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Canadian Centre for Health Economics
Centre canadien en économie de la santé

Working Paper Series
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Working Paper No: 170003

www.canadiancentreforhealtheconomics.ca

April 6, 2017

Canadian Centre for Health Economics
Centre canadien en économie de la santé
155 College Street
Toronto, Ontario

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Efficiency estimation with panel quantile regression: An application using longitudinal data from nursing homes in Ontario, Canada

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Abstract

This paper investigates the technical efficiency of nursing homes on Ontario, Canada. We apply Quantile Regression (QR) with a Mundlak specification to a panel dataset of 627 nursing homes, observed over 15 years. Results from the QR models found chain affiliation and urban location to be positive predictors of technical efficiency in the context of a case-mix adjusted volume based outcome measure. The effect of profit status varied across the conditional quantiles. The analysis presented in this paper aims to demonstrate a novel approach to efficiency measurement, and suggests that cost containment strategies (e.g., prospective reimbursement) and restrictions on long-term care bed supply in the market may continue to foster the expansion of nursing home chains in this sector.

JEL Classification: C23; D2

Keywords: long-term care; nursing homes; technical efficiency; quantile regression; panel data

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1 Introduction

Spending on long-term care (LTC) in developed countries continues to grow in tandem with the increasing proportion of seniors in the population (Canadian Institute for Health Information (CIHI) 2011, Hartman et al. 2015). Historically, health care spending has outpaced inflation and general economic growth, which has resulted in concerns about the sustainability of health care, in general, and LTC in particular (Blomqvist and Busby 2014, Cameron et al. 2014, Hartman et al. 2015, Kaiser Family Foundation 2013). Despite the attenuated growth rates since the economic recession of 2008, observed trends in health care spending following past economic downturns suggest that growth will likely accelerate once economic conditions improve (Hartman et al. 2015).

One approach to contain health care spending is to improve the efficiency of service delivery, by identifying and implementing care delivery models that maximize the amount of (quality adjusted) service provided using the same quantity of inputs. Despite the growing importance of LTC services, efficiency analyses have not been extensively applied to this sector. More than 50% of the efficiency studies in health care examined the performance of hospitals and health maintenance organizations; while less than 10% have focused on the performance of nursing homes (Hollingsworth and Peacock 2008). To date, of the 28 studies that have been published on the efficiency of nursing homes, only six involved the use of panel data (Farsi and Filippini 2004, Farsi et al. 2005, Garavaglia et al. 2011, Knox et al. 2007, Sexton et al. 1989, Zhang et al. 2008). This is a critical feature if we are to assess whether certain organizational attributes, such as for-profit ownership or chain affiliation, have a consistent and predictable influence on individual provider's performance (Hsiao 2003, Schmidt and Sickles 1984).

The focus on LTC is warranted because of the anticipated increase in the demand for institutional LTC and pressures to meet this demand through better allocation of scarce health care resources.

Prospective payment models have emerged as the primary funding mechanism to control spending in publicly-funded programs across the U.S. and Canada. Under this funding model, payments to health care providers are predetermined based on the amount of care patients are expected to consume and set at a fixed rate. Because reimbursement amounts are calculated *a priori*, prospective payments have the potential to encourage providers to operate more efficiently within their allocated resources.

In Ontario, nursing homes are publicly-funded through a prospective payment system. Much like the Medicare program in the U.S., nursing homes in Ontario receive a case-mix adjusted per diem payment. However, unlike Medicare Part A, funding for care provided in nursing homes - in fact, this applies to other health services provided in Ontario - comes entirely from provincial tax revenue and there are no restrictions over a resident's length of stay. The only out-of-pocket payments to residents are charges for accommodation, which is annually set by the Ontario Ministry of Health and Long-Term Care (MOHLTC). In 2015, the co-payment was between 56.93and80.18 per day, depending on whether the resident stays in a shared or private room (MOHLTC, 2015). Patients who fall below the poverty line are exempted from these accommodation charges.

Nursing homes in Ontario can modify the number of beds they keep in operation but of those in operation they must maintain an occupancy rate of 97% to receive 100% of their provincial capitated (i.e. per patient per day) public funding (MOHLTC, 2013a) with no adjustments for quality of care[2]. The compensation for nursing homes is therefore primarily encouraging of volume of care delivery with a rough adjustment for case-mix.

Publicly funded nursing homes, regardless of their profit status, are required to remit unspent funds to the MOHLTC at the end of each fiscal year (MOHLTC, 2013b). Nursing homes can

[2]Facilities can adjust the number of approved beds they have in operation and can expand the number of approved beds through amendments to their existing license with the Provincial Ministry of Health and Long-Term Care (`http://www.health.gov.on.ca/en/pro/programs/ltcredev/docs/licensing_overview_lhin_presentation.pdf`).

however, retain any residual on out-of-pocket accommodation charges within the fee limits described above, and fees associated with non-medical services (e.g., transportation services, TV/cable, etc.). Nursing homes, if they provide care services that are publicly funded cannot at the same time deliver privately funded care alongside to other residents - they are either in the publicly funded service care delivery model or they must operate in the private pay market.

It would seem that these regulations in the publicly funded market, would make for a fairly restrictive operating environment for these firms. Interestingly, the publicly funded LTC sector is populated by for-profit (the majority), not-for profit, and publicly run firms - some of which belong to chain organizations. This suggests that there may well be some firm level characteristics that influence nursing homes' approaches to producing care and the potential for differences in terms of performance with regard to efficiency of care delivery.

Where certain firm characteristics are found to be beneficial, the empirical results could inform policy designs to improve access and care delivery. For example, firms belonging to a chain may benefit from economies of scale. If chain affiliation is found to positively affect nursing homes ability to deliver care, then there may be scope to facilitate bulk purchasing or knowledge translation about best practices to say, publicly operated firms that do not currently have the ability to organize as chains. On the other hand, rural location may impose limits on the ability to produce care of a nursing home compared to urban-based homes. Efficiency analyses based on the estimation of a best performance frontier could be used to quantify the implications of the added constraint of rural location in order to adjust fees paid for care delivery to homes in rural jurisdictions.

We aim in this paper to show how a panel quantile regression (QR) approach can be used to estimate a production function for care, and extend it for use in evaluating the relative technical efficiency of nursing homes in the LTC sector. QR offers more information with regard to the impact of explanatory variables at different parts of the outcome distribution compared to analyses based only on the conditional mean. This is increasingly important in a variety of applications where knowledge about outcomes and the factors that drive those outcomes at particular points of the distribution are of interest. In this paper we use the panel QR approach applied to data from Ontario, Canada to contribute to the larger literature on efficiency measurement in health care and within that to the literature on long-term care (LTC). The interest is in defining a best performance frontier and assessing the relative position of firms compared to their peers - that is, conditional on firm characteristics.

This paper aims to contribute to the existing literature in several ways. In the first instance, we use the QR approach to estimate a production function that corresponds to the best performance frontier for the LTC sector and show how that may be used as a benchmark to assess the relative technical efficiency of nursing homes in Ontario. Second, we show how QR may be used in combination with the Mundlak (1978) specification to tackle the issue of unobserved firm characteristics in a production function context. Third, we show how the QR approach allows for an examination of between firm characteristics such as profit-status and chain ownership on technical efficiency without having to make strict distributional assumptions about the nature of the inefficiency.

The paper begins with a brief overview of the studies that have examined the efficiency of nursing homes. Section 3 describes the data used in this study. Section 4 describes the methods and model specification. Section 5 reports the results. Section 6 discusses the study findings and Section 7 discusses the limitations. Finally, Section 8 concludes.

2 Efficiency Analysis of Nursing Homes in Ontario

Existing empirical evidence suggests that for-profit facilities tend to operate with greater efficiency and at lower operating cost than not-for-profit facilities (Anderson et al. 1999, Davis 1993, Meiners 1982, Rosko et al. 1995, Zhang et al. 2008). This seems to be especially true for facilities that are members of a chain organization (Arling et al. 1987, Cohen and Dubay 1990, McKay 1991). However, with the absence of statistically significant differences in some studies (Meiners 1982, Vitaliano and Toren 1994) and contradictory findings in others (Anderson et al. 1999), there is no consensus on the impacts of for-profit ownership or chain affiliation on efficiency.

