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Contributions

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Ownership and Exit Behavior: Evidence from the Home Health Care Market

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Abstract: In the US health care system a high fraction of suppliers are not-for-profit companies. Some argue that non-profits are “for-profits in disguise” and I test this proposition in a quasi-experimental way by examining the exit behavior of home health care firms after a legislative change considerably reduced reimbursed visits per patient. The change allows me to construct a cross provider measure of restriction in reimbursement and to use this measure and time-series variation due to the passage of the law in my estimates. I find that exits among for-profit firms are higher than those of not-for-profit firms, rejecting the null that these sectors responded to the legislation in similar ways. In addition, my results expand the view that “not-for-profit” firms are a form of “trapped capital.” There is little capital investment in the home health care market, so the higher exit rates of for-profit firms after the law change indicate the possible role of labor inputs in generating differences in exit behavior across sectors.

Keywords: long-term care, government restriction in Financing, not-for-profit

JEL codes: I11, L31, H32

1 Introduction

A large fraction of firms in the United States operate as non-profits, coexisting with for-profit and government firms. For example, in 2008, there were 1.58 million non-profit organizations in the United States.

Despite the large presence of non-profit firms in health care and other industries, such as education and the arts, there is little consensus on the reasons behind the existence of the non-profit sector (Gertler and Kuan 2009).

In health care, the focus of this study, the debate regarding whether non-profit firms maximize additional outcomes other than profits is fueled by empirical research that often finds few differences in responses to financial incentives

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between the two organizational types. These findings are consistent with the idea that “non-profit” might just be a label used by non-profit firms in order to enjoy the advantage of tax-free status so that, in the end, non-profit firms are just “for-profit in disguise” (Weisbrod 1988, 1998).

Here I concentrate on studying exit behavior by for-profit/not-for-profit status in the home health care market. The main contribution of this study is to provide the first causal estimate of the impact of limits in reimbursement on exit rates of for-profit and not-for-profit home health agencies. I find that exit rates for for-profit agencies are higher than exit rates for not-for-profit agencies as a consequence of the imposition of limits in reimbursement from the government, thereby rejecting the hypothesis that not-for-profit home health agencies are “for-profits in disguise” in their exit behavior.

Looking at differential exit behavior between for-profit and not-for-profit firms as a consequence of changes in financial incentives is important because the focus of the outcome to study, in particular exit behavior, might be critical in uncovering where the differences in behavior between for-profit and not-for-profit firms really lie, and, therefore, where the hypothesis of not-for-profits as “for-profits in disguise” is most likely to be rejected.

The idea that exit is a crucial outcome to consider in order to uncover differences in performance between for-profit and not-for-profit firms is suggested by recent work of Harrison and Laincz (2008), who use data from the Small Business Administration and data from the National Center for Charitable Statistics and note that between 1990 and 2000 the exit rate of non-profit firms is about one third of the exit rate of the whole sample of firms.

Furthermore, Hansmann, Kessler, and McClellan (2003) note that the study of the rapidity of exit by for-profit/not-for-profit status is “a largely neglected aspect of hospital performance”, and further suggest that overinvestment in capital and therefore slower exit rates of not-for-profit firms as compared to for-profit firms might be generic in the non-profit sector.

However, it is unclear whether lower exit rates exist for not-for-profit firms as compared to for-profit firms only when there is the possibility of “trapping capital,” or whether low capital and limited opportunities to overinvest also result in slower exit rates for not-for-profit than for for-profit firms.

Here I contribute to filling the gap in the literature on exit by for-profit/not-for-profit status by looking at differences in exit behavior in response to financial incentives between for-profit and not-for-profit firms in the home health care market, where there are virtually null capital investments. I find that for-profit home health agencies exit at faster rates than not-for-profit home health agencies as a consequence of changes in financial incentives. Because home health agencies only provide labor services, these results point toward the role of labor

as an important dimension to consider in order to understand exit behavior by for-profit/not-for-profit status.

In my analysis I use a policy change in Medicare reimbursement for home health care introduced by the Balanced Budget Act of 1997, in which timing and characteristics are exogenous to the choice of each firm, as a quasi-experiment to estimate whether changes in financial incentives differentially affected exit for for-profit and not-for-profit home health care providers, after conditioning on agency and area-specific characteristics (as well as for-profit status and its interaction with the other control variables).

My paper differs from previous literature on the impact of the IPS on the home health care market along the following dimensions. First, although previous literature on the IPS and home health care has exploited time-series (Horwitz 2005; Horwitz and Nichols 2009), and time-series and cross-sectional variation at the state level to study the impact of the IPS on several outcomes (McKnight 2006; Golberstein et al. 2009; Orsini 2010), my study is the first study to use time-series and cross-sectional variation at the agency level. Also, previous literature was interested in changes in offerings by hospitals of home health care by ownership status (Horwitz 2005; Horwitz and Nichols 2009). Because the research question in the previous literature is different from mine, it is not possible to know from previous research whether the home health agency ceased to exist once the hospital no longer offered home health care services or whether the home health agency simply changed owner. My focus is on exit of home health agencies independently of whether they are hospital owned or not. Here I use data for California between 1994 and 2000, and in these data the vast majority of home health agencies are not owned by in-patient facilities.

The home health care market in the 1990s facilitates econometric identification of responses to financial incentives by for-profit and not-for profit status because home health care providers receive the vast majority of their revenue from Medicare. Therefore these providers cannot buffer decreases in financial incentives from one source with other sources.

The imposition of the IPS had a large impact on service offering and the sharpness of the change facilitates the analysis. In Figures 1 and 2 I show that for the United States as a whole, as well as for California, there has been a sharp decline between 1997 and 2000 in the number of visits per person served and in the number of visits received by Medicare beneficiaries.

What are the welfare implications of the IPS?

First, it is important to understand whether the IPS impacted the health of Medicare beneficiaries. McKnight (2006) did not find that the IPS impacted measures of health and mortality of Medicare beneficiaries. However, Golberstein et al. (2009) finds that the IPS caused an increase in informal

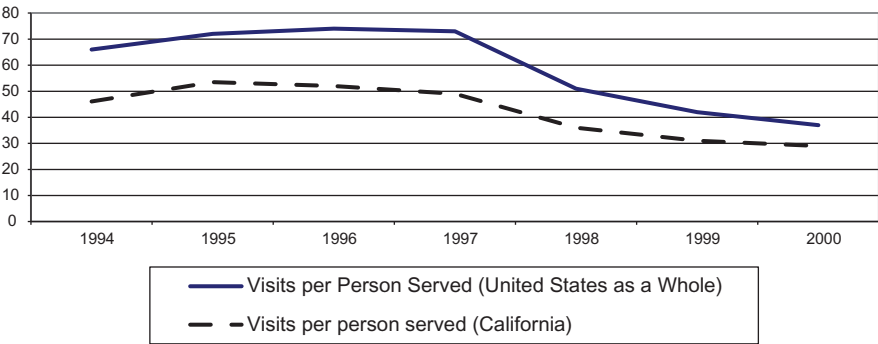


Figure 1: Change in the number of Medicare Home Health Care visits per person served, in the United States as a whole and in California, 1994–2000.

Note: Data are from Medicare and Medicaid Statistical Supplements, various years.

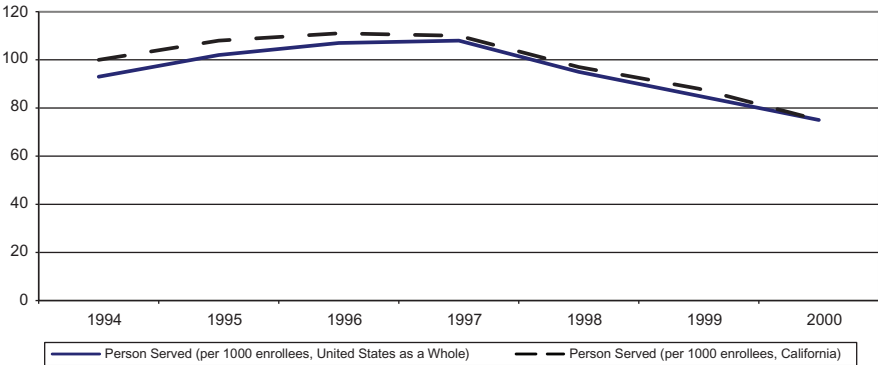


Figure 2: Change in the number of person served by Medicare Home Health Care (per 1000 enrollees) in the United States as a whole and in California 1994–2000.

