey years.

We use probit models to estimate the probability of having private insurance among workers. Appendix table A2 shows the marginal effects from the probit models. Since all variables are binary, the table reports the marginal effects of going from 0 to 1 for each. We obtained similar results from the FHS and the CPS. Our results suggest that residential area, earnings, industry, firm size, educational level, and family poverty levels predict the probability of having private insurance well. The workers from smaller firms and workers in non-goods producing industries are less likely to have health insurance. Earning and FPL are positively associated with having health insurance. The workers living in the two largest metropolitan counties in Wisconsin are more likely to have private insurance than those living in other areas. Self-employment is negatively associated with private insurance.

Table 1. Summary Statistics for Administrative Data

	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
Male	41.4%	43.0%	43.4%
Dane County	5.8%	5.1%	5.6%
Milwaukee County	26.6%	21.8%	23.4%
Youngest child <= 5	63.3%	60.8%	61.5%
Youngest child > 5 and <13	23.0%	27.7%	24.3%
Youngest child 13-18	13.7%	11.5%	14.2%
Adult <34	85.6%	80.6%	82.5%
Adult 34-54	13.8%	18.1%	16.5%
Adult 54-65	0.6%	1.2%	1.0%
Less than High School	71.2%	66.3%	74.1%
High School Graduate	23.2%	26.8%	20.9%
Some College	5.6%	6.9%	5.0%
FPL <= 150%	93.1%	69.7%	81.2%
FPL 151-200%	6.7%	20.0%	13.8%
FPL 201-300%	0.2%	8.6%	4.1%
FPL > 300%	0.0%	1.8%	0.9%
Self Employed	27.0%	36.4%	28.8%
Employed (UI match)	60.1%	70.7%	64.5%
Of which:			
Goods Industry	7.7%	11.6%	9.6%
Service Industry	92.3%	88.4%	90.4%
Full Time	90.8%	94.4%	93.8%
Part Time	9.2%	5.6%	6.2%
Small (non-DOL) Firm	76.1%	71.0%	73.0%
Large (DOL) Firm	23.9%	29.0%	27.0%
Number of Observations	472,772	91,975	326,327

Sources: Authors' tabulations from WI CARES System, UI System, and Department of Labor

Note: Observations consist of new enrollees; all of the enrollees in January 2006 are left-censored, so we cannot observe the start-date of their spells. We exclude these censored observations from our analysis. Individual-level variables are for the highest earner in the case and, for those cases with no earners, the oldest case member.

Table 2: What Percentage of Newly Enrolled Individuals Were Privately Insured At or Near the Time of Enrollment?

	Estimate			[Lower Bound, Upper Bound]		
	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
All	19.3%	34.4%	21.2%	[13.6%, 26.7%]	[29.1%, 41.7%]	[16.0%, 28.7%]
	[.180, .201]	[.331, .357]	[.200, .223]			
By Poverty Level						
< 150	18.9%	30.4%	18.9%	[13.2%, 26.3%]	[25.4%, 38.2%]	[14.3%, 26.2%]
	[.173, .203]	[.290, .318]	[.176, .202]			
> 150	26.8%	43.5%	31.3%	[18.8%, 34.3%]	[37.4%, 49.8%]	[23.6%, 39.4%]
	[.250, .287]	[.420, .450]	[.297, .329]			
150-200	23.9%	42.4%	27.6%	[18.3%, 33.9%]	[37.2% 50.4%]	[21.5%, 37.8%]
	[.227, .252]	[.408, .439]	[.261, .292]			
200-300	37.8%	41.0%	32.9%	[33.8%, 45.8%]	[37.9%, 49.1%]	[28.7%, 43.2%]
	[.370, .387]	[.397, .423]	[.317, .341]			
300+	35.0%	39.7%	37.0%	[29.2%, 42.3%]	[37.4%, 45.9%]	[32.5%, 45.4%]
	[.342, .357]	[.378, .415]	[.356, .384]			
By County						
Urban	19.1%	35.1%	21.7%	[15.2%, 29.0%]	[31.1%, 43.7%]	[17.8%, 30.9%]
	[.177, .204]	[.338, .364]	[.206, .229]			
Rural	16.3%	32.0%	18.8%	[12.7%, 25.7%]	[27.9%, 40.6%]	[15.1%, 27.5%]
	[.153, .174]	[.308, .333]	[.178, .198]			

Sources: Authors' tabulations from WI CARES System, UI System, and Department of Labor

Note: Tabulations include only new enrollees; all of the enrollees in January 2006 are left-censored, so we cannot observe the start-date of their spells. We exclude these censored observations from our analysis. We report in brackets 95% normal bootstrap confidence intervals from at least 300 replications. All differences by column (across time periods) are significantly different from one another at the 95% level.