Our current knowledge about the impact of organizational structures on technical efficiency is derived largely from cross-sectional studies. Observations based on data from a single period have constrained external validity as they are often unable to account for time-invariant, unobserved individual differences (i.e., heterogeneity) that may exist between facilities. This may explain, at least partially, the lack of consensus among prior efficiency studies. Panel data, on the other hand, controls for these unobserved influences and trends over time. The use of panel data is advantageous because it accounts for the possibility that facilities could be confronted with an external shock (e.g., workers strike, policy changes, and economic recessions) in any given year, in ways that may affect their performance. These external shocks may cause unsystematic shifts in their production frontier. Using observations on the same facilities over multiple years mitigates the possibility of such bias. Studies on the efficiency of nursing homes have been undertaken in the U.S. (Knox et al. 2007, Sexton et al. 1989, Zhang et al. 2008), Switzerland (Farsi and Filippini 2004, Farsi et al. 2005), and Italy (Garavaglia et al. 2011). These studies have applied a mix of SFA, Data Envelopment Analysis (DEA) and quantile regressions, and ranged between two and nine years of observation time.

Zhang et al. (2008) applied DEA to study the technical efficiency of 8,361 nursing homes operating in the U.S., following the implementation of a prospective payment system under Medicare. They used administrative data from the Medicare Cost Report database for a period of 7 years, and found the for-profit nursing homes were more efficient than not-for-profit and government-owned homes. Knox et al. (2007) studied a sample of 900 nursing homes in Texas, which were primarily funded through prospective, fixed-rate reimbursements from the Medicaid program. Like most nursing homes in the U.S. and in Ontario, the nursing homes in Texas relied heavily on public funding - approximately 60% from Medicaid, and 16% from Medicare (Knox et al. 2007). Similar to findings by Zhang et al. (2008), they found for-profit nursing homes produced more resident care days than not-for-profit homes - despite their lower occupancy rates.

Internationally, similar conclusions were drawn by Farsi and Filippini (2004) in Switzerland, in which they found privately-owned not-for-profit homes were more cost efficient than municipal homes. Garavaglia et al.'s (2011) examination of Italian nursing homes in the Lombardy Region found private nursing homes (for-profit and not-for-profit combined) to be more cost efficient than municipal homes.

Another strand of the literature speaks to the impact of market concentration on firm performance, where market concentration is typically measured by the Herfindahl-Hirschman Index (HHI). For example, Nyman and Bricker (1989) in a cross-sectional DEA, raise the possibility that increased competition among nursing homes may result in competition based on quality of care as a means of attracting new patients, which may affect the estimated efficiency scores.

A by-product of cost containment policies imposed by state and provincial governments in North America is the growth of larger scale operations in the U.S. and Canada, and the emergence of chain organizations (Baum 1999, Kaffenberger 2000). Prior empirical research on staffing in nursing homes has found variations in staffing intensity by profit status and chain affiliation. Furthermore, for-profit nursing homes - especially those belonging to a chain organization - were shown to have provided lower levels of direct care, including nursing care (Banaszak-Holl and Hines 1996, Berta et al. 2005, Bravo et al. 1998, Comondore et al. 2009, Harrington et al. 2001, Harrington et al. 2012, Hsu et al. 2016, McGregor et al. 2005, McGregor et al. 2010). Naturally, this leads to questions regarding the implications of organizational structure on efficiency. To our knowledge, only two studies have investigated the impact of chain affiliation on efficiency using longitudinal data (Sexton et al. 1989, Zhang et al. 2008).

Facilities that are owned and operated as a part of a chain can benefit from the chain's formalized sharing of information and human resources, centralized purchasing power, and other competitive advantages in the local market. Therefore, we would expect nursing homes operated by a corporate chain to be more efficient than independent facilities. This hypothesis was supported in the work of Zhang et al. (2008), who found chain-owned homes to be more efficient than independent homes, when resident acuity and resident case mix were separately controlled for. When the variables for both quality and resident acuity were included in the same regression model, the effect of chain affiliation was not statistically significant, similar to findings from Sexton et al. (1989).

In terms of methods, applications of QR in the context of health and the health care sector have increased over the past decade (Stifel and Averett, 2009; Koenker and Hallock, 2001; Siciliani et al., 2013; Goldman and Zissimopoulos, 2003). However, this approach has been applied infrequently in productivity and efficiency analyses of health care providers (Knox et al., 2007). To our knowledge, Knox et al., 2007 is the only study to examine technical efficiency of nursing homes using panel data and QR. They did not in that paper address the potential for correlation of the explanatory variables and unobserved, time-invariant heterogeneity - thereby raising the possibility of biased estimates of the coefficients and technical efficiency scores in cases where this assumption is violated.

3 Data

Data used for this analysis came from Statistics Canada's Residential Care Facilities Survey (RCFS). The RCFS is the only national database that provides information on staffing levels and operating expenditures for publicly-funded nursing homes. The dataset used for the analysis includes all facilities with four or more beds that were funded, licensed and/or approved by the Ontario Provincial Ministry of Health and Long-Term Care and/or Community and Social Services (Statistics Canada, 2012).

The dataset captures 91.7% to 95.8% of all operating facilities in the Province between 2003 and 2007. From 2007 to 2011 - years when the provincial Ministry of Health provided utilization summaries by ownership type - our sample represents 93.9% of nursing home beds available in the Province, on average, or 90.9% of for-profit beds, 96.4% of not-for-profit beds, and 99.8% of municipal LTC beds. Our analysis is based on an unbalanced panel consisting of 627 nursing homes, for a total of 6,744 observations over the 15 years. 161 homes (25.7%) provide information in all 15 cycles, while the remaining facilities provide between 1 to 14 cycles of data.

Access to RCFS data was approved by Statistics Canada, and analysis was conducted at the Toronto Region Research Data Centre (Toronto RDC). Ethics approval for this study was received from the University of Toronto Research Ethics Committee.

4 Methods

4.1 Model Specification

We estimate a Cobb-Douglas production function, which for facility i in year t, is given by:

$$y_{it} = x'_{it}\beta + z'_i\gamma - \mu_i + \epsilon_{it} \tag{1}$$

The output variable y_{it} is resident days of care for facility i in period t, which is adjusted by case-mix[3] (Rosko and Mutter, 2008). x'_{it} is a vector of time-varying variables, including labour and capital inputs. z'_i is a vector of time-invariant, firm level characteristics, which includes profit status and chain membership. Technical inefficiency is given by μ_i, and ϵ_{it} represents the iid error term.

The first data collection cycle in our sample is the 1996/1997 fiscal year, which is the reference year in our regression model. Because we have an unbalanced panel, each facility i contains T observations - where T has a maximum of 15 cycles.

The independent variables in our model include five categories of labor input, a capital input and reported expenditure on care-related supplies. Labor inputs are measured in terms of total hours of care provided by full-time, part-time and casual employees whose salaries or wages are paid to them by the nursing home. These include registered nurses (RNs), registered practical nurses (RPNs), health care aides (HCAs), therapists, and general services staff. The capital input is based on the number of beds that are licensed and staffed[4]. Non-labor inputs include expenditure on non-medical supplies, such as continence supplies, equipment used in physical and other forms of therapy, and

[3] Resident case mix was coded from a level of care variable developed by Statistics Canada for the administration of the RCFS. A description of this measure is presented in Textbox 1 (Appendix).

[4] The number of beds was measured by the total number of beds that were licensed and staffed (i.e., available for resident care) within each facility. This variable was included in categories, since including it as a continuous variable introduced a collinearity issue with the labor inputs. Two dichotomously coded variables capturing facilities in the top ($\geq$ 75-th percentile) and bottom ($\leq$ 25-th percentile) quartiles were used.

other nursing care supplies. Other time-varying variables include market concentration as captured by the Herfindahl-Hirshman Index, and a mortality-based quality indicator. All monetary values are adjusted to 2010 Canadian dollars.

Firm characteristics hypothesized to have an influence over the production of care include: profit status (i.e., for-profit, not-for-profit and municipality-owned nursing homes), chain affiliation, and urban location (for municipalities with a population of at least 10,000 people),

A mortality-based quality measure is used in this study since clinical outcomes (e.g. fall rates, bed sore rates) were not captured by the RCFS. The use of mortality as a proxy for quality of care has been used in other studies along with available clinical measures (Hillmer et al., 2005; Mukamel and Spector, 2000). The case mix-adjusted excess mortality ratio we use compares the observed mortality to an expected mortality, given the nursing homes' distribution of residents by age, sex, and level of care (see Appendix: Textbox 1). Similar to other age, sex and risk-adjusted mortality measures, the purpose of including this variable was to capture to the extent possible given the dataset, variations in quality of care across nursing homes.