Note: Data are from Medicare and Medicaid Statistical Supplements, various years.

care, and Orsini (2010) finds that the IPS caused Medicare beneficiaries to give up independent living. Golberstein et al. (2009) and Orsini (2010) also find that poor Medicare beneficiaries were disproportionately affected by the IPS.

Second, my analysis shows that for-profit home health agencies were more likely to exit compared to not-for-profit agencies as a consequence of the cuts introduced by the IPS, changing the relative composition of for-profit and not-for-profit providers. This result suggests that another important aspect to understand, but one I cannot investigate in this paper due to data limitations, is the impact of the change in the composition of for-profit/not-for-profit agencies on the quality of care of home health care patients.

My results are consistent with two broad theories of organizational behavior.

First, my findings are consistent with the theory stating that the crucial difference between for-profit and not-for-profit firms rests in their different preferences: for-profit firms' only goal is to maximize profits and not-for-profit firms not only care about profits but also are "mission oriented" (Rose-Akerman 1996; Lakdawalla and Philipson 2006).

This theory predicts in the home health care market that not-for-profit home health agencies will exit at a slower rate compared to for-profit home health agencies. Not-for-profit home health agencies could afford exiting at lower rates than for-profit home health agencies if, for example, employees at not-for-profit agencies are more willing to increase their share of voluntary work when the reimbursement change hits.¹ The channel pointing toward a possible increase in donated labor in not-for-profit firms is also plausible in light of recent empirical evidence that shows that workers who work in the not-for-profit sector donate more labor than workers who work in the for-profit sector (Gregg et al. 2011).

Results in this paper are also consistent with a theory of organizational behavior which states that the crucial difference between for-profit and not-for-profit firms stands in the ease with which for-profit firms can appropriate profits. Hansmann (1996) states "the critical characteristic of a non-profit firm is that it is barred from distributing any profits it earns to persons who exercise control over the firm." However, as Glaeser and Sheifer (2001) report, profits can be redistributed by the non-profit firms through perquisites such as longer vacations, lower levels of effort, more benefits, etc...

Under the assumption that such perquisites are considered less valuable than cash, such a theory predicts that not-for-profit firms will respond less quickly than for-profit firms to changes in financial incentives, because reducing perquisites when cash flow declines will not be perceived as negatively as reducing cash benefits. Unfortunately, I lack in my data information on perquisites, so I am unable to distinguish between the two theories above.

This article proceeds as follows: Section 2 provides background information on the home health care market and the IPS; Section 3 presents the data and the empirical framework; Section 4 presents the results and Section 5 concludes.

¹ Unfortunately, my data do not allow me to check whether this channel is relevant because I do not have information on how many hours of donated labor employees provide. However, this is potentially a very important aspect to consider in the home health care market given that home health agencies only provide labor services. Moreover, Medicare reimbursement for home health care explicitly is meant to cover labor costs and there is no reimbursement for equipment, so that when the reimbursement change hits, labor costs are directly affected.

2 Background

In the period under study, Medicare home health care consists of health care services provided in the home of eligible Medicare patients through periodic visits. Six services are provided to “home-bound” patients in need of “intermittent” and “part-time” care (Health Care Financing Administration 2000): skilled nursing, physical therapy, occupational therapy, speech therapy, medical social work, and home health aide.

Medicare certification is assigned to a home health care agency after the agency has been surveyed and found to be compliant with the regulations (GAO 1997). Medicare payments to home health agencies for the services provided are adjusted to take into account the differences in wages across areas. For example, because urban areas tend to have higher wages compared to rural ones, the baseline Medicare payment for a specific service is multiplied by an adjustment index that reflects the different compensation levels across urban and rural areas.² This rule, together with evidence suggesting that home health care agencies that are Medicare certified provide a substantial fraction of their services to Medicare patients and therefore receive most of their revenue from Medicare, allows me to reasonably identify the market in which an agency operates using the geographic areas corresponding to different adjustment indexes.³

Because in the period under study Medicare reimbursement is the main source of funds for home health agencies and Medicare does not cover any equipment for home health care, home health services most likely consist almost exclusively of labor services.

Home health agencies represent the agents that are directly impacted by any Medicare reimbursement change introduced by the Balanced Budget Act in 1997.

Before the enactment of the BBA in 1997, each home health agency only faced a limit on the maximum reimbursement for each type of visit. With this reimbursement scheme, each agency had the incentive to minimizing the intensity of care per visit and to increase the number of visits per patient. In fact, aggregate data show that the number of visits per Medicare beneficiary went

² Also, since different urban areas have different wages, the adjustment index across cities varies. This rule implies that two agencies that locate in the same geographic area as defined by the reimbursement adjustment index receive the same reimbursement for each type of service provided.

³ In fact, it seems quite plausible to imagine that agencies that are located in the same area for reimbursement purposes, might share similar unobservable characteristics that are correlated with their location choice.

from 1.14 in 1988 to 7.8 in 1996 (Health Care Financing Administration, various years).

The expansion in the provision of services was accompanied by a skyrocketing increase in Medicare home health care expenditures that went from \$1.94 billion in 1988 to \$16.76 billion in 1996.⁴ The number of providers went from 5695 in 1990 to 10127 in 1996.⁵

This very quick and large growth in spending for Medicare home health care raised critiques of the generous reimbursement considered responsible for favoring abuses (Murtaugh et al. 2003). In the BBA enacted by Congress in 1997, there are provisions intended to impose a limit on the increasing expenditures on Medicare home health care.

The change introduced by the law involved two steps. First, from 1997 to 2000, an Interim Payment System (IPS) was established that put a cap on how much each home health care agency would be reimbursed per patient per year. The law implied that agencies which entered the Medicare home health care market on or before October 1, 1993 faced a cap that had two parts: 75% of the value was based on each agency's 1994 average per patient cost and 25% was based on the average per patient cost of the agency's census division. For agencies which entered the home health care market after October 1, 1993 the limit was calculated as the median limit of freestanding agencies in the United States which entered the market on or before October 1, 1993. The second step started in October 2000 when the Prospective Payment System was implemented.⁶ Here I concentrate on the first change in reimbursement: the IPS.

In this paper I concentrate on the sample of agencies that entered the market on or before October 1, 1993 (and their branches even if added from October 2, 1993 until 2000) because my data do not allow me to construct an agency-specific measure of reimbursement restriction for the other agencies (see Appendix D). Although it is unfortunate that I am not able to use cross-sectional variation for agencies that entered the market after October 1, 1993, such agencies had 33% of market share as measured by the number of visits provided to people who were at least 65 years of age.⁷

⁴ Figures are in nominal dollars.

⁵ Data are from the National Association for Home Care and Hospice and can be found on the web at: <http://www.nahc.org/Consumer/hcstats.html>.

⁶ Under PPS, a home health care agency receives a single payment for all items and services furnished during each 60-day episode of care.

⁷ I have used time-series variation only to study exit of agencies which entered the market after October 1, 1993 and their branches, but estimation results were noisy.

3 Data and Empirical Framework

3.1 Data and Summary Statistics

I use two sources of data: Annual Utilization Data for Home Health Care Agencies and Hospices for years 1994 to 2000 provided by the Office of Statewide Health Planning and Development (OSHPD) of the state of California, and March Current Population Survey (CPS) data.

The Annual Utilization Data for Home Health Care Agencies and Hospices datasets contain information from two sources: a questionnaire filled out by each home health care agency and administrative data added by the OSHPD.⁸ An important feature of the data is the information regarding whether an agency is licensed in any given year. Since the OSHPD is the entity that releases the licenses, it knows whether an agency has been licensed for the year but has not responded to the questionnaire.⁹ This information is available in the dataset released by the OSHPD.

The dataset also has a permanent identifier attached to each home health agency which allows it to be traced over time; the date in which the agency was licensed for the first time; information on whether the agency is licensed in any given year; information on whether an agency is a branch or a parent.

Information regarding whether an agency is a parent or a branch is useful because the BBA requires that the limit per user needs to be calculated with parent and branches considered as one single entity.¹⁰ Here I could not identify agencies that are part of a chain¹¹ and there are arguments that support the possibility that agencies that are part of a chain might respond more or less to restrictions in government financing. The literature does not offer guidance that might be readily extended to the market under study. For example, Chakravarty et al. (2006) have found that being part of a chain significantly decreases exit for

8 Conversations with the staff at the California Department of Health Services (DHS) clarified that failure to report should imply the revocation of the agency's license by the DHS. However, the rule is so drastic that it has never been applied.

