Health Inspection and Quality of Care in Nursing Homes*

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Abstract

There are ample studies evaluating various approaches to improving the quality of care in the U.S. nursing home industry. This paper assesses the dynamic inspections conducted by the Center of Medicare and Medicaid (CMS) to enforce quality improvement. We use a dynamic discrete choice model to estimate the value of the five-star rating system and the costs of investment, assuming that nursing homes invest in the quality of care to minimize the long-run compliance costs. Using the nationwide facility-quarter level data from 2014 to 2018, we estimate the investment cost to be around $???. A back-of-the-envelope analysis shows that the average gain in consumer surplus in a nursing home is about $ *** per investment. The study implies that such quality investment improves social welfare.

JEL Codes: I1, L1, L5

Keywords: Nursing Homes, Dynamic Discrete Choice, Quality of Care, Inspection, Enforcement, Star Rating, Fines, Deficiencies

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1 Introduction

The inefficient quality of care in the U.S. nursing home industry has been a concern for decades (Grabowski, 2001; Grabowski and Town, 2011; Hackmann, 2019). To enhance nursing homes' quality, the Center of Medicare & Medicaid (CMS) conducts random inspections, where the CMS investigates health deficiencies and enforce nursing homes to correct them. This paper constructs a dynamic discrete choice (DDC) model of nursing homes' investment in the quality of care to minimize the long-run cost for compliance.

This research is motivated by the mechanism of enforcement and by the institutional features of nursing homes. First, the CMS reports the enforcement record publicly online after the inspection, eliminating the information asymmetry between consumers and nursing homes. According to Zhao, 2016, such information transparency is effective in quality improvement, how this dynamic regime works is understudied. Second, the nursing home industry lacks the incentive to improve quality due to the restricted competition (Ching et al., 2015) and the low Medicaid reimbursement rate (Hackmann and Pohl, 2018). Given that scholars have proposed solutions for quality improvement (Hackmann, 2019; Lin, 2015), to understand how the inspection works are still meaningful to offer alternative counterfactual policies to enhance equilibrium quality.

As mentioned above, the CMS reports the inspection results to the public, making it possible to collect such data of 0.32 million observations ranging from 2014 to 2018. The data contain nursing homes' inspection dates, deficiency counts, fine amounts, inspection ratings, and other non-inspection characteristics such as nursing hours, patient counts, and bed counts.

We do not directly observe the investment in quality of care in the data set. Therefore, we infer an investment if the nursing home increases its total nursing hours of registered nurses (RN) by at least one RN's working load. This inference is plausible for the following reasons. First, RNs play a vital role in nursing homes' care-giving. They hold the highest nursing position in nursing homes, as they oversee the rest of the nursing staff's activities as well as each patient's overall health and medical history. Second, Nevidjon and Erickson, 2001 and Ching et al., 2015 suggest that nurses are in shortage, and it takes time to train skilled nurses. Third, adding RNs' nursing hours is costly for nursing homes, especially the low Medicaid reimbursement rates discourage nursing homes to increase nursing hours (Hackmann, 2019).

Using this data, we characterize and estimate how nursing homes invest for compliance in the response of CMS's enforcement. The CMS inspects a nursing home without an announcement, at a rate of one standard inspection per year plus complaint-based inspection, if any. During an inspection procedure, the inspector checks whether health deficiencies occur and enforces the nursing home to correct them. The nursing home is assigned a publicly revealed star rating (one the worst and five the best) and receives Civil Monetary Penalties if immediate jeopardy exists. A nursing home chooses to invest if the investment cost is lower than the expected incremental cost in fines and deficiencies without investment. While a static choice model could describe and estimate the investment choice versus the expected inspection cost, it does not consider the long-run effects of both investment and inspection. For this consideration, we adopt a dynamic discrete choice (DDC) model of investment, as described below.

In our DDC model, the state variable includes three aspects: 1) the current inspection rating (IR), 2) the accumulated quarters since the last inspection, and 3) the indicator of investment in the previous quarter. Although the DDC model relies on a game between a nursing home's investment and the inspector's inspection decision, we do not model the inspector's utility function due to the identification challenge. Instead, we take the random inspection as given and calculate a conditional inspection probability. We then show detailed evidence that the state variables jointly affect the conditional inspection probability, which plays an important role in the transition of states.

The state's transition depends on whether an inspection occurs. If there is no inspection, the IR remains, and the quarter accumulation increases by one. If an inspection occurs, the IR transitions to a new rating and quarter accumulations renew to be zero. Whether there is an inspection, the lag-investment indicator in the next period always follows the current investment decision.

At the beginning of each period, the nursing home and the inspector simultaneously decide on investment and inspection, respectively. The cost of investment is fixed but with an idiosyncratic shock. While the inspection probability does not depend on the investment (more discussion in Appendix), the outcome does. If an inspection occurs, an investment is supposed to decrease the expected deficiencies, fines, and the probability of transiting to a worse star rating.