The HHI of market concentration was calculated on the basis of the number of beds available in each facility, out of the total bed supply in that facility's Census Subdivision. Higher values of the HHI correspond to a more concentrated market. An HHI score above 0.25 is considered to be an indication of a highly concentrated market according to the market concentration scale created by the U.S. Department of Justice and the Federal Trade Commission's Horizontal Merger Guideline (2010).

Table I presents a profile of nursing homes in Ontario in operation between the 1996/1997 and 2010/2011 fiscal years. More than half (56.8%) of the nursing homes in Ontario are for-profit i.e. owned and operated by a proprietary entity. Among these, a majority (82.7%) are part of a chain organization. Not-for-profit homes represent 25.8% of providers in Ontario, while municipal homes make up the remaining 17.4% on average over the sample period. Municipal nursing homes are significantly larger (i.e., have more beds), on average, than for-profit and not-for-profit homes (p ¡ 0.001). Approximately half (50.7%) of the nursing homes are located in urban centers.

<Table I. Profile of Ontario nursing homes and summary statistics for labor inputs, 1996/1997 to 2010/2011>

With the exception of the visible increase in the number of hours of care provided by HCAs (26.7%), there are minimal changes in staffing levels among other labor categories over the 15-year study period (Figure 1).

<Figure 1. Average hours of care per resident day, by staffing category>

Figure 2 shows the distribution of LTC beds by profit status from 1996/97 to 2010/2011. It is important to note that the number of beds per facility is not fixed over time, and that there are differences in the growth of these beds over time across ownership types. In the analysis to follow, we include dummies for facility size based on the number of beds to control for scale effects (lower and upper quartiles).

<Figure 2. Distribution of long-term care beds in Ontario, by profit status and chain affiliation>

Figure 3 shows the average occupancy rate of LTC homes by profit status from 1996/97 to 2010/2011. We can see from the Figure that the occupancy rate is not fixed, and that it varies by profit status.

<Figure 3. Average occupancy rate in Ontario's long-term care homes, by profit status>

4.2 Estimation

4.2.1 Stochastic Frontier Analysis

Stochastic frontier models using panel data have been traditionally estimated using Fixed Effects (FE) and Random Effects (RE) models (Greene, 2005). The FE estimator produces estimates of the slope parameters that control for all time-invariant factors in the analysis, and is an attractive method because it does not impose distributional assumptions on the inefficiency term (Jacobs et al., 2006). However, efficiency estimates generated with this approach contain all between-firm heterogeneity (Greene, 2005). Thus, the estimated technical efficiency scores obtained from a production function estimated with this model will be biased if time-invariant variables affect the production process (Feng and Horrace, 2007). Observable between firm characteristics in our model include profit status, chain ownership, and rurality, which should theoretically be related to output, and have been shown to be potentially significant predictors of nursing home production (Hsu et al., 2015).

A RE Generalized Least Squares (GLS)[5] specification, on the other hand, allows for the inclusion of time-invariant variables, thereby allowing us to distinguish true inefficiency from other observed between-firm characteristics. Although the RE estimator assumes statistical independence of the time-varying variables and the time-invariant inefficiency term (Jacobs et al., 2006), one can use the Mundlak (1978) specification to relax this (Farsi et al., 2005). The RE estimator, however, makes distributional assumptions on the inefficiency term - namely, it assumes that inefficiency is randomly distributed with constant mean and variance (Kumbhakar and Lovell, 2000). Moreover, in the calculation of the technical inefficiency scores, one firm is assumed to be 100% efficient, and

[5] RE stochastic frontier models can also be estimated using maximum likelihood in a panel setting, but this approach faces criticism due to rather strict distributional assumptions vis vis the inefficiency term (Jacobs et al., 2006). In applied work, the true distribution of inefficiency is of course, never known, and the wrong distributional assumption can lead to highly biased results (Liu et al., 2008).

the other firms are ranked in relation to the fully efficient firm (Kumbhakar and Lovell, 2000). This approach produces biased technical efficiency scores when the sample contains a large number of efficient firms (Feng and Horrace, 2012, Laporte and Rohit Dass, 2016).

An alternative to the parametric RE and FE methods is the semi-parametric QR approach applied to panel data, which has been shown to overcome the limitations of stochastic frontier models in a panel setting (Laporte and Rohit Dass, 2016).

4.2.2 Quantile Regression

QR is an approach that evaluates the marginal effects of a set of covariates, x, across τ quantiles in the distribution of the response variable, y, for each observation i (Koenker and Bassett, 1978).

The QR estimator solves

$$\min_{\alpha\in\mathbb{R},\beta\in\mathbb{R}^k} \sum_{i=1}^{N} c_\tau(y_i - x_i\beta) \tag{2}$$

where c_τ is the check function, given by:

$$c_\tau(u) = (\tau 1[\mu \geq 0] + (1-\tau)1[\mu < 0]|\mu)$$

where μ is the residual and 1 [] is the indicator function, equal to one if the statement in the brackets is true and zero otherwise (Wooldridge, 2010). The estimated coefficients are based on the entire weighted sample, where the weights depend on the chosen quantile to be estimated.

The panel version of (2) can be written as:

$$y_{it} = x'_{it}\beta + z'_i\gamma + \mu_i + \epsilon_{it}, \quad Quant_\tau(\epsilon_{it}, x_i, \mu_i) = 0, \quad t = 1...T \tag{3}$$

Similar to the RE specification, pooled QR on (3) is subject to bias if the explanatory variables are correlated with μ_i. Unlike the linear model, dealing with this endogeneity in a QR framework has been challenging to due to the non-linearity and non-smoothness of the QR criterion function (Graham et al, 2015). The "within" deviation from individual mean transformation, which allowed us to estimate the FE model without introducing individual intercepts in the linear context, is not available for quantiles (Koenker, 2004). Moreover, introducing individual intercepts results in an "incidental parameters" problem for short T. This implies that QR will do a poor job in estimating the fixed effects, and these poor estimates lead to bias in the estimates of the other covariates (Wooldridge, 2010). RE type procedures have also been introduced for QR, which estimate random intercepts for each individual in a given sample (Geraci and Bottai, 2007; Liu and Bottai, 2009). These approaches, however, do not solve the endogeneity problem, and one would have to make distributional assumptions on the RE term.

Another approach to dealing with the unobserved heterogeneity problem is to extend Mundlak's (1978) specification to QR, or $\mu_i = \psi + \theta\bar{x}_i + \delta_i$ (Wooldridge, 2010; Bache et al., 2013). Plugging this into (3) gives:

$$y_{it} = \psi + x_{it}'\beta + \bar{x}_i'\theta + z_i'\gamma + \nu_{it} \tag{4}$$

Where ν_{it} is the composite error term. If ν_{it} is independent of x_i, then β and θ can be estimated using pooled QR of y_{it} on 1, x_{it}, and $\bar{x}_i$ (Wooldridge, 2010)[6].

In terms of technical efficiency, as noted above QR does not make distributional assumptions about the error term. Hence, similar to the FE approach, QR does not make distributional assumptions about the inefficiency (since μ_i is calculated from ϵ_{it}). Laporte and Rohit Dass (2016) recommend estimation of a pooled QR model, where ϵ_{it} is averaged across time for each firm to obtain μ_i, which is then substituted into:

[6] Correlation between z_i and ν_{it} would likely need to be solved using an Instrumental Variables approach. We do not explore this in this paper.

$$TE = e^{\mu_i} \tag{5}$$

In this way, technical efficiency is not treated as a random variable to be estimated. QR distinguishes between inefficiency and noise by using the top performing firms as a benchmark for the other firms in the sample, where the influence of inefficient firms is down weighted in the calculation of the fitted frontier. In other words, because QR models *conditional* rather than *unconditional* quantiles, firms in the upper percentiles (say 80th) will be the firms who, conditional on inputs and observable firm level characteristics, were able to achieve an amount of output that is on or above the fitted frontier.