9 I consider an agency to be in the market in year t if it had been licensed in year t . I believe this to be a reasonable assumption, bearing in mind that an agency has to pay for the licensing process each year and it is doubtful that an agency would pay for a license and not use it at all.

10 I explain in the Appendix 1 how I identified the branches belonging to each parent in my dataset.

11 A chain in this article refers to a group of agencies composed of several parents and branches with the same name (for example, Kaiser Home Health). See Appendix 1 that explains why I cannot study agencies part of a chain.

for-profit compared to not-for-profit hospitals, but does not have any impact on the behavior of not-for-profit hospitals. This finding does not necessarily hold for home health care agencies. Indeed, if being part of a chain implies that agencies are able to learn faster than other agencies about the changing market opportunities, then agencies that are part of a chain might respond faster to changed market conditions. Unfortunately, I cannot properly test whether agencies that belong to a chain behave differently from agencies that do not, as this would require me to be able to construct a cross-agency measure of variation.

Table 1 summarizes information I could obtain from the Center for Medicare and Medicaid services for the United States as a whole. This information identifies ownership mix, the presence of branches, and information on the fraction of agencies which are in-patient facility based. From statistics in the table, California does not seem extremely different from the United States as a whole. There is a larger fraction of for-profit home health agencies in California compared to the United States as a whole, whereas the fraction of not-for-profit home health agencies is similar in California compared to the United States as a whole.

Table 1: Characteristics of home health agencies in the United States and in California, 1994.

	US as a whole	California ^a
Fraction for profit	51.99	61.9
Fraction not-for-profit	30.54	32.14
In-patient facility based	25.65	32 ^b
Without branches	85.49	83.53

Notes: Data for the United States as a whole are from the Center for Medicare and Medicaid services.

^aEstimation sample, agencies licensed on or before October 1, 1993. ^bData from OSHPD files for year 1993.

3.2 A Cross-Provider Variation of Restriction in Reimbursement

My identification strategy to estimate the impact of the imposition of limits in reimbursement on exit for for-profit and not-for-profit home health care agencies relies on comparing the exit rates of agencies that were more restricted by the policy change with the exit rates of agencies that were less restricted by the policy change. This requires me to construct an agency-specific measure of reimbursement tightness.

The BBA states that starting in October 1997, each agency is subject to an average per beneficiary limit that is a blend between the average agency's 1994 per patient cost and the average per patient's cost in the agency's census division.¹² The first challenge is then to identify an appropriate agency-specific measure of 1994 average per-patient cost. McKnight (2006) proposed the average number of Medicare visits per patient as a measure of per-patient cost of providing Medicare home health care services, and this measure has been used also by Golberstein et al. (2009) and Orsini (2010). In this paper, I follow the previous literature and use the following measure of average per patient cost in 1994:

$$\text{visits94} = (V_i)/(N_i) \quad (1)$$

where V_i is the number of visits for agency i for patients that are at least 65 years of age and N_i is the number of people at least 65 years old that the agency has treated in 1994. In other words, I use the total number of visits provided by an agency to patients 65 or older as a proxy for the number of Medicare visits provided by the agency to patients that are at least 65 years of age or older. This approximation is reasonable because 93.7% of people 65 or older¹³ are enrolled in Medicare in California.¹⁴

For agencies that entered the market on or before October 1, 1993, the BBA stated that from 1997 onwards each home health care agency faced a limit in reimbursement based on the blend of the average per-patient cost of the agency in 1994 (75% of the limit) and the average per-patient cost in the agency census

¹² A census division is a cluster of states. California belongs to the Pacific census division. The other census divisions can be found here: http://www.census.gov/geo/www/us_regdiv.pdf.

¹³ My calculation comes from 1994 March Current Population Survey data.

¹⁴ Also, in 1994 there was no limit on the number of visits that an elderly Medicare beneficiary could receive. Moreover, Medicaid, which also provides coverage for home health care to the disabled elderly, is in general the payer of last resort and covers services that are not covered by Medicare, including some housekeeping services (Harrington et al, 2000) and medical supplies and equipment (Ettner 1994). Although those services are surely valuable for many disabled elderly, during the time under study Medicaid was still a relatively small funding source for home health care services (Harrington and Estes 1994). There is a further complication introduced by the Health Care Financing Administration in its rules of implementation of the Interim Payment System that impacts the way eq. (1) is calculated when a home health care agency has one or more branches. The regulations specify that parent and branches need to be considered as a single entity when computing the average per patient limit. Therefore, following as closely as possible the law, in the case of a home health care agency that has one or more branches, V_i is the sum of visits for patients that are 65 years of age or older across the parent and all branches and N_i is the sum of patients that are at least 65 years old across the parent and all branches.

division (25% of the limit). For all agencies in California, the average per-patient cost in the agency census division is the same, because they are all located in the same census division, so the figure calculated in eq. (1) needs to be blended for each agency with the same census division per-patient limit. This means that the higher the variable visits_{94} , the more restrictive is the final blended per-patient limit faced by each agency from 1997. In other words, visits_{94} represents the cross-provider measure of restriction in reimbursement that I am using in my econometric analysis of exit.¹⁵

In the datasets for years 1994 to 2000, there are also agencies that were not in the market on or before October 1, 1993. The law states that these agencies are assigned the median limit available to freestanding agencies in the United States in the market on or before October 1, 1993. Unfortunately, from 1995 onwards, my data do not allow me to identify the number of patients 65 years of age or older, a necessary component to calculate a cross-sectional limit of these agencies (refer to Appendix D for an explanation of the limit the BBA assigned to these agencies). Thus, I focus my attention on agencies that entered the market on or before October 1, 1993 and their branches (even if added at a later date). In 1994 such agencies had 67% of the market share as measured by the number of visits provided to people who were at least 65 years of age.

In my analysis I compare changes in exit rates of agencies with a higher value of visits_{94} with changes in exit rates of agencies with a lower value of visits_{94} . The identifying assumption is that absent the IPS trends in exit rates should not be different for agencies with a higher value of the variable visits_{94} compared to agencies with a lower value of the variable visits_{94} . Although this is an identifying assumption and therefore it is not testable, for it to be reasonable it should not be the case that *trends* in exit rates for home health agencies

15 To see how a higher value of visits_{94} means that after 1997 an agency faces a tighter reimbursement limit, consider the following example. Consider two agencies with a number of visits per user in 1994 equal to 10 and 11, respectively. Assume that the Census division average number of visits per user is 5. The limit per user faced by agency 1 from 1997 onwards is $0.75 \cdot 10 + 0.25 \cdot 5 = 8.75$ and the limit per user faced by the second agency is $0.75 \cdot 11 + 0.25 \cdot 5 = 9.5$.

In this example, after 1997, agency 1 is not reimbursed 1.25 visits per user compared to its 1994 level, and agency 2 is not reimbursed 1.5 visits per user compared to its 1994 level. Because service offerings increased between 1994 and 1997, under the identifying assumption of lack of differential trends in increase in service offerings between agency 1 and agency 2, agency 2 in the post-policy period faces a limit that, compared to its average utilization in 1994, is more restrictive (by a factor of 0.25 visits) than the one faced by agency 1. In other words, an increase equal to 1 in the variable visits_{94} gives the impact of precluding reimbursement of 0.25 additional visits per user compared to 1994 levels. To recover the impact of precluding reimbursement of one additional visit per user, which is to say the impact of a decline in reimbursement of one visit per user, I must consider an increase in visits_{94} equal to 4.

with a higher value of the variable *visit94* are different from *trends* in exit rates for home health agencies with a lower value of the variable *visit94* during the years before the IPS. In Figures 3 I divided both for-profit and not-for-profit agencies in two groups based on the *visit94* variable for each group. I constructed the figures as follows: I sorted the agencies by the variable *visits94* and then took the median value of the variable *visits94* and consider all agencies with a value of the variable *visits94* below the median as agencies with a low limit of the variable *visits94*. Then I plot in the figures the fraction of agencies in the group that exit. Yearly exit rates for those agencies with a high value of the variable *visits94* and for those agencies with a low value of the variable *visits94* for each year for each year and each ownership type are plotted in Figure 3(a) and 3(b) with the lines called “fraction exiting high limit” and “fraction exiting low limit” respectively.