Table 3: Data Sources for Crowd-out Estimates

Panel A

What Percentage of Newly Enrolled Individuals Were Privately Insured the at or near Enrollment?

	Estimate			Upper Bound		
	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
All	19.3%	34.4%	21.2%	26.9%	41.7%	28.7%
By source						
TPL	13.6%	29.1%	16.0%	13.6%	29.1%	16.0%
DOL / CPS	5.7%	5.3%	5.2%	13.3%	12.7%	12.7%

Panel B

What Percentage of Newly Enrolled Individuals Dropped Private Insurance Prior to Disenrolling From BC+ (within 7 Months of Enrollment)?

	Estimate			Upper Bound		
	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
All	8.9%	10.6%	9.9%	16.7%	34.5%	20.8%
By source						
TPL	3.1%	5.5%	4.7%	3.1%	5.5%	4.7%
DOL / CPS	5.8%	5.1%	5.2%	13.6%	29.1%	16.0%

Sources: Authors' tabulations from WI CARES System, UI System, and Department of Labor

Note: Table shows the portion of each estimate that comes from the two potential sources: the third party liability database (TPL) and the Department of Labor data (DOL) with Current Population Survey (CPS) predictions. We first look for a match in TPL, then in DOL if no TPL match is found. While reported here for the total population, relative proportions remain similar by subgroup. Left-censored observations are excluded.

Table 4. What Percentage of Newly Enrolled Individuals Dropped Private Insurance Prior to Disenrolling From BC+ (within 7 Months of Enrollment)?

	Estimate			[Lower Bound, Upper Bound]		
	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
All	8.9%	10.6%	9.9%	[3.1%, 16.4%]	[5.4%, 18.1%]	[4.7%, 17.4%]
	[.076, .102]	[.097, .118]	[.088, .111]			
By Poverty Level						
< 150	8.7%	9.8%	8.7%	[3.1%, 16.2%]	[4.9%, 17.7%]	[4.1%, 16.0%]
	[.073, .100]	[.087, .110]	[.075, .098]			
> 150	12.2%	12.9%	15.4%	[4.1%, 19.6%]	[6.8%, 19.2%]	[7.7%, 23.5%]
	[.104, .140]	[.117, .140]	[.138, .169]			
150-200	9.3%	11.0%	12.5%	[4.1%, 19.7%]	[6.0%, 19.2%]	[6.6%, 22.9%]
	[.082, .105]	[.098, .122]	[.110, .139]			
200-300	9.5%	9.5%	12.9%	[5.5%, 17.5%]	[7.6%, 18.7%]	[9.6%, 24.1%]
	[.089, .102]	[.090, .100]	[.121, .137]			
300+	10.6%	13.3%	20.0%	[5.4%, 18.5%]	[12.0%, 20.5%]	[15.8%, 28.7%]
	[.099, .112]	[.125, .141]	[.191, .211]			
By County						
Urban	7.2%	10.2%	9.2%	[3.6%, 17.4%]	[6.5%, 19.1%]	[5.5%, 18.6%]
	[.063, .081]	[.093, .111]	[.082, .101]			
Rural	6.2%	8.7%	7.9%	[2.9%, 15.9%]	[4.9%, 17.6%]	[4.3%, 16.7%]
	[.055, .070]	[.078, .096]	[.070, .088]			

Sources: Authors' tabulations from WI CARES System, UI System, and Department of Labor

Note: Tabulations include only new enrollees; all of the enrollees in January 2006 are left-censored, so we cannot observe the start-date of their spells. We exclude these censored observations from our analysis. We report in brackets 95% normal bootstrap confidence intervals from at least 300 replications. All differences by column (across time periods) are significantly different from one another at the 95% level with the exception of the above 150 and 200-300 income groups in the pre-reform and transitional periods.

Table 5. What Percentage of Newly Enrolled Individuals Dropped Private Insurance Prior to Enrolling in BC+?