QR assigns positive and negative residuals based on the chosen quantile estimated (Hao and Naiman, 2007). For example, at the 90-th percentile, 10% of firms would be assigned a positive residual, and 90% of firms would be assigned a negative residual. Hence, we would expect the 90-th percentile to perform best regarding technical efficiency scores when there are fewer fully efficient firms. That being said, the 80-th percentile has been shown to perform well even with a large number of fully efficient firms in the sample (Liu et al. 2008; Laporte and Rohit Dass, 2016). Since the true distribution of inefficiency is never known in applied work, we calculate technical efficiency scores at the 80-th, 85-th, and 90-th percentiles, and report the coefficient estimates at these percentiles as well. For the calculation of standard errors, we follow the bootstrapping procedure of Abrevaya and Dahl (2008) & Bache et al. (2013).

We also report the estimated coefficients across all the quantiles for labour inputs in Figure 2 and for firm characteristics (urban location, HHI, chain, profit status) in Figure 3 to show how the effects of these variables vary across the conditional distribution. For comparison purposes, we also estimate a RE stochastic frontier model via GLS with Mundlak specification.

QR estimations are performed in R version 2.15.3 (R Core Team, 2013), using the 'rqpd' package (Koenker and Bache, 2011). The SFA-RE models are estimated in Stata/SE version 13.0 (StataCorp, 2013).

5 Empirical Results

5.1 Quantile Regression Results

Table II presents the coefficient estimates for production frontiers estimated at the $\tau = 0.80$, 0.85 and 0.90 quantiles. Among the labor inputs, the output elasticity with respect to RPNs is the greatest across top-performing nursing homes: a 10% increase in service hours provided by RPNs is associated with an increase of approximately 0.4% in the total number of resident care days provided at the 80-th, 85-th and 90-th percentiles. The output elasticities with respect to other labor inputs at the 80-th percentile are 0.26% for RNs, 0.28% for HCAs, 0.3% for therapists, and 0.28% for general services staff, respectively with a bit of variation at the 85th and 90th percentiles. The category of 'other care-related expenses' is also positively associated with output but only significantly so at the 80th percentile with a 10% increase in expenditure in this category associated with a 0.04% increase in resident care days.

The effect of ownership type is not statistically significant in the frontiers estimated for the 80-th, 85-th, and 90-th quantiles. Chain ownership is positive and significant ($p < 0.05$) across all quantiles (i.e. 10th - 90th percentiles). Specifically, chain-owned nursing homes are able to provide approximately 4% more days of care across the highest quantiles compared to independent facilities, all else being equal.

<Table II. QR Cobb-Douglas production frontier for Ontario nursing homes, 1996/1997 to

2010/2011>

Urban nursing homes produce 7% more resident days of care, all else being equal, compared to homes located in rural regions ($p < 0.001$). Market concentration, as captured by the HHI, is not significant at the 80-th, 85-th and 90-th quantiles.

The estimated coefficient for the mortality ratio is negative and statistically significant ($p < 0.01$) at the 85-th and 90-th percentiles, with a 1-unit increase associated with a 2.7% and 3.6% decline in resident days of care. This variable is not significant at the 80th percentile.

Examining the estimated coefficients across all the quantiles, there is evidence of variation in the output elasticities for the labour inputs (Figure 4) and firm characteristics (Figure 5).

<Figure 4. Estimated coefficients (output elasticities) for labor inputs across quantiles>

<Figure 5. Estimated coefficients for firm characteristics across quantiles>

Statistical significance of the Mundlak means suggests correlation between the time-varying variables and the inefficiency term. These means are significant for all of the labor inputs, with the exception of general services staff in the higher percentiles. This lends support to the pooled QR approach with the means of the time-varying variables included in the regression.

5.2 Technical Efficiency

Differences in technical efficiency due to characteristics of the organizations can be inferred directly from the regression models. The mean predicted technical efficiency for the three upper quantiles (i.e., the 80-th, 85-th, and 90-th percentiles) were 88.5% (Standard deviation [SD] = 10.7%), 86.5% (SD = 10.9%) and 83.5% (SD = 11.1%). These estimates suggest that, after controlling for all observable differences between nursing homes in Ontario, residual variations between these facilities were small. In comparison, the mean technical efficiency scores in the SFA (balanced and unbalanced) models (Appendix: Table III) were 51.2% and 71.6% for the unbalanced and balanced panels, respectively. The scores from the SFA model are likely biased due to the large number of efficient firms in the sample (Laporte and Rohit Dass, 2016). Post hoc examination of the technical efficiency ranking revealed that the benchmark set in the unbalanced SFA panel was based on a single observation from a firm that was only in the RCFS database for one year. In fact, when this observation is removed, the estimated technical efficiency is more comparable to the balanced SFA panel results (data not shown). Results from our sensitivity analyses suggest that the QR models are more robust to the inclusion of outliers; when we estimate the QR models on a balanced panel, the estimated technical efficiencies were 90.2% (SD = 8.5%), 88.2% (SD = 9.1%), and 86.1% (SD = 9.8%) for the 80-th, 85-th, and 90-th percentiles, respectively.

6 Discussion

Results from our estimation across the quantiles reveal observable differences in the effects of labour inputs and other firm characteristics on resident days across the output distribution in Ontario. This highlights one of the benefits of the panel QR approach, as it allows the policy analyst to examine which factors significantly affect nursing homes at different conditional quantiles of the outcome, while controlling for potential correlation of time-varying variables and unobserved firm characteristics.

Some characteristics such as chain membership are a significant predictor of resident days care across all of the quantiles, which may reflect a greater ability to transfer knowledge (e.g. best practices, standardized training, etc.), and potential for cost-sharing (e.g., bulk purchasing of care supplies). This finding suggests that in a highly regulated environment, where cost containment strategies imposed by the government restrict the profit margins of private operators, chain organizations seem to have emerged as a viable model of service delivery. Future research into variations within and across chain organizations to better understand the sources of potential efficiency gains would seem to be merited.

Overall, nursing homes in Ontario were found to be relatively technically efficient (over 80%). This is consistent with our expectations given the existing funding structure and the requirement to maintain a 97% occupancy rate over the year. We note that the efficiency scores obtained from SFA-RE yielded much lower average technical efficiency scores for the sector. This is consistent with the Monte Carlo simulation results reported in Laporte and Rohit Dass (2016) that show downward bias in SFA estimates of technical efficiency when the sample consisted of a large number of efficient firms.

It is important that the analysis of technical efficiency and the estimates thereof are reliable even in the context of markets where we expect that the technical efficiency may be quite high. This is because such estimates form an essential base for other analyses such as assessments of the allocative efficiency within and across sectors that require disentangling of the components of efficiency.

7 Limitations

The aim of this paper was to set out a framework within which to explore the determinants of nursing home productivity and assess the relative technical efficiency of nursing homes based on the estimation of a production frontier. The approach we investigate can accommodate other potentially important aspects of output such as a more robust set of quality of care indicators, which were absent from the current study. While the RCFS dataset provided some very useful detail at the firm level and over an extensive period of time that helped to illustrate the technique, it does not contain clinically-meaningful measures of quality of care. Part of this is due to the fact that nursing homes in Ontario over the data period are paid on the basis of volume of care with no payments that take account of quality of care. Thus, there was no need for it to be captured in the data with regard to payments. We employed an empirical technique that allows for unobserved firm level characteristics to be correlated with our time-varying explanatory variables, which may have captured some of the variation in quality of care. Nonetheless, future research that can draw upon more comprehensive data should include more detailed quality measures to ascertain whether the relationships we observe using a case-mix adjusted volume based measure of output hold.

A second potential limitation of this study is the assumption that the technical efficiency scores are time-invariant. If this is the case, then the endogeneity issue with respect to the inputs is solved using the Mundlak specification, and the calculated technical efficiency scores are consistent. However, if the technical efficiency is instead time varying, then an Instrumental Variables (IV) approach may be better suited to deal with the endogeneity of the inputs. Although there is a nascent literature on panel QR-IV (see for example, Lee, 2007), the details of the approach are far from settled in the panel QR literature. It seems likely that this would be a potentially fruitful avenue for future research.