Figure 3(a) and 3(b) shows for both for-profit and not-for-profit agencies that trends in exit rates were quite similar for agencies with a high limit of the variable *visits94* and agencies with a low limit of the variable *visits94*, justifying the quasi experimental design used in this paper. Figure 3(a) also shows that exit rates of for-profit firms with a high value of the variable *visits94* were higher than exit rates of for-profit firms with a low value of the variable *visits94*, whereas the pattern shown in Figure 3(b) for not-for-profit firms is not as clear.

3.3 Econometric Specifications

I first estimate a linear regression model of the following form:

$$y_{it} = \beta_0 + \beta_1 \text{Visits94}_i * \text{Post}_t + \beta_2 \text{Visits94}_i * \text{Post}_t * \text{Forprofit}_i + \beta_3 \text{Forprofit}_i + \beta_4' X_{it} + \epsilon_{it} \quad (2)$$

To estimate eq. (2), I pull all observations for years 1994–2000 on home health agencies that were licensed on or before October 1, 1993 (and their branches, even if licensed from October 2, 1993 until 2000). The dependent variable is a dummy variable indicating whether an agency exited in year t . Post_{it} is a variable equal to 0 from 1994 until 1996 and equal to 1 for years 1997–2000; Forprofit_i is a dummy equal to 1 if the home health agency is for-profit and equal to 0 otherwise. Finally, X_{it} are variables that include a dummy equal to 1 for the post-policy period and its interaction with the for-profit dummy, and agencies’ characteristics, namely *visits94_i*, and its interaction with the for-profit dummy, so that the model above allows each variable to have a differential effect on exit for for-profit and not-for-profit firms. I also include a dummy indicating whether the agency was first licensed before 1989 and its interaction with the for-profit

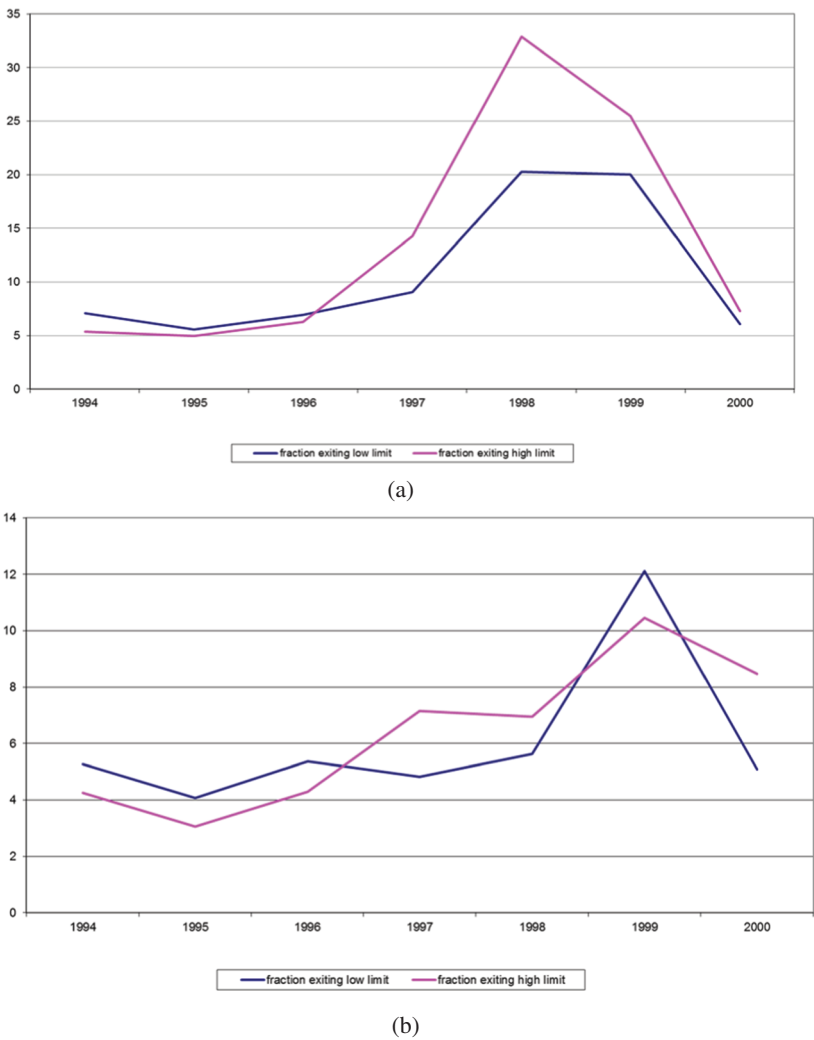


Figure 3: Exit rates for for-profit and not-for-profit home health care agencies, 1994–1996. (a) For-profit. (b) Not-for-profit.

Source: OSHPD data for the Stock and Flow sample of agencies used in the estimation. Each group of agencies (profit and not-for-profit) are divided in 2 groups based on the median value of the variable visits94. Those with a value of visits94 above the median are the agencies with a “high-limit” and those with a value of visits94 below the median are the agencies with a “low limit”.

dummy. Such a variable is tied to the history of Medicare home health care. In fact, changes in the interpretation of what “part time” and “intermittent care” meant from 1989 onwards made it much easier for agencies to expand services to Medicare patients and this, in turn, increased incentives to agencies to enter. Thus, the variable that controls for entry after 1989 controls for possible heterogeneity in my sample. I also include a cubic of the logarithm of the number of years an agency has been in the market (and its interaction with the for-profit dummy) and a dummy equal to 1 if the agency is a branch and its interaction with the for-profit dummy. I cluster the standard errors of the linear model above at the agency (and its branches) level.

Next, I estimate the impact of the IPS on the conditional probability of exit for for-profit and not-for-profit home health agencies using a grouped hazard framework, which makes use of the information in the data on the year in which each agency first entered the market. Specifically, to provide a causal estimate of the impact of the imposition of limits in reimbursement on exit of home health care agencies by for-profit/not-for-profit status, I use a combination of a stock and flow sample of home health agencies.¹⁶

As Berger and Black (1998) argue, the use of a mixed stock and flow sample when it is possible to correct for length-biased sampling is preferable to the use of only a stock or only a flow sample. In fact, the use of a flow sample, namely the sample of spells that begin during the time period spanned by the panel data, presents the disadvantage of estimates biased towards short spells, because spells ongoing at the time in which the panel starts are not used in the analysis. On the other end, the use of only a stock sample, namely the sample of ongoing spells at the time in which the panel starts, presents the drawback that a stock sample- by excluding spells that start during the time spanned by the panel, namely the flow sample is biased toward long spells. Moreover, a stock sample suffers from length bias because at any point in time, longer spells have a greater probability of being in progress, and therefore of being observed in the panel, than do shorter spells. This means that if a researcher simply includes all spells in progress during the time spanned by the panel, the estimates will be biased toward longer spells unless it is possible to correct for length bias inherent in remaining censored spells. Berger and Black (1998) argue that it is possible to correct for length bias when the date in which the spells begins is known in the data. In this case it is possible to condition on the length of the elapsed spell by specifying the likelihood function from which to estimate the hazard function.

¹⁶ Berger and Black (1998) also use a combination of a stock and a flow sample to study Medicaid spells.

In this application, because I know when a home health agency first entered the market, I can correct for length-biased sampling. This means that I can use a combination of a stock and a flow sample when studying the impact of imposition of limits in reimbursement on exit behavior of home health agencies by for-profit/not-for-profit status, hereby overcoming the bias that would arise from the use of only a flow sample or only a stock sample, or even the bias that would arise by the use of a mixed stock and flow sample where there is no correction for length biased sampling.