The variation in such decreased inspection outcomes plus the investment frequency identifies the structural parameters of investment cost and inspection costs. Consider a simple case where the outcome only includes fines. Nursing homes invest only when the decrease in fine is more than the investment cost. Thus, the variation in investment probability identifies how the value of investment compares with the dollar-valued fines. Given the decrease in fines, the more frequent investment is observed, the lower cost for investment.

Our computation follows Rust, 1987 to use a nested fixed-point algorithm, searching parameters that maximize the likelihood calculated based on the Bellman equation, taking the advantage of the logit assumption of the idiosyncratic shock. We then use a probit regression to predict inspection and use tobit regressions to predict deficiencies and fines. And finally, we estimate the star rating transition probabilities with a multinomial logit model.

The main findings include the following: The investment cost is about \$31.12 thousand, while correcting deficiencies is not costly. On the other hand, a low star rating is strongly inferior, where we normalize the utility of 5-Star to 0. The dollar-valued disutility is about \$265.60 thousand for being 1-Star. The disutility for 2- and 3-Star are \$143.43 thousand and \$172.81 thousand respectively. Getting a rating of 4-Star is not much different from 5-Star. These disutility parameters incorporate the reduced-form profitability for different star ratings.

To calculate the change in social welfare due to an investment, we compare the investment costs against the consumer surplus based on values estimated in the literature. First, we revisit Hackmann, 2019 for structural parameters of dollar-valued quality and estimate a quarterly \$111.73 thousand increase in consumer surplus. Since the effect of investment extends to the next period, we measure the welfare at the bi-year level. In half of a year, the gain in consumer welfare is \$137.64 thousand. Second, we revisit Ching et al., 2015 to calculate consumer welfare due to a change in patient counts. Our results suggest that investment also results in decreasing admissions to increase nursing hours per capita. The loss in welfare due to less utilization is about \$20.76 thousand per investment. Overall, the change in social welfare due to investment is \$116.9 thousand. Hence, we conclude that social welfare in a nursing home sharply increases due to an investment.

Our research contributes to two margins of the literature: 1) the quality in the nursing home industry and 2) the inspection and enforcement. First, in the literature, scholars have investigated ways to improve nursing homes' quality of care: encouraging entry (Hackmann, 2019; Lin, 2015), eliminating the low-quality facility (Lin, 2015), raising the Medicaid reimbursement rate (Hackmann, 2019), and decreasing information asymmetry of quality (Zhao, 2016). Our research extends the investigation by combining the ¡°low-quality elimination¡± and ¡°quality revelation¡± in this study and unfolds the dynamic enforcement and indicate the investment is effective to improve quality of care.

Second, scholars study inspection and enforcement in various settings, such as environmental pollution (Blundell et al., 2020), food safety (Ibanez and Toffel, 2019), employee compliance (Nielsen and Smyth, 2008), tax audit (Maitra et al., 2007), and worker safety (Ko et al., 2010). As far as we know, our work is the first to apply inspection and enforcement, especially dynamic enforcement, to the nursing home industry.

The remaining sections are organized as follows. We describe the background of the nursing home industry and the inspection regime in Section 2. Section 3 is the data description and visualized preliminary evidence. Then, in Section 4, we characterize a dynamic enforcement model, describe the computation method, and discuss the identification strategy. In Section 5, we present the estimation results of the choice model. Section 6 concludes.

2 Background of Study

2.1 Quality in Nursing Homes

The low inefficient quality of care, measured in the aspects of deficiency (Lin, 2014) and nursing hours (Hackmann, 2019; Nevidjon and Erickson, 2001), in the U.S. nursing home industry has been a concern for decades. Such inefficient quality yields worse clinical outcomes, harming the vulnerable older adults who stay in nursing homes. Two main industrial features lead to low quality in the equilibrium. One is the lack of competition, resulting from the high entry costs and information asymmetry between patients and nursing home care facilities. The other is the lack of profitability, where, despite an excess demand from Medicaid-covered patients, the Medicaid reimbursement rates are too low to incentivize the nursing homes to improve quality.

A series of studies have examined policy effectiveness in improving nursing home care quality through the competition and the profitability channel. Hackmann, 2019 investigated the impact of higher regulated Medicaid reimbursement rates versus a higher number of local competitors. The findings suggest that moderate increases in Medicaid reimbursement rates improve the quality of care while the gain from introducing an additional competitor in each market is relatively small. Lin, 2015 also finds little quality improvement from encouraging entry but documents the heterogeneous competition effects that firms mainly compete against firms with similar quality levels.

Besides the competition from sources other than the number of suppliers, Grabowski and Town, 2011 explore the competition driven by nursing home quality transparency, and find a positive impact. Furthermore, the increase in quality information transparency may interact with the market structure and improve the quality of care more in markets with higher concentration (Zhao, 2016).

2.2 Health Inspection

The CMS enforces nursing homes for compliance through random inspection from two aspects. First, inspectors force nursing homes to correct deficiencies within a short period and check the correction through a revisit. If the nursing home does not correct the deficiency, it is assigned with a "past non-compliance" tag. Second, inspectors reveal the inspection outcomes to the public so that any violation harms a nursing home's reputation.