8 Conclusions

This paper explores an application of panel QR to data for nursing homes as the basis of assessing their relative technical efficiency. We use a panel QR approach with Mundlak (1978) specification to overcome the shortcomings of other existing parametric and non-parametric methods. In particular, this specification allows for the inclusion of time-invariant variables, produces estimates of the time-varying variables that control for all time-invariant factors, does not make distributional assumptions on the inefficiency term, and produces technical efficiency scores that are robust to the number of efficient firms in the sample. We find that LTC homes in Ontario have performed efficiently over the study period, which is likely due to the tight regulatory environment within which they operate. We also find chain membership and urban location to be significant, positive predictors of output across the conditional distribution, suggesting possible ways to improve technical efficiency to increase volume as an alternative to simply increasing the number of beds in this sector.

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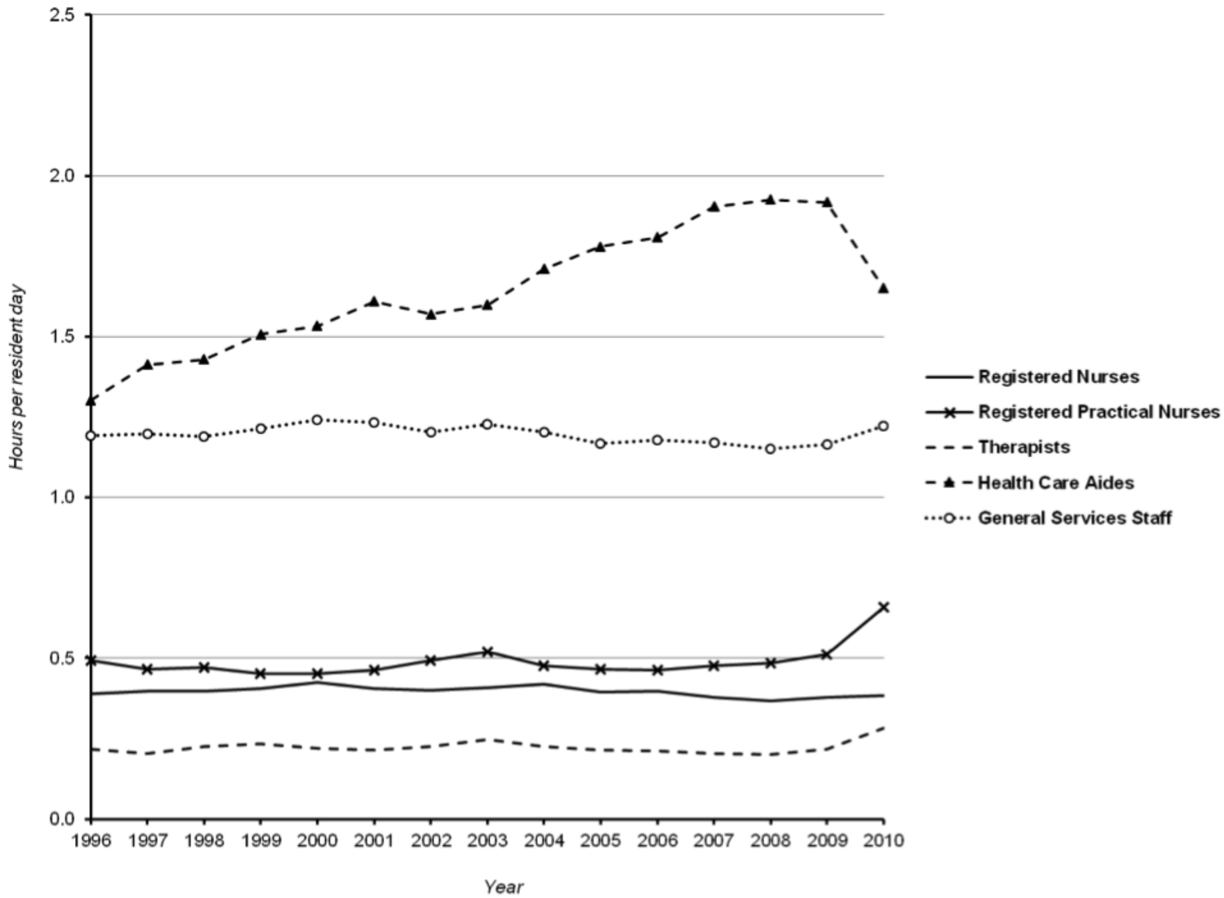
Tables and Figures

Table 1: Profile of Ontario nursing homes and summary statistics for labor inputs, 1996/1997 to 2010/2011

	Type of ownership			
Number of facilities^{i}	For-profit (n = 356)	Not-for-profit (n = 162)	Municipal (n = 109)	All (n = 627)
Facility Characteristics				
Chain owned (% of facilities)	82.7^{ii}	38.5^{ii}	...	55.5
Urban location (% of facilities)	48.7^{ii}	54.2^{ii}	51.8	50.7
Number of beds (average per facility)	$109.0^{ii,iii}$	$116.9^{ii,iv}$	$167.4^{iii,iv}$	122
	[58.0]	[79.9]	[84.0]	[72.9]
Case-mix adjusted excess mortality	$1.00^{ii,iii}$	$0.98^{ii,iv}$	$1.03^{iii,iv}$	1
	[0.31]	[0.29]	[0.27]	[0.30]
Output				
Case-mix adjusted resident care days,	$38{,}856^{ii,iii}$	$41{,}932^{ii,iv}$	$59{,}738^{iii,iv}$	43,582
average per facility per year	[20,296]	[28,265]	[29,824]	[25,743]
Inputs				
Total hours paid to direct care and general services staff, average per facility per year				
Registered nurses (RNs)	$13{,}923^{ii,iii}$	$16{,}169^{ii,iv}$	$23{,}669^{i}ii, iv$	16,334
	[7,831]	[12,558]	[17,819]	[12,147]
Registered practical nurses (RPNs)	$15{,}891^{ii,iii}$	$22{,}825^{ii,iv}$	$44{,}037^{iii,iv}$	22,968
	[15,581]	[38,674]	[41,686]	[30,899]
Therapists	$8{,}522^{iii}$	$9{,}768^{iv}$	$13{,}570^{iii,iv}$	9,792
	[11,971]	[18,286]	[34,805]	[19,925]
Health care aides (HCAs)	$64{,}463^{ii,iii}$	$71{,}806^{ii,iv}$	$98{,}143^{iii,iv}$	72,689
	[41,975]	[60,246]	[67,321]	[54,026]
General services staff	$39{,}113^{ii,iii}$	$56{,}425^{ii,iv}$	$87{,}449^{iii,iv}$	52,639
	[24,095]	[47,780]	[48,164]	[40,931]
Total expenditure on care supplies,	$1{,}676{,}237^{ii,iii}$	$1{,}909{,}918^{ii,iv}$	$2{,}273{,}198^{iii,iv}$	1,848,370
average per facility per year (in 2010 Canadian dollars)	[1,448,962]	[2,071,949]	[1,737,344]	[1,697,300]