To construct the hazard function, I first consider the random variable T_i measuring the time in which a home health agency stays in the market. I assume that a home health agency is in the market in year t if it has been licensed in year t . This assumption seems reasonable for two reasons. First, in the period under study a home health care agency can receive its license to operate contingent upon Medicare certification, so the licensed agencies in the data are Medicare certified home health care agencies. Also, because an agency pays for being licensed in each year and cannot operate without license, this seems a reasonable modeling assumption. Therefore, I consider a home health care agency not to be in the market in year t (i.e. I code year t as the year in which exit happens) if the agency is not licensed in year t . For an agency entering the market at time t_{0i} , I model the conditional probability of exit at year t given survival until year -1 , i.e. the hazard function as follows:¹⁷

$$\lambda_t(t_{0i}, t_i) = \frac{1}{1 + \exp\{-[\alpha_0 + \alpha_1 \text{Visits94}_i^* + \alpha_2 \text{Visits94}_i^* \text{Post}_t^* \text{Forprofit}_i + \alpha_3 \text{Forprofit}_i + \alpha'_3 X_i(t_{0i} + t)]\}} \quad (3)$$

where α_0 is a constant, $X_i(t_{0i} + t)$ are variables already described before for the linear model, including the duration dependence controls and their interaction with the for-profit dummy to take into account the effect of the passage of time since entry in the market on exit. I assume that the duration dependence $h(t)$ can be described by a polynomial in $\log t$.¹⁸ The differential effect of the BBA on for-profit home health care agencies is captured by the average marginal effect of the variable $\text{Visits94}_i^* \text{Post}_t^* \text{Forprofit}_i$, and the effect of the BBA on not-for-profit providers is captured by the average marginal effect of $\text{Visits94}_i^* \text{Post}_t^*$.¹⁹ More specifically, the average marginal effect of $\text{Visits94}_i^* \text{Post}_t^*$ captures the average

¹⁷ As it is done in Ham and Rea (1987).

¹⁸ The highest degree polynomial for which coefficients are different from 0 is 3.

¹⁹ I assume that all time-varying covariates are strictly exogenous (Wooldridge 2010), meaning that the path of the covariate is independent of whether the observation leaves the initial state.

marginal effect on exit for not-for-profit home health care agencies of the decline in reimbursement of 0.25 visits per user. The average marginal effect of the variable $Visits94_i * Post_t * Forprofit_i$ capture the extra average marginal effect (compared to the marginal effect of not-for-profit agencies) on exit for for-profit home health care agencies of the decline in reimbursement of 0.25 visits per user. Next, I need to select the sample over which to estimate the hazard in eq. (3). I report in Appendix B the details of the construction of the likelihood function.

4 Estimation Results

4.1 Baseline Models

Tables 2 and 3 report the average marginal effects of $Visits94_i * Post_t$ for the linear model in eq. (2) and for the non-linear model in eq. (3), and the average marginal effect of its interaction with the for-profit dummy. The first information conveyed by all specifications of Tables 2 and 3 is that the policy change affected exit more for for-profit agencies than for not-for-profit agencies; namely, the marginal effects of are positive and precisely estimated with the linear and non-linear model. Table 2 also shows that the estimates of the marginal effects of the variable $Visits94_i * Post_t$, which measure the impact of the IPS on not-for-profit agencies in the linear model, are imprecise. However, in Tables 2 and 3 the marginal effects of the variables $Visits94_i * Post_t$ and $Visits94_i * Post_t * Forprofit_i$ of the non-linear model are within the 95% confidence intervals of the marginal effects of the linear model, so the estimates from the two models are not inconsistent with each other. The baseline model in column 1 of Tables 2 and 3 suggests that a decline in reimbursement of 0.25 visits per user increases exit for a for-profit agency by approximately 0.156 percentage points in the linear model and by approximately 0.429 ($0.156 + 0.273 = 0.429$) percentage points in the non-linear model. For not-for-profit agencies, the marginal effect in the non-linear model in column 1 of Table 3 suggests that a decline in reimbursement of 0.25 visits per user increases exit for a not-for-profit agency by approximately 0.156 percentage points.

Adopting the conservative estimate that as a consequence of the IPS the typical for-profit home health agency was not reimbursed 2.3 visits per user

Here, the path of the time-varying covariate capturing the impact of the Balanced Budget Act is determined by a law change, so that this assumption seems reasonable.

Table 2: Estimation results: The outcome is a dummy equal to 1 if the home health agency exits in year t . Linear model estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
$Visits94_i * Post_t$	0.00056 (0.00052)	0.00034 (0.00057)	0.00053 (0.00052)	0.00049 (0.00052)	0.00048 (0.00052)	0.00048 (0.00052)
$Visits94_i * Post_t * Forprofit_i$	0.00156** (0.0006)	0.00186*** (0.00071)	0.00163** (0.00068)	0.00171** (0.00067)	0.00170** (0.00067)	0.00172** (0.00067)
Dummy for branch and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Polynomial of log duration dependence and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Counties dummies, and their interaction with for-profit dummy	–	–	Yes	–	–	–
Market Dummies, all separate markets and their interaction with for-profit dummy	–	–	–	Yes	–	–
Market dummies, partially identified markets and their interaction with for-profit dummy	–	–	–	–	Yes	Yes
Log population Over 65	–	–	–	–	–	Yes
N	3,111	3,111	3,111	3,111	3,111	3,111

Notes: The symbols *, **, and *** mean statistically significant at the 10, 5 and 1% level, respectively. $visits94_i = (V_i)/(N_i)$, where V_i is the number of visits for agency i for patients who are at least 65 years of age and N_i is the number of people at least 65 years old who the agency has treated. V_i and N_i are calculated using also the number of visits and patients of branches in case branches were in the market in 1994. Other control variables in all specifications are a dummy equal to 1 for years 1997–2000 and its interaction with the for-profit dummy, a dummy equal to 1 if the agency is for-profit. Other controls in columns 2–6 include a dummy equal to 1 if the agency was licensed after 1989 and its interaction with the for-profit dummy.

Table 3: Estimation results: The outcome is a dummy equal to 1 if the home health agency exits in year t . non-linear model estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
$Visits94_i * Post_t$	0.00156*** (0.00051)	0.00144*** (0.00050)	0.00147** (0.00057)	0.00158*** (0.00057)	0.00153*** (0.00052)	0.00155** (0.00073)
$Visits94_i * Post_t * Forprofit_i$	0.00273*** (0.00099)	0.00299** (0.00118)	0.00249** (0.00123)	0.00268** (0.00117)	0.00295** (0.00132)	0.00294** (0.00133)
Dummy for branch and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Polynomial of log duration dependence and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Countries dummies, and their interaction with for-profit dummy	–	–	Yes	–	–	–
Market Dummies, all separate markets and their interaction with for-profit dummy	–	–	–	Yes	–	–
Market Dummies, partially identified markets and their interaction with for-profit dummy	–	–	–	–	Yes	Yes
Log Population Over 65	–	–	–	–	–	Yes
N	3,111	3,111	3,111	3,111	3,111	3,111

Notes: The symbols *, **, and *** mean statistically significant at the 10, 5 and 1% level, respectively. $visits94_i = (V_i)/(N_i)$, where V_i is the number of visits for agency i for patients who are at least 65 years of age and N_i is the number of people at least 65 years old who the agency has treated. V_i and N_i are calculated using also the number of visits and patients of branches in case branches were in the market in 1994. Other control variables in all specifications are a dummy equal to 1 for years 1997–2000 and its interaction with the for-profit dummy, a dummy equal to 1 if the agency is for-profit. Other controls in columns 2–6 include a dummy equal to 1 if the agency was licensed after 1989 and its interaction with the for-profit dummy.

(see Appendix C for details of this calculation), I calculate that the IPS caused an increase equal to 3.95 ($2.3 \times 4 \times 0.429$) percent points in the fraction of for-profit agencies that exited the market. Using estimates for the linear model the IPS caused an increase equal to 1.435 ($2.3 \times 4 \times 0.156$) percentage points in the fraction of for-profit agencies that exited the market.

For not-for-profit firms, adopting the conservative estimate that as a consequence of the IPS the typical not-for-profit home health agency was not reimbursed 0.44 visits per user, estimates of the non-linear model suggest that the IPS caused an increase equal to 0.27 ($0.156 \times 0.44 / 0.25$) percent points in the fraction of not-for-profit agencies that exited the market. Back of the envelope calculations for the non-linear model imply that the IPS was responsible for 22.8% of exits in the period 1997–2000 for for-profit agencies and was responsible for 3.5% of exits in the period 1997–2000 for not-for-profit agencies. In total, the IPS was responsible for 19.01% of exits from the market from 1997 to 2000. For the linear model, estimates for not-for-profits are noisy so I can provide back of the envelope calculations of the impact of the IPS on exit for for-profit agencies: the IPS was responsible for 8.11% of for-profit exits from the market in years 1997–2000. Estimates of a specification that adds a dummy equal to 1 if the agency is a branch and its interaction with the for-profit dummy and a polynomial of the natural logarithm of the years in which an agency has been in the market and its interaction with the for-profit dummy in column 2 of Tables 2 and 3 is very similar to estimates in column 1.