Specifically, the state agent inspects every nursing home without pre-announcement. The inspection frequency is one regular per year plus complaint-based inspection, if any. During an inspection, the inspector investigates health deficiencies and marks them with a deficiency score (the lower the better). After an inspection, a nursing home has to correct all the deficiencies, if any, within an instant period. The inspector will randomly revisit the nursing home to check the correction. If any deficiency is not corrected, the agent marks the nursing home with "past non-compliance" tag. Among the deficiencies, if immediate jeopardy exists, the agent might impose Civil Monetary Penalties through per-day or per-case fines.

The CMS also use a star rating to conclude the inspection outcome, one the worst and five the best. The rating is set based upon the deficiency score in the inspected nursing home. CMS then weights the average deficiency score from the most recent two surveys of each nursing home.[1] Next, CMS ranks nursing homes in each state based on their weighted deficiency score. In each state, the top 20% in the weighted deficiency score (the worst) are marked with "1-Star", while the bottom 10% in the deficiency score (the best) are marked with "5-Star". The remaining 70% in the middle are evenly distributed to "2-Star", "3-Star" and "4-Star" by the rank of deficiency scores. If a nursing home's deficiency score falls out of current criteria due to the change of others' score, the inspection rating will not change until the next inspection.

In all, through the health inspection and its outcome a nursing home will:

[1] The the most recent score takes into account 60%, and the previous takes up 40%.

- be assigned with a star rating, which is kept until the next inspection;
- correct all the deficiencies, if any, within an instant period;
- be imposed with Civil Monetary Penalties, if immediate jeopardy exists.

To avoid deficiency correcting cost, being penalized (cash loss), or being assigned with a low Star (loss in reputation), nursing homes have incentive to invest in the quality, especially when they expect inspections are likely to occur.

3 Data

3.1 Data Overview

We collected data from CMS's Nursing Home Compare (NHC), merging the Provider Information, the Deficiency Record, and the Penalty Record. The dataset contains the nationwide facility-quarter level information from 2014 to 2018. We identify a facility-by-quarter observation through each nursing home's unique Medicare Provider Number and the data filing date. The data include nursing homes' ratings, beds, patients, and nursing hours per patient-day. Based on each inspection record, the data file contains the inspection data, deficiency counts and severity, and the penalties to the inspected nursing homes.

In this dataset, investment is not directly observed. Think about other ways to model investment. Hard to think that skilled nursing staffs decrease in each year. Leave it to Miao. Instead, we infer an investment if a nursing home increases its nursing hours of registered nurses (RN) to some extent. This inference is plausible because of the following reasons. First, registered nurses play a vital role in a nursing home's caregiving. RNs hold the highest nursing position in nursing homes, as they oversee the activities of the rest of the nursing staff. Instead of just focusing on patients' immediate needs, RNs are responsible for overseeing each patient's overall health and medical histories. Second, Nevidjon and Erickson, 2001 and Ching et al., 2015 suggest that nurses are in shortage, and it takes time to train skilled nurses. Third, adding RN's nursing hours is costly for nursing homes, especially the low Medicaid reimbursement rate discourages nursing homes from increasing nursing hours (Hackmann, 2019). Hence, we mark an investment if the (annualized) increase in RN's nursing hours exceeds 2,080 hours, the RN's annual working time. Thus,

$$\text{Inv}_{j,t} = \mathbf{1}\{\Delta\text{Hours}^{RN}_{j,t} \times \text{Patients}_{j,t} \times 365 > 2,080\}$$

where j, t are indices of nursing homes and quarters. ΔHours^{RN} is the increased nursing hours per patient-day from quarter $t-1$, and $\text{Patients}_{j,t}$ is the average number of patients in nursing home j. Hence, the product of these two terms is the total change of nursing hours per day. Multiplying 365 days generates the annualized increase of nursing hours.

3.2 Summary Statistics

Updated summary stat table, fewer 1 and 5 star, more 2-4 star, more total obs than previous, reason unknown, but fewer obs in the regression, probably due to the definition of inspection timing. Table 1 summarizes the statistics of variables at the facility-quarter level from 2014 to 2018. The samples are partitioned into three categories according to the inspection rating: 1 Star, 2-4 Star and 5 Star. These columns reflects how the mean of each variables varies by inspection ratings.