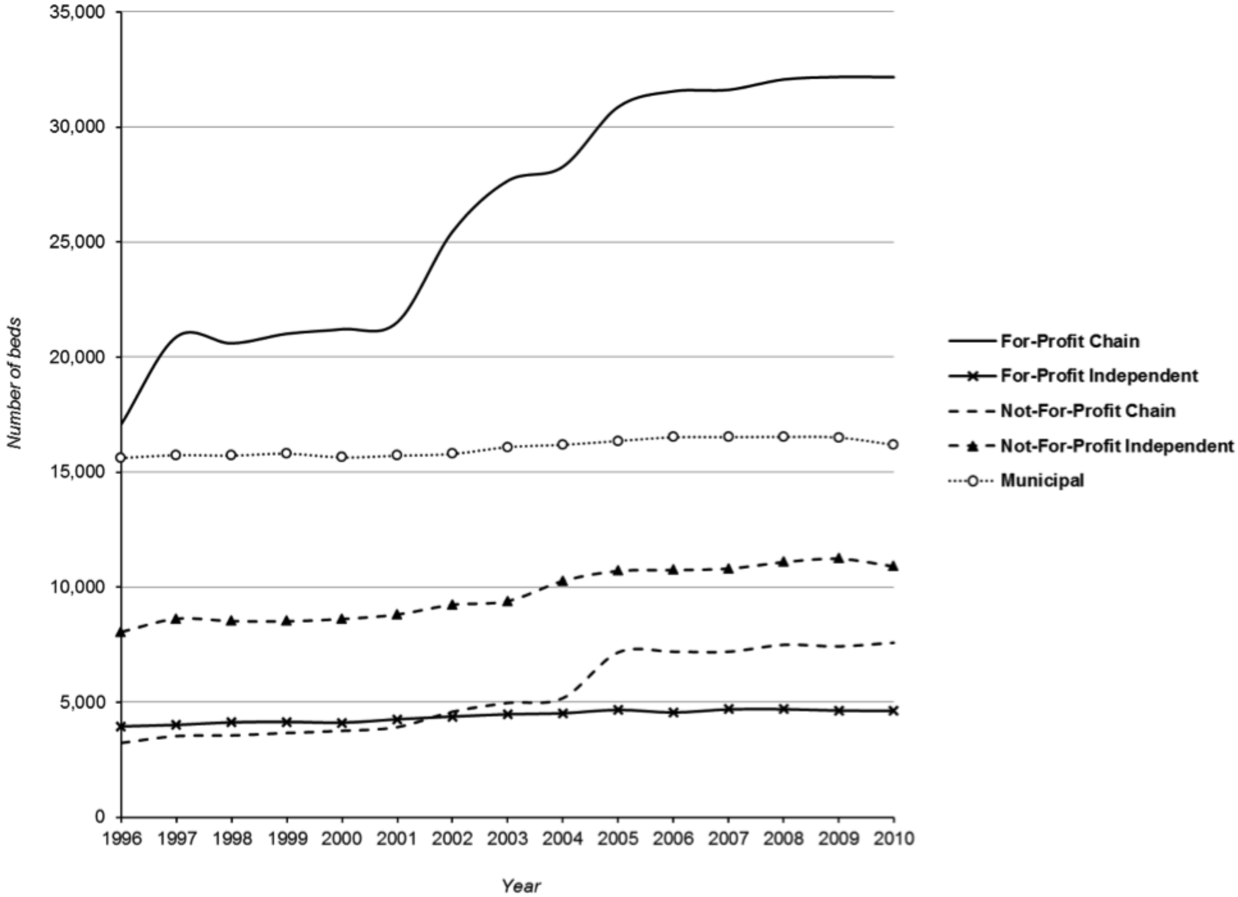
Standard deviations are presented in parentheses.
... not applicable
i. Total number of facilities that were in operation for at least one year between 1996/1997 and 2010/2010.
ii. Denotes a statistically significant difference ($p < 0.05$) between for-profit and not-for-profit facilities.
iii. Denotes a statistically significant difference ($p < 0.05$) between for-profit and municipal facilities.
iv. Denotes a statistically significant difference ($p < 0.05$) between not-for-profit and municipal facilities.

Figure 1: Average hours of care per resident day, by staffing category



Source: Hsu A, Berta W, Coyte PC, Laporte A. 2016. Staffing in Ontario's long-term care homes: Differences by profit status and chain ownership over 15 years. *Canadian Journal on Aging.* In press.

Figure 2: Distribution of long-term care beds in Ontario, by profit status and chain affiliation



Source: Hsu A, Berta W, Coyte PC, Laporte A. 2016. Staffing in Ontario's long-term care homes: Differences by profit status and chain ownership over 15 years. *Canadian Journal on Aging.* In press.

Figure 3: Average occupancy rate in Ontario's long-term care homes, by profit status

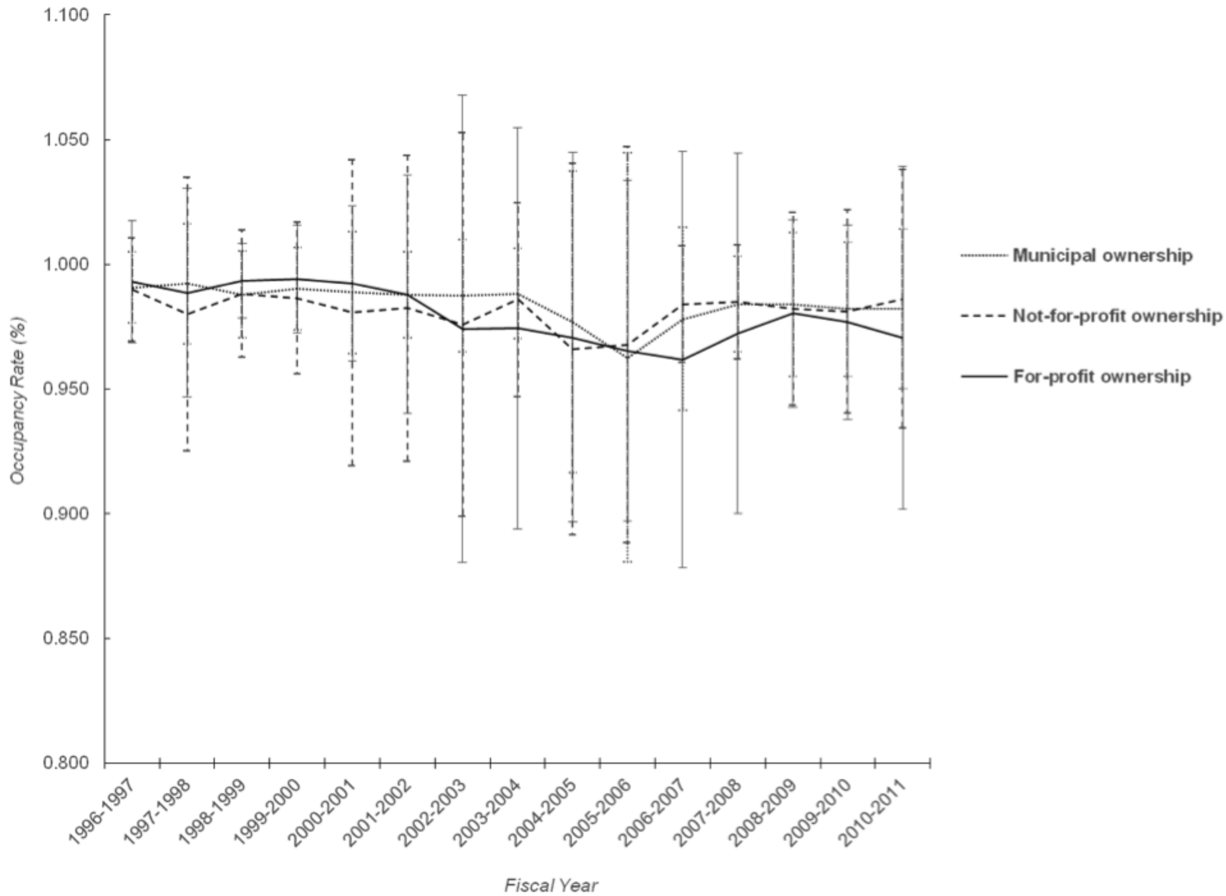


Table 2: QR Cobb-Douglas production frontier for Ontario nursing homes, 1996/1997 to 2010/2011