4.2 Robustness Checks

4.2.1 Adding Geographic Controls

Here I add controls for market location as a measure of the competitive environment faced by the agencies. Because of the low entry and exit barriers in the home health care market, agencies can enter and exit quickly with little cost, so the competitors for each home health agency are not only represented by home health agencies on the market but also by potential entrants in that area. This means that the market dummy is likely to be the most complete measure of competition for each agency, because it implicitly includes potential entrants besides agencies that have already been licensed.

Estimates of the impact of a decline in reimbursement of 0.25 visits per user on exit rates of for-profit and not-for-profit agencies are reported in Tables 2 and 3, column 4. These numbers are similar to the baseline estimates reported in the previous section.

Also in Tables 2 and 3, in column 3, I examine a specification which considers counties as markets and estimates are again very similar to estimates in columns 1 and 2.²⁰

4.2.2 Adding a Demand Shifter

I next insert a demand shifter given by the natural logarithm of the population at least 65 years of age in the market using March Current Population Survey (CPS) data. When using CPS data, I cannot identify all 26 markets in which the agencies are located; for confidentiality reasons the census does not make them public. This means that some smaller counties are grouped in a residual category. Fortunately, the restriction is not too severe, so that I am able to identify 24 out of 26 markets in the data. Moreover, estimates of the relevant marginal effects in Tables 2 and 3 when I can identify 26 markets (column 4) and when I can only identify 24 markets (column 5) are very similar.

Column 6 of Tables 2 and 3 presents estimates of the marginal effects when controlling for the demand shifter, which again are really similar to the baseline specification.²¹

4.2.3 Weighted Results

In this section, I present estimation results from the linear and non-linear model where I weight the data using the propensity score to balance the key covariate, *visit94*, in the pre-policy period between for-profits and not-for-profits. In fact, Figure 4 shows that the distribution of the variable *visits94* is not the same for for-profit and not-for-profit firms. The goal of the approach presented here is to

20 In Appendix 5 I also present estimation results from an agency-specific fixed effect model as a robustness check. Results show that for-profit agencies were more likely to exit as a consequence of the IPS compared to not-for-profit agencies.

21 I also have tried other specifications where I tested whether the IPS impacted exit for branches differently compared to parents separately for the sample of for-profit and not-for-profit agencies with a linear and non-linear specification where the main variable of interest was the interaction of the variable with a dummy equal to 1 if the agency was a branch. I also looked at whether not-for-profits in markets with high for-profit penetration were more likely to exit as a consequence of the IPS compared to not-for-profits in markets with lower for-profit penetration using different cutoffs for identifying areas with high for-profit penetration. In all cases coefficients and marginal effects the main variable of interest, the variable interacted with a dummy equal to 1 for high for-profit penetration were never precisely estimated.

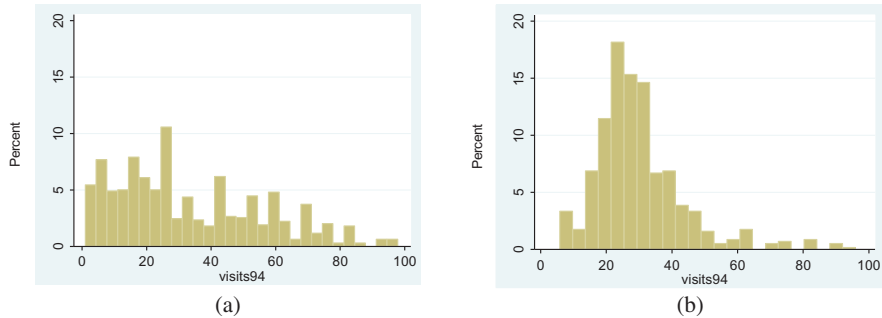


Figure 4: Histograms of the variable *visits94* for for-profit and not-for-profit agencies for years 1994–1996 and 1997–2000. (a) For-Profit 1994–1996; (b) Not-For-Profit 1994–1996.

reweight the data so that agencies with higher value of the *visits94* variable are not more or less likely to be in the for-profit or not-for-profit sample in the pre-policy period. I focus on the key variable *visits94* in estimating the propensity scores as it is the main variable of interest and also because results in the previous section show that estimation results are really similar across different specifications.

I proceed in two steps. In the first step I use data from the *pre-policy period*, years 1994–1996, and estimate a propensity score logit model where the outcome is a dummy equal to 1 if the observation is a for-profit agency, and use as explanatory variables a constant and the variable *visits94*. I then use the parameter estimates from the logit model so estimated to generate the predicted probabilities to be a for-profit agency, p , for the entire sample for years 1994–2000, and weight each observation by the probability of being in the opposite group. This means that firms in the for-profit sample receive a weight equal to p and firms in the not-for-profit sample receive weights equal to $1-p$. In the second step I use weights p and $1-p$ to estimate the linear and non-linear models presented in Section 3. Like other inverse-probability weighting techniques (Hirano, Imbens, and Ridder 2003), this approach balances key observable characteristics between two groups and it is described in Li, Zaslavsky, and Landrum (2007). This approach was used, for instance, by Chatterji and Meara (2010) in a linear model to balanced covariates between two groups. Tables 4 and 5 present the results of this exercise for the linear and non-linear models. In both cases weighted estimates are very similar to unweighted estimates in Tables 2 and 3 and this, in turn, provides support to the interpretation that for-profit home health agencies respond differently to financial incentives when compared to not-for-profit home health agencies.

Table 4: Estimation results: The outcome is a dummy equal to 1 if the home health agency exits in year t . linear model weighted estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Visits94 _{<i>i</i>} *Post _{<i>t</i>}	0.00059 (0.00053)	0.00035 (0.00057)	0.00050 (0.00053)	0.00047 (0.00053)	0.00047 (0.00053)	0.00047 (0.00053)
Visits94 _{<i>i</i>} *Post _{<i>t</i>} * Forprofit _{<i>i</i>}	0.0016** (0.00067)	0.00191*** (0.00071)	0.00169** (0.00069)	0.00178*** (0.00068)	0.00177*** (0.00068)	0.00179*** (0.00068)
Dummy for branch and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Polynomial of log duration dependence and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Counties dummies, and their interaction with for-profit dummy	–	–	Yes	–	–	–
Market Dummies, all separate markets and their interaction with for-profit dummy	–	–	–	Yes	–	–
Market Dummies, partially identified markets and their interaction with for-profit dummy	–	–	–	–	Yes	Yes
Log Population Over 65	–	–	–	–	–	Yes
<i>N</i>	3,111	3,111	3,111	3,111	3,111	3,111

Notes: *, **, and *** mean statistically significant at the 10, 5 and 1% level, respectively. $visits94_{it} = (V_i)/(N_i)$, where V_i is the number of visits for agency i for patients who are at least 65 years of age and N_i is the number of people at least 65 years old who the agency has treated. V_i and N_i are calculated using also the number of visits and patients of branches in case branches were in the market in 1994. Other control variables in all specifications are a dummy equal to 1 for years 1997–2000 and its interaction with the for-profit dummy, a dummy equal to 1 if the agency is for-profit. Other controls in columns 2–6 include a dummy equal to 1 if the agency was licensed after 1989 and its interaction with the for-profit dummy.