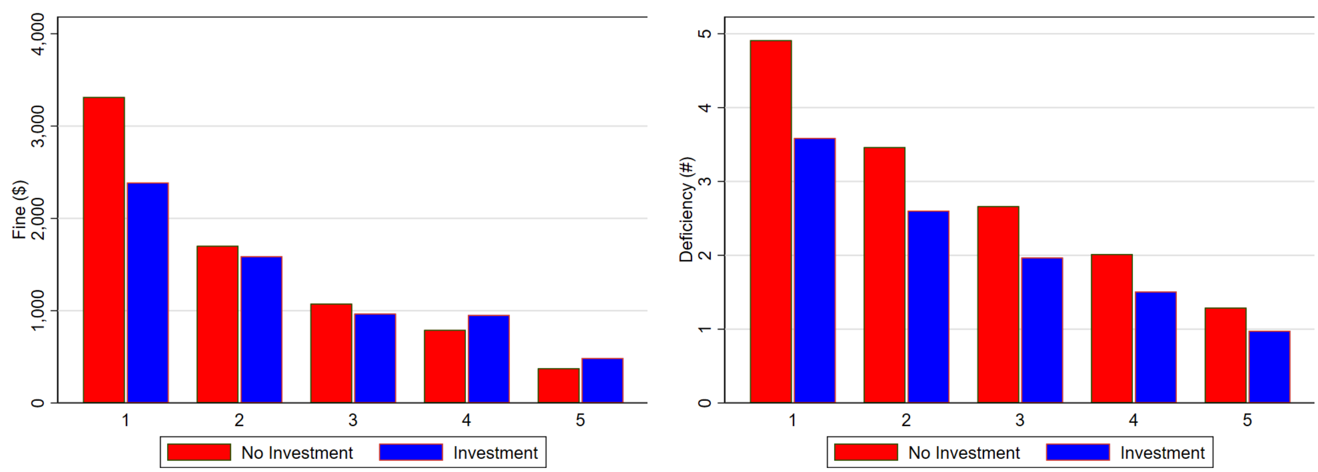
Table 1: Summary Statistics (by Inspection Rating)

	1 Star		2-4 Star		5 Star		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
# Deficiencies	4.38	(9.74)	2.69	(6.66)	1.39	(4.05)	2.88	(7.21)
Deficiencies | Ins = 1	9.88	(12.64)	7.95	(9.46)	5.05	(6.41)	8.19	(10.21)
Fine (1000$)	2.56	(26.14)	0.99	(15.69)	0.31	(5.79)	1.22	(17.60)
Fine (1000$) | Ins = 1	4.78	(23.01)	2.35	(15.08)	1.09	(9.86)	2.84	(17.10)
Inspection	0.44	(0.50)	0.34	(0.47)	0.27	(0.45)	0.35	(0.48)
Invest (0/1)	0.21	(0.41)	0.19	(0.39)	0.17	(0.37)	0.19	(0.39)
# Beds	120.13	(63.00)	105.12	(59.31)	86.62	(63.37)	106.10	(61.14)
# Patients	95.69	(54.70)	86.00	(53.11)	72.73	(57.15)	86.49	(54.21)
Observations	61,065	19.6%	217,177	69.8%	33,019	10.6%	311,261	
Observations | Ins =1	27,038	24.7%	73,418	67.0%	9,078	8.3%	109,534	

Full Data including those without lag investment. The variable patient has fewer obs than others, not explicitly listed here. See Report/SummaryStat/SummaryStat.csv, conditional fine has fewer obs than conditional def due to dropping extreme top 1% fine.

For the inspection aspects, not surprisingly, the fines and deficiencies decrease with the stars. The inspection and investment frequency are higher among the 1-star-facility than the others, and the frequency declines as the rating goes up. Updated graphs, need to rewrite the description later. Figure B7 also shows the quadratic fit of investment frequency separated by inspection ratings. In the graph, the curve is the fitted frequency and the shade area is the 95% confidence level. In each panel, the first five graphs are the fit from 1 Star to 5 Star, and the sixth graph is the comparison of the fitted curve between 1 Star and 5 Star.

Panel (a) presents the fit of investment and the quarters since the most recent inspection. We omit the samples whose length of quarters are above 6 quarters because the agent generally inspects annually plus complaint-based inspection. The expanding confidence interval rightward also confirms that the sample size shrinks along with the length of quarters, indicating that fewer nursing homes are inspected till the accumulated quarters reach 6. In panel (b), the horizontal axis is the predicted inspection probability in a Probit model as shown Appendix C. The organization of this panel is the same as panel (a). Both panels suggest that nursing homes are more likely to invest as the expected inspection probability increases. Such pattern is also a preliminary evidence of the choice model.