	Estimate		
	Jan 06 - Jan 08	Feb 08 - Mar 08	Apr 08 - May 09
All	2.3%	1.7%	2.3%
By Poverty Level			
150-200	2.4%	2.3%	2.8%
200-300	0.1%	0.5%	0.9%
300+	0.3%	0.6%	0.5%
By County			
Urban	2.4%	1.6%	2.2%
Rural	2.3%	1.8%	2.4%

Sources: Authors' tabulations from WI CARES System and UI System

Note: Table counts those who may have dropped their employer-sponsored insurance in anticipation of enrolling. Only those above 150% FL who are not otherwise counted as crowded out are included. Tabulations include only new enrollees; all of the enrollees in January 2006 are left-censored, so we cannot observe the start-date of their spells. We exclude these censored observations from our analysis. As these are simple tabulations of the administrative data as described in the text, no standard errors are reported.

Table A1. Descriptive Statistics FHS and CPS Samples

	FHS	CPS
	Mean	Mean
Private Insurance	0.86	0.82
Public Insurance	0.08	0.11
Survey Year 2008	0.52	0.32
Survey Year 2009	-	0.34
Male	0.37	0.68
Dane County	0.08	0.09
Milwaukee County	0.17	0.26
Youngest Child <5	0.32	0.4
Youngest Child 5-13	0.51	0.26
Highest earner <34	-	0.26
Highest earner 34-54	-	0.71
Self-Employed	0.11	0.1
Full Time Worker	0.85	-
Firm with 50 or fewer workers	0.38	0.37
FPL 151-200%	0.09	0.06
FPL 200-300%	0.23	0.19
FPL>300%	0.56	0.62
High School Graduate	0.33	0.29
Some College	0.67	0.66
Goods-producing industry	-	0.31
Highest earner <$10k	-	0.02
Highest earner $10-15k	-	0.03
Highest earner $15-20k	-	0.03
Highest earner $20-30k	-	0.12

Notes: Table shows weighted sample means for the populations used in the probit models, the 2007 and 2008 Wisconsin Family Health Surveys (FHS) and the 2007-2010 Current Population Surveys (CPS). Not all variables were available in both surveys. Unavailable variables are indicated by a dash. Details of sample and variable construction are available in the text.

Table A2. Marginal Effects from Probit Models of P(ESI)

	FHS	CPS
2007	-	0.012
	-	[0.02]
2008	0.02	-0.02
	[0.02]	[0.046]
Male	0.009	-0.017
	[0.021]	[0.02]
Dane County	-0.042	0.069*
	[0.046]	[0.035]
Milwaukee County	-0.034	0.039*
	[0.033]	[0.018]
Has child <=5	-0.042*	-0.018
	[0.02]	[0.019]
Has child > 5 and <13	0.014	-0.023
	[0.022]	[0.022]
Adult <34	-	-0.059
	-	[0.044]
Adult 34-54	-	-0.015
	-	[0.042]
Earnings <10k	-	-0.306**
	-	[0.062]
Earnings 10-15k	-	-0.191**
	-	[0.045]
Earnings 15-20k	-	-0.123**
	-	[0.037]
Earnings 20-30k	-	-0.073**
	-	[0.024]
Goods Industry	-	0.076**
	-	[0.019]
Self Employed	-0.094**	-0.031
	[0.035]	[0.026]
Full Time	0.011	-
	[0.02]	-
Small Firm	-0.094**	-0.074**
	[0.024]	[0.017]
FPL 151-200%	0.102**	0.029
	[0.026]	[0.029]
FPL 201-300%	0.194**	0.084**
	[0.03]	[0.028]
FPL > 300%	0.280**	0.176**
	[0.021]	[0.028]
High School Graduate	0.126*	0.069*
	[0.063]	[0.03]
Some College	0.203**	0.124**
	[0.062]	[0.031]
Observations	2016	2685

Notes: Standard errors in brackets. ** p<0.01, * p<0.05. This table shows the marginal effects from probit models in the two survey data sets used to predict the probability of private insurance over the administrative data in the calculation of equation 1, the 2007 and 2008 Wisconsin Family Health Surveys (FHS) and the 2007-2010 Current Population Surveys (CPS). Not all variables were available in both surveys. Unavailable variables are indicated by a dash. Details of sample and variable construction are available in the text.