	QR(0.80)		QR(0.85)		QR(0.90)	
Main equation coefficients ($\mathbf{X}_{it}$)						
Intercept	4.147	***	4.186	***	4.52	***
	[0.312]		[0.367]		[0.435]	
Inputs						
ln(Registered nurses)	0.026	*	0.02		0.025	
	[0.011]		[0.013]		[0.013]	
ln(Registered practical nurses)	0.043	***	0.045	***	0.038	***
	[0.009]		[0.010]		[0.011]	
ln(Health care aides)	0.028	***	0.026	***	0.024	**
	[0.006]		[0.007]		[0.007]	
ln(Therapists)	0.03	***	0.032	***	0.038	***
	[0.009]		[0.009]		[0.010]	
ln(General services staff)	0.028	***	0.031	**	0.037	**
	[0.008]		[0.011]		[0.014]	
ln(Care-related expenses)	0.004	*	0.003		0.002	
	[0.002]		[0.002]		[0.001]	
Explanatory variables						
Municipal ownership	-0.035		-0.023		0.002	
	[0.025]		[0.029]		[0.033]	
Not-for-profit ownership	0.008		0.012		0.017	
	[0.019]		[0.019]		[0.021]	
Chain member	0.036	*	0.04	*	0.046	*
	[0.016]		[0.016]		[0.018]	
Urban location	0.065	***	0.073	***	0.078	***
	[0.014]		[0.016]		[0.018]	
Market concentration (HHI)	0.029		0.034		0.035	
	[0.025]		[0.025]		[0.031]	
Case-mix adjusted excess mortality	-0.013		-0.027	**	-0.036	***
	[0.008]		[0.009]		[0.011]	
Beds (lower quartile)	-0.132	***	-0.164	***	-0.208	***
	[0.038]		[0.042]		[0.045]	
Beds (upper quartile)	0.254	***	0.28	***	0.309	***
	[0.047]		[0.041]		[0.047]	
Year						
1997	-0.014		-0.019		-0.028	*
	[0.009]		[0.011]		[0.014]	
1998	-0.02	*	-0.024	*	-0.034	*
	[0.009]		[0.012]		[0.014]	
1999	-0.027	**	-0.019		-0.042	**
	[0.010]		[0.013]		[0.013]	
2000	-0.033	***	-0.028	*	-0.042	**
	[0.010]		[0.012]		[0.013]	
2001	-0.029	**	-0.02		-0.032	*
	[0.011]		[0.012]		[0.015]	
2002	-0.029	**	-0.026	*	-0.036	**
	[0.010]		[0.013]		[0.013]	
2003	-0.029	**	-0.03	*	-0.041	**
	[0.011]		[0.013]		[0.014]	
2004	-0.02		-0.007		-0.012	
	[0.014]		[0.016]		[0.017]	
2005	-0.009		0.007		-0.006	
	[0.013]		[0.016]		[0.018]	

Table 2 Cont'd: QR Cobb-Douglas production frontier for Ontario nursing homes, 1996/1997 to 2010/2011

2006	-0.012		0.006		-0.011	
	[0.013]		[0.016]		[0.017]	
2007	-0.016		-0.002		-0.011	
	[0.012]		[0.016]		[0.017]	
2008	-0.015		-0.002		-0.012	
	[0.013]		[0.017]		[0.017]	
2009	-0.018		0.001		-0.009	
	[0.015]		[0.017]		[0.017]	
2010	-0.028	*	-0.018		-0.031	
	[0.014]		[0.017]		[0.017]	
Mundlak variables ($\mathbf{Z}_{it}$)						
ln(Registered nurses)	0.189	***	0.205	***	0.196	***
	[0.032]		[0.030]		[0.034]	
ln(Registered practical nurses)	0.119	***	0.109	***	0.098	***
	[0.021]		[0.022]		[0.020]	
ln(Health care aides)	0.103	***	0.097	***	0.092	***
	[0.018]		[0.022]		[0.025]	
ln(Therapists)	0.113	**	0.114	**	0.102	**
	[0.035]		[0.038]		[0.038]	
ln(General services staff)	-0.031	*	-0.028		-0.033	
	[0.015]		[0.017]		[0.018]	
ln(Care-related expenses)	0.015		0.014		0.018	
	[0.013]		[0.011]		[0.012]	
Case-mix adjusted excess mortality	-0.061		-0.064		-0.073	
	[0.048]		[0.056]		[0.058]	
Facility size (lower quartile)	-0.107	*	-0.079		-0.065	
	[0.045]		[0.050]		[0.051]	
Facility size (upper quartile)	-0.039		-0.059		-0.059	
	[0.054]		[0.052]		[0.058]	
Mean predicted technical efficiency	0.885		0.865		0.835	
	[0.107]		[0.109]		[0.111]	

Notes:
Output (Y_{it}) = Case mixed adjusted days of resident care.
Standard errors are presented in parentheses.
* indicates significance at $0.01 < p \leq 0.05$.
** indicates significance at $0.001 < p \leq 0.01$.
*** indicates significance at $p \leq 0.001$

Figure 4: Estimated coefficients (output elasticities) for labor inputs across quantiles

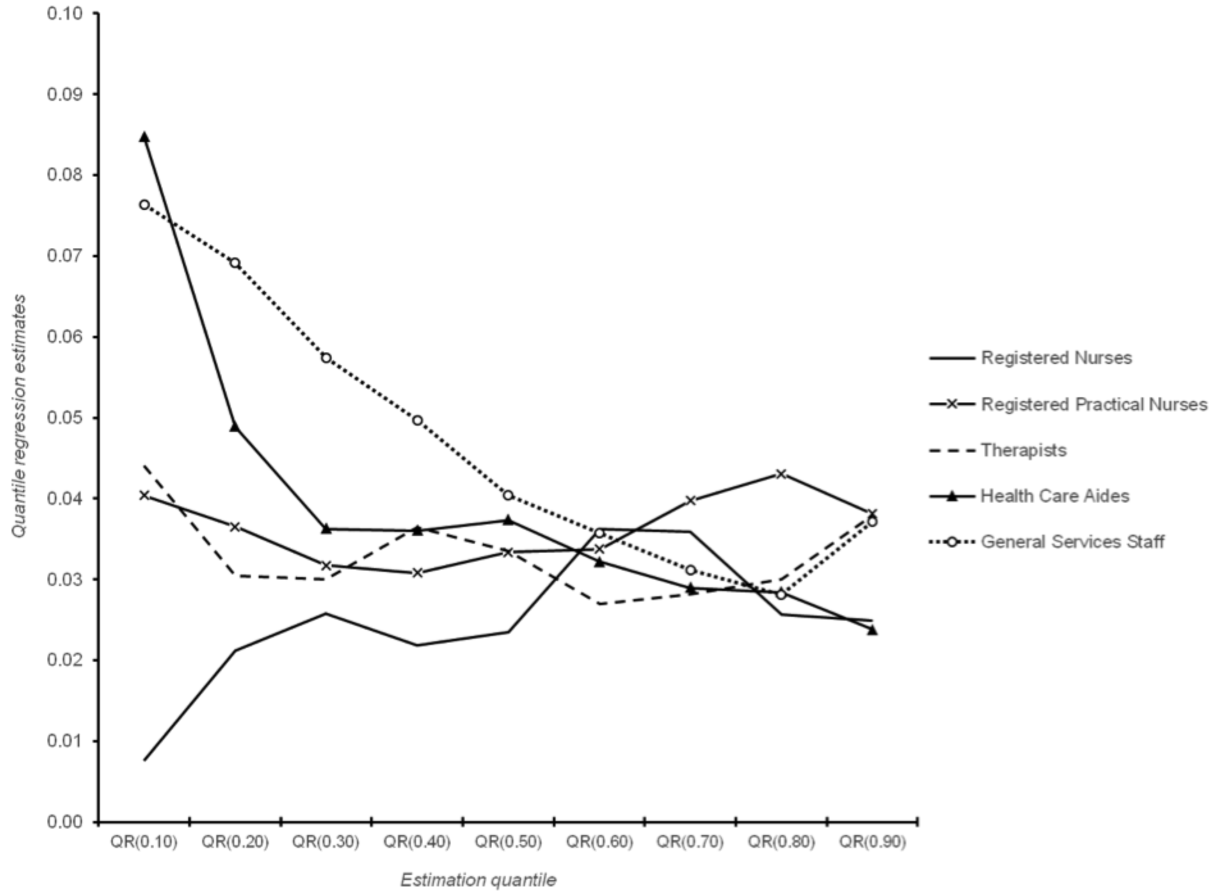
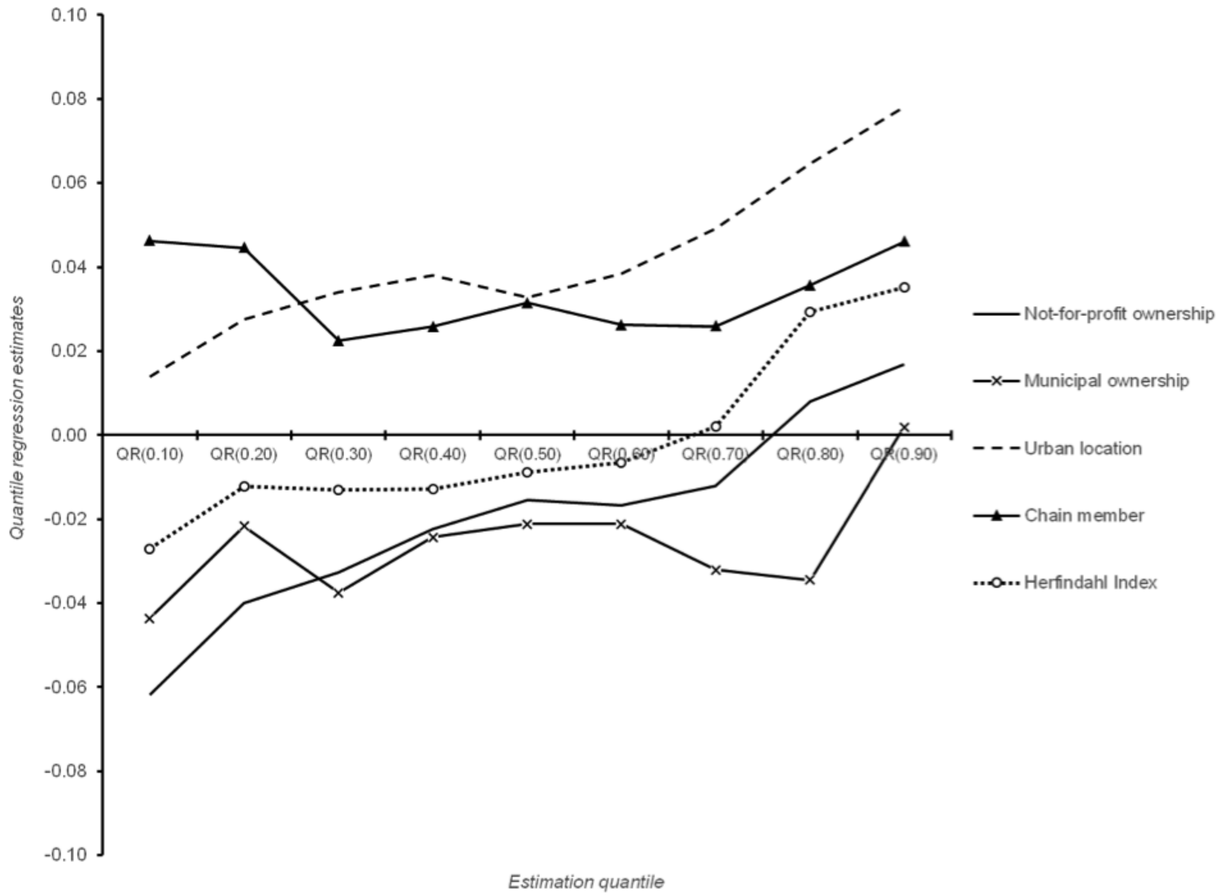