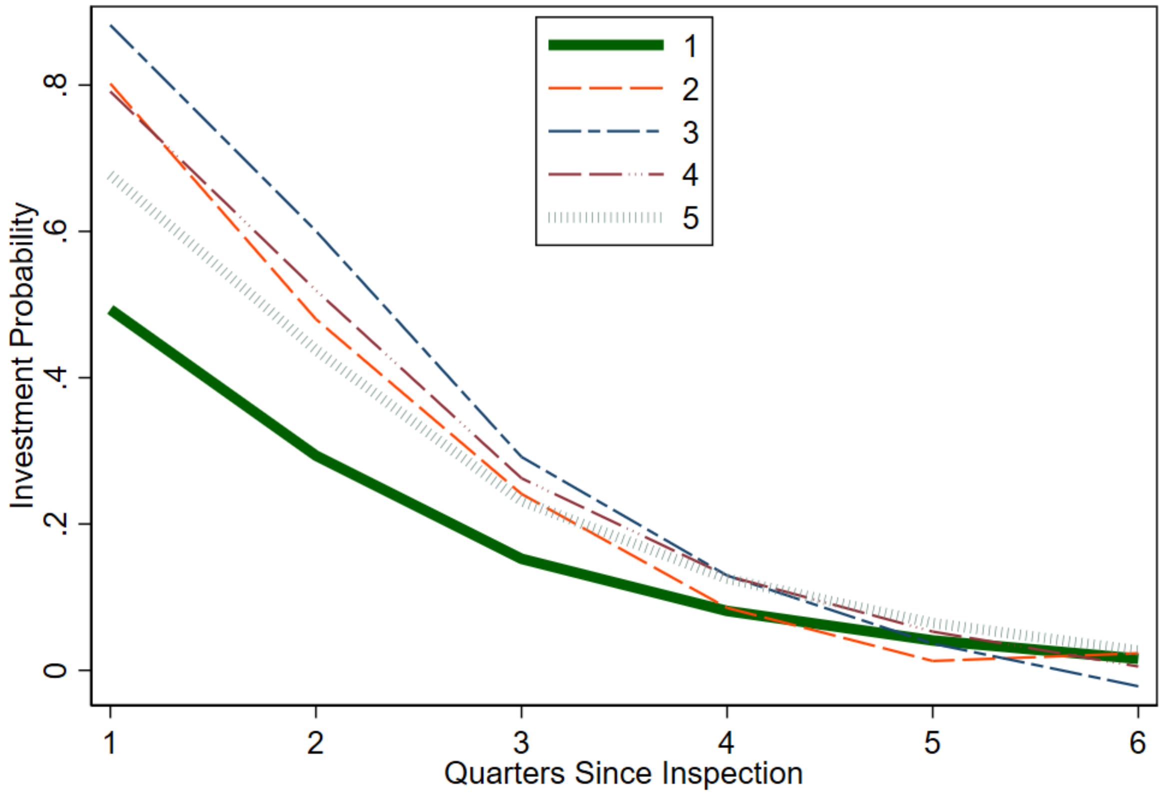


(a) Fine ($) by Lagged IR

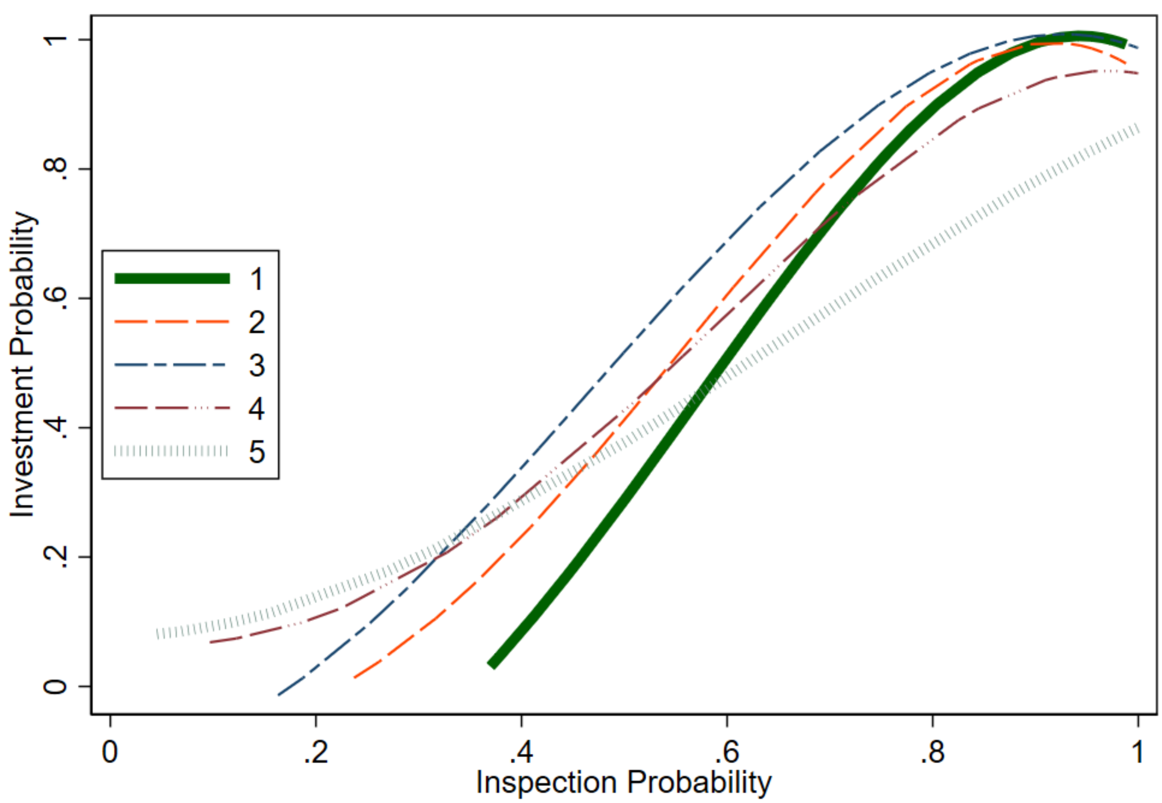
(b) Deficiency (#) by Lagged IR

Figure 2: Effect of Investment

Figure 2 provides evidence of the effectiveness of investment. Panel (a) is the average fine that nursing homes are penalized given the inspection rating before the inspection. The fine decreases with the investment especially if the inspection rating is 1 Star. The effect of other groups is not significant and even bends upward in 4-Star and 5-Star groups. Panel (b) suggests that investment could decrease the deficiency counts found in the inspection, and the effect is the most apparent in 1-Star facilities.



(a) Quarters Since Inspection



(b) Predicted Inspection Probability

Figure 1: Investment Frequency by Inspection Rating: Quadratic Fit

4 Empirical Strategy

4.1 Model

A nursing home's manager minimizes the expected discounted cost for compliance in health inspection. Each period, the manager decides to invest in the quality of care or not. Formally, the choice set is $\mathcal{C} = \{0, 1\}$. Let I_{jt} denote a nursing home j's investment decision in period t. Hereafter we omit the subscript of nursing home index j and period index t when the omission does not introduce confusion.

The state variables summarize sufficient information for each nursing home to make investment decisions. These variables include 1) the inspection rating, $IR = 1, \cdots, 5$, which represents the outcome of the last inspection. This rating is set by the inspection agent and does not change until the next inspection takes place; 2) the accumulated period since the last inspection, Δt^{ins}, and 3) the investment decision in the previous period, $LI = 0, 1$. The reason for using the lagged investment decision is explained in the appendix. Let $\Omega = \{IR, \Delta t^{ins}, LI\}$ denote the state and let $\mathbf{\Omega}$ denote the space of states.