Table 5: Estimation results: The outcome is a dummy equal to 1 if the home health agency exits in year t . Non-linear model weighted estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
$Visits94_i * Post_t$	0.00162*** (0.00052)	0.00151*** (0.00051)	0.00152*** (0.00044)	0.00164*** (0.00046)	0.00158*** (0.00051)	0.00158** (0.00071)
$Visits94_i * Post_t * Forprofit_i$	0.00289*** (0.00100)	0.00311*** (0.00119)	0.00278** (0.00139)	0.00274** (0.00115)	0.00294*** (0.00105)	0.00294*** (0.00108)
Dummy for branch and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Polynomial of log duration dependence and its interaction with for-profit dummy	–	Yes	Yes	Yes	Yes	Yes
Counties dummies, and their interaction with for-profit dummy	–	–	Yes	–	–	–
Market Dummies, all separate markets and their interaction with for-profit dummy	–	–	–	Yes	–	–
Market Dummies, partially identified markets and their interaction with for-profit dummy	–	–	–	–	Yes	Yes
Log Population Over 65	–	–	–	–	–	Yes
N	3,111	3,111	3,111	3,111	3,111	3,111

Notes: The symbols *, **, and *** mean statistically significant at the 10, 5 and 1% level, respectively. $visits94_i = (V_i)/(N_i)$, where V_i is the number of visits for agency i for patients who are at least 65 years of age and N_i is the number of people at least 65 years old who the agency has treated. V_i and N_i are calculated using also the number of visits and patients of branches in case branches were in the market in 1994. Other control variables in all specifications are a dummy equal to 1 for years 1997–2000 and its interaction with the for-profit dummy, a dummy equal to 1 if the agency is for-profit. Other controls in columns 2–6 include a dummy equal to 1 if the agency was licensed after 1989 and its interaction with the for-profit dummy.

5 Conclusion

Many studies look at whether the behavior of not-for-profit firms differs from the behavior of for-profit firms, and many find support for the idea that not-for-profit firms are “for-profits in disguise.”

In healthcare, previous research on hospitals highlights that rapidity of exit from a market is a largely neglected form of performance. Such research finds that rapidity of exit from a market uncovers large differences in behavior between not-for-profit and for-profit firms which act as a form of “trapped capital” in the hospital industry (Hansmann et al. 2003).

Here I study rapidity of exit in the home health care market, a market characterized by virtually null capital investment, and find that even in this market not-for-profit home health agencies exit at slower rates than for-profit home health agencies. These findings reject the idea that not-for-profit home health agencies are “for-profits in disguise” and suggest that even when capital is virtually nonexistent, for-profit and not-for-profit firms exhibit different exit behavior.

Unfortunately, my data do not have information on worker’s behavior within the agencies, so it is not possible for me to detect the role played by volunteer labor in not-for-profit home health agencies compared to for-profit home health agencies. I also do not have data on perquisites and their change as a consequence of the IPS, but looking at these aspects seems an important avenue for future research to pursue to uncover the role of labor inputs in allowing not-for-profit firms to exit at slower rates than for-profit firms in industries where the role of “trapped capital” is necessarily limited.

Appendix A

Ideally, I would like to be able to determine for each parent agency the branches that belong to it. Unfortunately, this information is not available. Instead, I am able to identify for each year between 1995 and 2000 which agencies received a license together for the first time. Because agencies can receive a license together only if they are a parent and its branches, information on agencies that received a license together is equivalent to information on a group of agencies that contain the parent and its branches. Therefore, if an agency that was first licensed and certified for Medicare in 1970 opens a branch in 1996, the 1996 dataset contains a variable indicating that for the first time that year the two agencies received a license together. However, if an agency that was first licensed in 1970 opened a branch in 1971 and both agencies were still open in

the period under study, the information on the agencies being a group composed by a parent and its branches would be missing.

Moreover, the 1994 dataset does not contain information regarding which agencies received a license together for the first time during 1994. The information indicating which agencies had a consolidated license for the first time in year t is available in the electronic dataset for years 1995 to 2000.

In this article, I try to recreate the needed information, namely which entities are a parent and its branches on the market in each year. To achieve this, I first observe that for each year the agencies that have a license together for the first time that year had the same name. For example, the parent “Assisted Home Recovery” in 1996 opened a branch that was also called “Assisted Home Recovery.” Since for each year I know the name of each agency and whether an agency is a parent or a branch, I recreated the agencies that were parents and their branches by matching them by name.

In most cases, home health care agencies were stand-alone firms or entities composed of only one agency that declared itself to be a parent and only one or several agencies with the same name that declared themselves to be branches. In some other cases there were several parents and branches that had the same name (for example Kaiser Home Health), so it was not possible to identify which were the branches to attribute to a parent. This is a heterogeneous group. Part of the agencies in this group is subject to the per-agency limit for agencies that had been in the market for at least a year by October 1, 1994; others entered the market at a later date. In any case I must delete them. These agencies in total have 28% of the market share of the number of visits provided to elderly at least 65 years of age in 1994. Among these agencies, 70% are for-profit. The firms part of a chain are a bit different along some observable characteristics, in contrast to agencies that were in the market for at least a year by October 1, 1994 and that are not part of a chain. For example, agencies part of a chain are a little bit “younger” than the agencies in the sample I am using in this article, with the median agency in the sample of agencies as part of a chain that entered the market in 1992, and the agency in the 75th percentile that entered the market in 1986. For the sample of agencies that were in the market for at least a year before October 1, 1994 the median year of entry is 1990, and the agency in the 75th percentile entered the market in 1994. 81% of agencies that are part of a chain are for-profit compared to 65% of the agencies in the market by October 1, 1993. Also, 6.4% of the agencies that are part of a chain are located in the market called “rural” for Medicare reimbursement purposes, whereas 10.38% of the firms in the sample of “old agencies” are located in a rural area. Although differences along observable characteristics are not very pronounced, they do exist. Moreover, since being part of a chain is

a choice variable, chances are that the two types of providers might be different also along unobservable traits.

Appendix B

This appendix explains how the likelihood function combining a stock and flow sample is constructed. The flow sample consists of agencies that enter the spell and are at risk of leaving the spell during the observation time, namely between 1994 and 2000. In my application, the only new agencies for which I can construct a measure of impact of the policy change that enter the market during the observation period are the ones that are branches of existing agencies. Therefore, here I use the flow sample of agencies that enter the market from 1994 until 2000.

The stock sample consists of home health care agencies in the market on or before October 1, 1993 (and their branches, also those entering the market from October 2 until December 31, 1993). My data allow me to perform the adjustment to the likelihood function to take into account the length of elapsed spells because I know the exact date in which each agency is first licensed by the OSHPD. I assume exogenous censoring (Wooldridge 2010), meaning that once conditioning on the duration dependence and the other covariates, censoring is independent of the process determining the survival of the agencies in the market. This assumption seems reasonable here, because censoring in 2000 is due to another policy change, the Prospective Payment System for home health care agencies. The likelihood function can be constructed noticing that durations t_i of firms in the market can belong to four sets. The first set consists of uncensored flow sample durations that start and end during the observation period 1994–2000, and I denote the duration of these spells with t_i^* . The contribution of the firms that have these durations to the likelihood function is:

$$f_i(t_{0i}, t_i^*) = \left\{ \prod_{t=r}^{t_i^*-1} [1 - \lambda_i(t_{0i}, t_i)] \lambda_i(t_{0i}, t_i^*) \right\} \quad (4)$$

The second set of observations consists of durations that start during the observation period 1994–2000 but do not end during such period, i.e. durations that are censored. If the censoring point is in \bar{t}_i , then the contribution of each observation belonging to this sample to the likelihood function is:

$$[1 - F_i(t_{0i}, \bar{t}_i)] = \prod_{t=r}^{\bar{t}_i} [1 - \lambda_i(t_{0i}, t)] \quad (5)$$

For the stock sample, consider first the probability that an agency that entered in the market at time t_{0i} before the observation period 1994–2000 lasts at least until time $l-1$ (the period before the start of my observation period). This probability is equal to:

$$[1 - F_i(t_{0i}, t_{l-1})] = \prod_{t=s}^{l-1} [1 - \lambda_i(t_{0i}, t)] \quad (6)$$

Equation (5) is the conditional probability correction to the probability of exit in year t during the period 1994–2000 for an agency in the stock sample. In other words, the contribution to the likelihood function from an uncensored stock sample observation is:

$$g_i(t_{0i}, t_i^*) = \frac{\left\{ \prod_{t=s}^{t_i^*-1} [1 - \lambda_i(t_{0i}, t)] \right\} \lambda_i(t_{0i}, t_i^*)}{[1 - F_i(t_{0i}, t_{l-1})]} \quad (7)$$

Finally, the probability of being in the market after 2000 for agencies that were already in the market before 1994 is the contribution from agencies that form the censored stock sample. For these observations as well, the likelihood function is corrected for the length of the elapsed spells:

$$[1 - G_i(t_{0i}, \bar{t}_i)] = \frac{\prod_{t=s}^{\bar{t}_i} [1 - \lambda_i(t_{0i}, t)]}{[1 - F_i(t_{0i}, t_{l-1})]} \quad (8)$$

The complete likelihood function is:

$$L = \prod_{i \in FNC} f_i(t_{0i}, t_i^*) \prod_{i \in FC} [1 - F_i(t_{0i}, \bar{t}_i)] \prod_{i \in SNC} g_i(t_{0i}, t_i^*) \prod_{i \in SC} [1 - G_i(t_{0i}, \bar{t}_i)] \quad (9)$$

where FC indicates the set of observations from the censored flow sample, FNC denotes the set of observations from the uncensored flow sample, SC denotes the set of observations from the censored stock sample and SNC is the set of observations from the uncensored stock sample.