Figure 5: Estimated coefficients for firm characteristics across quantiles



Appendix

Textbox 1. Level-of-care typology used in the Residential Care Facilities Survey (RCFS)

Room and Board - for residents paying only for the use of a room. No services or type of care are received. Refers to care and services provided through retirement homes and there should be limited provision of this in long-term care homes).
Type I Care - refers to care provided to a person who is ambulatory and/or independently mobile, who has decreased physical and/or mental faculties, and who requires primarily supervision and/or some assistance with activities of daily living and provision for meeting psycho-social needs through social and recreational services. The period of time during which care is required is indeterminate and related to the individual condition but is less than 90 minutes in a 24 hour day.
Type II Care - refers to as extended care in Ontario, and is required by a person with a relatively stabilised (physical or mental) chronic disease or functional disability. They have reached the apparent limit of recovery, and are not likely to change in the near future. They have relatively little need for the diagnostic and therapeutic services of a hospital, but require personal care for a total of 1.5 to 2.5 hours in a 24-hour day, with medical and professional nursing supervision and provision for meeting psychosocial needs.
Type III Care - refers to as chronic care in Ontario, and is required by a person who is chronically ill and/or has a functional disability (physical or mental), whose acute phase of illness is over, whose vital processes may or may not be stable, whose potential for rehabilitation may be limited, and who requires a range of therapeutic services, medical management, and skilled nursing care plus provision for meeting psychosocial needs. A minimum of 2.5 hours of individual therapeutic and/or medical care is required in a 24-hour day.
Higher Type Care - for persons who need substantially more nursing and/or medical care than described above. It is assumed that there would be very few residents who would be receiving care of this type. Care above Type III is usually provided in hospitals.

Source: Statistics Canada. 2012. Residential Care Facilities Survey 2010/2011, Instructions and Definitions.

Table 4: SFA Cobb-Douglas production frontier for Ontario nursing homes, 1996/1997 to 2010/2011

	SFA (unbalanced panel)		SFA (balanced panel)	
Main equation coefficients ($\mathbf{X}_{it}$)				
Intercept	3.962	***	2.642	***
	[0.306]		[0.723]	
Inputs				
ln(Registered nurses)	0.029	***	0.036	**
	[0.009]		[0.013]	
ln(Registered practical nurses)	0.043	***	0.049	***
	[0.007]		[0.013]	
ln(Health care aides)	0.036	***	0.036	***
	[0.005]		[0.009]	
ln(Therapists)	0.038	***	0.054	***
	[0.006]		[0.013]	
ln(General services staff)	0.048	***	0.066	**
	[0.010]		[0.023]	
ln(Care-related expenses)	0.003	**	0.005	*
	[0.001]		[0.002]	
Explanatory variables				
Municipal ownership	-0.011		-0.026	
	[0.025]		[0.044]	
Not-for-profit ownership	-0.052	**	-0.042	
	[0.018]		[0.031]	
Chain member	0.037	*	0.037	
	[0.016]		[0.021]	
Urban location	0.015		0.036	
	[0.015]		[0.023]	
Market concentration (HHI)	-0.02		0.012	
	[0.035]		[0.052]	
Case-mix adjusted excess mortality	-0.015	*	-0.01	
	[0.007]		[0.008]	
Beds (lower quartile)	-0.132	***	-0.11	**
	[0.025]		[0.037]	
Beds (upper quartile)	0.249	***	0.153	**
	[0.033]		[0.056]	
Year				
1997	-0.02	***	-0.012	*
	[0.005]		[0.006]	
1998	-0.013	**	-0.013	*
	[0.005]		[0.006]	
1999	-0.015	**	-0.016	**
	[0.006]		[0.006]	
2000	-0.023	***	-0.021	**
	[0.007]		[0.007]	
2001	-0.024	***	-0.013	
	[0.007]		[0.007]	
2002	-0.028	***	-0.027	***
	[0.007]		[0.008]	
2003	-0.033	***	-0.033	***
	[0.007]		[0.009]	
2004	-0.028	***	-0.031	**
	[0.008]		[0.012]	
2005	-0.014		-0.023	
	[0.009]		[0.013]	

Table 4 Cont'd: SFA Cobb-Douglas production frontier for Ontario nursing homes, 1996/1997 to 2010/2011

2006	-0.017		-0.027	*
	[0.009]		[0.013]	
2007	-0.017		-0.029	*
	[0.009]		[0.013]	
2008	-0.012		-0.02	
	[0.009]		[0.013]	
2009	-0.016		-0.031	*
	[0.009]		[0.013]	
2010	-0.032	***	-0.043	**
	[0.010]		[0.015]	
Mundlak variables ($\mathbf{Z}_{it}$)				
ln(Registered nurses)	0.141	***	0.138	*
	[0.028]		[0.055]	
ln(Registered practical nurses)	0.085	***	0.061	
	[0.017]		[0.032]	
ln(Health care aides)	0.151	***	0.105	*
	[0.027]		[0.046]	
ln(Therapists)	0.091	*	0.036	
	[0.037]		[0.045]	
ln(General services staff)	-0.039	**	0.077	
	[0.015]		[0.058]	
ln(Care-related expenses)	0.031	*	0.09	**
	[0.012]		[0.029]	
Case-mix adjusted excess mortality	-0.006		-0.029	
	[0.056]		[0.062]	
Facility size (lower quartile)	-0.184	***	-0.06	
	[0.037]		[0.054]	
Facility size (upper quartile)	-0.053		0.01	
	[0.040]		[0.073]	
Mean predicted technical efficiency	0.512		0.716	
	[0.074]		[0.076]	

Notes:
Output (Y_{it}) = Case mixed adjusted days of resident care.
Standard errors are presented in parentheses.
* indicates significance at $0.01 < p \leq 0.05$.
** indicates significance at $0.001 < p \leq 0.01$.
*** indicates significance at $p \leq 0.001$