The timing of each inspection cycle is as follows. At the beginning of a period, conditional on the current state Ω, a nursing home privately observes a set of shocks $\boldsymbol{\epsilon} = (\epsilon_0, \epsilon_1)$ associated with each choice and the inspector privately receives a nursing home specific inspection shock ν. Then the nursing home manager and the inspector simultaneously decide whether to invest and whether to inspect. [2] We follow Blundell et al. (2020) to model the inspection as a function of each nursing home's state Ω. Specifically, the probability of inspection $Prob\{Ins(\Omega, \nu) = 1\} = Pr^{ins}(\Omega)$. And the nursing home decides whether to invest with a fixed investment cost given the choice-based shock, i.e., $\theta^{inv} I + \epsilon_I$.

Conditional on the investment decision, if an inspection takes place, the inspector detects health deficiencies, penalizes violations, calculates the quality score, and assigns the nursing home with a new star rating. Finally, the nursing home's cost given the inspection outcome is

$$c(I, \Omega, \xi^{def}, \xi^{fine}) = \mathbb{1}_{Ins} \times [\theta^{def} Def(I, \Omega, \xi^{def}) + \theta^{fine} Fine(I, \Omega, \xi^{fine}) + \sum_{k=1}^{4} \theta_k^R \mathbb{1}\{T(I, \Omega) = k\}]$$

where $Def(\cdot)$ and $Fine(\cdot)$ are inspection outcomes of deficiencies and fines respectively, with

[2] The actual decisions are sequential. However, since neither of the players can observe the other's decision before making their own decisions, the model is equivalent to a simultaneous game.

random shocks associated with deficiency, ξ^{def}, and fine, ξ^{fine}. $T(\cdot)$ represents the rating transition result. The five-star rating is the omitted category and all other ratings are relative to this one. $(\theta^{def}, \theta^{fine}, \{\theta_k^s\}_{k=1}^4)$ is the vector of inspection cost parameters. The fine parameter θ^{fine} is added to normalize the choice-based shocks to have a unit scale. The deficiency parameters θ^{def} thus capture the monetized cost of deficiencies relative to the fine parameter. Similarly, the rating parameters $\{\theta_k^s\}_{k=1}^4$ are the monetized cost of being in $1, \cdots, 4$ star rating relative to five-star rating and relative to the fine parameter. When there is no inspection in that period, there is no flow cost. Let $c(I, \Omega) = \mathbb{E}c(I, \Omega, \xi^{def}, \xi^{fine}) = Pr^{ins}(\Omega)\mathbb{E}[c(I, \Omega, \xi^{def}, \xi^{fine})|\mathbb{1}\{Ins\}]$ denote the expected cost conditional on the investment decision and the current state.