Appendix C

To understand the impact of the IPS on exit I adopt an approach similar to the one used by McKnight (2006) to quantify the impact of the IPS on the number of

home health visits for a typical state. McKnight (2006), using measures of utilization at the state level in note 16 of her paper writes:

I begin with HCFA's estimate that agencies that faced binding constraints would exceed the cost limits by an average of 12% (Federal Register, 1999). This 12% estimate is likely to understate the initial post-policy restrictiveness, since agencies had presumably adjusted some of their behavior by 1999. Applying this conservative 12% estimate to the average pre-policy (1996) utilization level of 73.6 visits per user, I determine that the typical agency that faced a binding cap provided 7.9 visits per user (in the pre-policy period) that would not be reimbursed in the post-policy period (Health Care Financing Review, 1996). Then, accounting for HCFA's estimate that the per-patient cap was not a binding constraint for 21% of agencies, I determine that an average agency in an average state faced a cap that precluded reimbursement of 6.32 visits that the average pre-policy beneficiary received (Federal Register, 1999). This provides a conservative estimate of the reimbursement constraint that the typical state faced after BBA 97. Since the coefficients in the tables measure the impact of a cap that precludes reimbursement for an additional 0.25 visits per user, I multiply the coefficient in the table by 25.28 (6.32×4) in order to estimate the impact for a typical state.

As in the McKnight's case, in my application the marginal effects in Tables 2 and 3 represent the impact of a cap imposed by the IPS that precludes reimbursement of another 0.25 visits per user (see note in Section 3.2). Ideally, I would like to have utilization rates for agencies in my sample for year 1996 and calculate for each agency by how much utilization levels in 1996 are above the limit imposed by the IPS. However, I cannot calculate for year 1996 the average number of visits for each agency to patients 65 or above because my data from year 1995 do not allow me to precisely calculate the number of visits for patients aged 65 or above (see Appendix C for a more in depth discussion of this issue of data limitation and its implication for the choice of the sample I use in the paper).

Therefore, I need to focus on utilization levels in 1994. Because the IPS stated that 25% of the reimbursement cap was based on the average utilization level of agencies within the California census division (the Pacific Census division), and such average utilization level is 44.5 (Health Care Financing Administration 1996), I start by calculating for each agency by how much utilization levels in 1994 are above the cap by calculating for year 1994 the difference between visits₉₄ and the limit imposed by the cap:

$$\text{Delta} = \text{visits}_{94} - (0.75 \text{ visits}_{94} + 0.25 \times 44.5)$$

I find that, on average, Delta is positive for 39% of for-profit agencies and the average value of Delta for these agencies is equal to 5.9 visits. This means that

an average for-profit agency after the IPS would not be reimbursed $0.39 \times 5.9 = 2.3$ visits. I perform the same calculation for not-for-profit agencies and find that there were 12.7% of not-for-profit agencies that after the IPS would not be reimbursed 3.52 visits. This means that an average not-for-profit agency after the IPS would not be reimbursed $0.127 \times 3.52 = 0.44$ visits.

The estimates above are conservative, because average utilization levels for home health care went up in California between 1994 and 1996 (Health Care Financing Administration, various years) so that a larger fraction of agencies than the fraction calculated here are likely to be constrained from 1997 onwards, and for those agencies Delta is likely to be larger than the Delta based on calculations for year 1994.

With these limitations in mind, I can use the above calculations to understand the impact of the IPS on exit for for-profit and not-for-profit agencies. Because the marginal effects in the tables measure the impact of a cap that precludes reimbursement for an additional 0.25 visits per user, in order to estimate the impact for a typical for-profit agency I multiply the marginal effects in Tables 2 and 3 by 9.2 (2.3×4) for for-profit agencies and by 1.76 ($0.44/0.25$) for not-for-profit agencies.

Appendix D

The IPS implied that the average yearly per patient reimbursement limit for home health care agencies which entered the market *after* October 1, 1993 was to be calculated as follows.

First, the Health Care Financing Administration selected all free standing agencies *in the United States* which entered the market *on or before* October 1, 1993.

Second, for all those freestanding agencies in the United States which entered the market on or before October 1, 1993, a yearly average per patient cap was calculated according to the rules in place for those agencies (i.e., as explained in the main text: 75%% of the cap based on the agency utilization levels in 1994 and 25% of the limit based on the average utilization level in 1994 in the agency's Census Division).

Third, all these freestanding agencies which entered the market on or before October 1, 1993 were sorted by the cap calculated above and the median agency was singled out. The limit of this median agency after the introduction of the IPS was also used as the yearly per patient cap for all agencies in the United States which entered the market after October 1, 1993 (adjusted by an algorithm that takes into account local salaries; see main

text for the explanation of local adjustment). Although this limit is calculated in dollars, in the example below I use utilization rates (as done in the main text for home health agencies entering the market on or before October 1, 1993 and as it was done in the previous literature on the IPS, starting with McKnight 2006).

So, just as an example, let us suppose that the median freestanding agency among all freestanding agencies in the United States which entered the market on or before October 1, 1993 had an average yearly per-patient utilization limit equal to 10, i.e. visits₉₄ is equal to 10 for the median agency.

How relatively restricted by the IPS is a Medicare Certified home health agency in California that entered the market after October 1, 1993? To answer this question I need to be able to calculate how many average visits per patient such agency was providing before the IPS. To illustrate this point, let's consider two agencies which entered the market after October 1, 1993: agency 1, with average per patient utilization in 1996 (the year before the policy change) equal to 11, and agency 2, with average per patient utilization in 1996 equal to 12. Agency 2 after the IPS is more restricted than agency 1 because it is providing 2 visits per patient more than the limit of the median agency equal to 10 and agency 1 is providing 1 visit per patient more than the limit of the median agency.

The example above illustrates that in order to be able to understand how relatively restricted by the IPS is an agency that entered the market in California after October 1, 1993, and in order to reliably use cross-section variation together with time-series variation in my analysis of exit, I need to have the possibility to calculate for such agency the yearly average number of visits per Medicare patients at least in the year before the policy change.

To construct the cross-section variation for agencies entering the market on or after October 1, 1993, similarly to what was needed to create the cross agency measure of restriction for agencies which entered the market on or before October 1, 1993, I need to have the average number of visits per patient aged 65 or older for the year before the policy change, namely year 1996.

However, my data do not allow me to construct such limit, because from 1995 I only have information on the number of patients that each agency treats divided in the following age intervals: patients less than 10 years of age; patients between 10 and 20; patients between 21 and 30; patients between 31 and 40; patients between 41 and 50; patients between 51 and 60; patients between 61 and 70; patients between 71 and 80; patients between 81 and 90; patients 91 or older. Therefore, I cannot create a reliable cross-sectional measure of restriction at the agency (and its branches) level.

Appendix E

Estimation Results: The outcome is a dummy equal to 1 if the home health agency exits in year t . Individual Agency Fixed Effects Model

	(1)	(2)	(3)
$Visits94_i * Post_t$	0.00050 (0.00063)	0.00030 (0.00062)	0.00039 (0.00063)
$Visits94_i * Post_t * Forprofit_i$	0.00153** (0.00070)	0.00143** (0.00070)	0.00150** (0.00072)
Polynomial of log duration dependence and its interaction with for-profit dummy	–	Yes	Yes
Log Population Over 65	–	–	Yes
N	3111	3111	3111

Notes: The symbol ** means statistically significance at the 5% level. $visits94_i = (V_i)/(N_i)$, where V_i is the number of visits for agency i for patients who are at least 65 years of age and N_i is the number of people at least 65 years old who the agency has treated. V_i and N_i are calculated using also the number of visits and patients of branches in case branches were in the market in 1994. The models include agency-specific fixed effect.

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