At the end of the period, the state transits according to the transition function Γ, from Ω, to $\Omega' = \Gamma(\Omega)$. Given that an inspection happens, the inspection rating transits according to function $T(\cdot)$ and the quarter accumulation resets to $\Delta t^{ins'} = 0$. Otherwise, if an inspection does not happen in that period, the inspection rating stays the same $IR' = IR$, and the quarter accumulation increases by one, but up to a cap, $\Delta t^{ins'} = \min\{\Delta t^{ins} + 1, \overline{\Delta t^{ins}}\}$. The bounded restriction is defined according to the inspection requirement. Should be explicit about the bound and need to support it using the inspection rule. Leave it to Miao. The lag-investment state in the next period is simply the investment decision in the current period $LI' = I$.

We formally state the four assumptions in our dynamic model and employ the Markov Perfect Equilibrium (MPE) concept to estimate the parameters of interest. Cite the papers that discuss the necessity of these assumptions. Actually I feel these are already stated and not important enough to be written like this.

Assumption 1. (Conditionally independent logit shocks of investment) *Conditional on Ω, ϵ_I is identically and independently distributed across nursing homes, periods, and choice I with a type 1 extreme value distribution.*

This assumption implies that differences in idiosyncratic error terms have a logistic distribution, which gives convenient expressions for value functions and conditional choice probabilities. With fine parameter, we can normalize the choice-based shocks to be extreme value type-I distributed with mean 0 and scale 1. The associated cumulative density function is $F(\epsilon_I) = \exp(-\exp(-\epsilon_I))$.

Assumption 2. (Exogenous shocks of inspection) *Conditional on Ω , ν is identically and independently distributed across nursing homes and periods.*

This means that before the inspection, a nursing home predicts the probability of inspection conditional on the current state Ω, and makes investment decisions based on the expected utility given this conditional inspection probability.

Assumption 3. (Conditionally independent normal shocks of deficiencies and fines) *Conditional on Ω, the shocks to deficiencies and fines, ξ^{def} and ξ^{fine}, are independently and normally distributed, i.e.*

$$\left[\begin{array}{c|c} \xi^{def} & \\ & \Omega \\ \xi^{fine} & \end{array}\right] \sim N(\boldsymbol{\mu}, \Sigma)$$

Where $\boldsymbol{\mu} = \mathbf{0}$ and $\Sigma_{ij} = 0$ for $i \neq j$. This implies that the expected deficiencies and fines can be estimated and predicted separately given the state variable Ω.

Assumption 4. (Markov transition process) *The transition function $T_k^s(\cdot)$ is only a function of the current information, Ω and investment I, regardless of any previous information.*

This assumes that the state transition follows a Markov process.

With a discount rate of $\beta < 1$, a nursing home's value function is the expected present discounted value of all the future costs, which can be written as the Bellman equation:

$$\begin{aligned} V(\Omega, \epsilon_I) &= \max_{I \in \{0,1\}} \theta^{inv} I + \epsilon_I + c(I, \Omega) + \beta \mathbb{E}\left[V(\Omega')|I, \Omega)\right] \\ &= \max_{I \in \{0,1\}} \begin{cases} \theta^{inv} + \epsilon_1 + c(1, \Omega) + & \beta \int \mathbb{E}_{\epsilon'}\left[V(\Omega')\right] dF(\Omega'|1, \Omega) \quad I = 1 \\ \epsilon_0 + c(0, \Omega) + & \beta \int \mathbb{E}_{\epsilon'}\left[V(\Omega')\right] dF(\Omega'|0, \Omega) \quad I = 0 \end{cases} \end{aligned}$$

All except the future term are defined above. The integration is taken over the possible new states Ω', conditional on the investment decision and the state. The transition is as discussed above. The expectation $\mathbb{E}_{\epsilon'}$ is taken over the future choice-based shocks:

$$\mathbb{E}_{\epsilon'} V(\Omega') = \int_{\epsilon_0} \int_{\epsilon_1} V(\Omega, \epsilon_I) dF(\epsilon_1) dF(\epsilon_0)$$

and with the conditional independent logit assumption, we can rewrite the right hand side of $\mathbb{E}_\epsilon V(\Omega)$ as:

$$\mathbb{E}_\epsilon V(\Omega) = \gamma + \log\left(\sum_{I \in \{0,1\}} \exp\left(\theta^{inv} + c(I, \Omega) + \beta \mathbb{E}[V(\Omega')|I, \Omega)]\right)\right)$$

where γ is the Euler constant.

4.2 Computation

Given a parameter vector $\boldsymbol{\theta}$, the Bellman equation yields the following investment probability with logit assumption:

$$P \equiv P(I=1|\Omega) = \frac{\exp(\theta^{inv} + c(1,\Omega) + \beta\mathbb{E}[V(\Omega')|1,\Omega)])}{\sum_{I\in\{0,1\}} \exp\left(\theta^{inv} I + c(I,\Omega) + \beta\mathbb{E}[V(\Omega')|I,\Omega)]\right)}$$

and this probability implies the likelihood function:

$$\mathcal{L}\left(\theta \mid \{I,\Omega\}_{j=1,2\ldots,J}^{t=1,2,\ldots,T}\right) = \prod_{t=1}^{T}\prod_{j=1}^{J} P^{I_{j,t}}(1-P)^{(1-I_{j,t})}$$

Taking logarithm implies the log-likelihood function:

$$\log(\mathcal{L})\left(\theta \mid \{I,\Omega\}_{j=1,2\ldots,J}^{t=1,2,\ldots,T}\right) = \sum_{t=1}^{T}\sum_{j=1}^{J} \left(I_{j,t}\log(P_{j,t}) + (1-I_{j,t})\log(1-P_{j,t})\right)$$

We follow Rust (1987) to apply the nested fixed point algorithm and estimate the parameters $\theta = (\theta^{inv}, \theta^{def}, \theta^{fine}, \{\theta^k\}_{k=1}^4)$. First, we propose a candidate parameter vector and use it to solve the Bellman equation by iteration, assuming $\beta = 0.9$. Then we simulate the decisions using the value function and fit to the data to calculate the log-likelihood. Finally, we adjust the candidate vector until the log-likelihood converges to a maximum.

The computation involves predicting inspection probability, expected deficiencies and fines, and the expected transition process. For the inspection probability $Pr^{ins}(\Omega)$, we run a probit regression on lag-investment, inspection rate indicators, and indicators of accumulation periods. And then, for deficiencies and fines, we implement a Tobit model on the investment indicator, the inspection indicator, and other state variables in predicting the inspection. When we predict the expected deficiencies and fines, we always make the inspection indicator equal one, and respectively predict outcomes in the circumstances with and without investment. Finally, we run a multi-logit to estimate the transition probabilities to each star ratings. The control variables and the prediction process are the same as predicting deficiencies and fines. We report the results in Appendix.

4.3 Identification

The identification argument follows Blundell et al., 2020. Consider a simple case where there are only two variables: expected fines and investment without the idiosyncratic shock. In this simple model, a nursing home invests only if the investment cost is smaller than the incremental fines without investment, i.e., $|\theta^{inv}| \leq |\theta^{fine}\Delta Fine|$. Hence, the ratio $\frac{\theta^{inv}}{\theta^{fine}}$ is identified by the smallest incremental fines that investment is observed.

Adding the idiosyncratic type 1 shock to investment cost allows me to identify the scale of θ^{inv} and θ^{fine}. For different incremental fines, we observe different investment probabilities. The variation in these probabilities identifies the scale. Still consider the simple case for instance, where an investment occurs only if $|\theta^{inv} + \epsilon| \leq |\theta^{fine}\Delta Fine|$. If the variation in probabilities is close to constant across different incremental fines, it means the magnitude of the shock outweighs the scale of θ^{inv} and θ^{fine}. On the other hand, if the investment probability varies a lot across incremental fines, then the shock magnitude is tiny compared with the parameter's scale. This identification variation relies on the *i.i.d.* assumption of the idiosyncratic shock. Hence, Assumption 1 must hold for this argument.

Then we extend this argument to the full model with other parameters. Although the identification follows a similar variation, we make additional explanations for each parameter. The identification of $\{\theta^k\}_{k=1}^4$ requires normalization. Because each rating's transition probability sums up to one, we cannot identify the actual (dis)utility of each rating. Instead, we normalize $\theta^5 = 0$ so that other θ^k represents the disutility compared with 5-Star.

Overall, the identification strategy requires a conditional expectation of inspections, fines, deficiencies, and transitions. This requirement is satisfied by Assumption 2 that nursing homes have no private information of ν, and by Assumption 3 that there is no unobserved serially correlated variable that affects deficiencies and fines.

Admittedly, the model does not include enough state variables for accurate prediction. In the real-world, the inspection is conducted by each state (Arizona, California, etc.) independently. Hence, the inspection probability in each state varies. Besides, each state has a different budget on inspection, and this budget can be affected by an in-state revenue shock. Hence, in the dynamic model, we should have a time-invariant state variable, state (Arizona, California, etc.), and a binary time-variant state variable, budget shock. In future work, we should input these state variables to the model, and they would provide accurate prediction and more variation for identification.

5 Results

5.1 Expected Inspection Outcomes

Table **??** shows the marginal effects of conditional inspection probability and expected deficiencies and fines.

Column 1 is the probit estimate of the conditional inspection probability. All the entries are the marginal effect at the mean level. The explanatory variables exclude current investment because the timing of inspection decision, as described in the model, does not rely on investment decision realization. The results suggest the following patterns. First, the investment in the previous quarter could decrease the inspection probability in current quarter. The possible channel is that investment decrease complaint-based inspection. Second, the inspection probability is decreasing in the inspection star rating. Last, after an inspection, the inspection probability is low in the following half a year, and this probability continuously rises since then.

Column 2 and Column 3 are respectively inspection outcomes of deficiency counts and fines. We estimate them through Tobit regressions. Both columns suggest the effectiveness of investment, either currently or previously. The entries are at mean level, while the effect of investment is strongly significant when the inspection rating is 1-Star. The inspection outcomes decrease in the inspection star rating, and the pattern in quarter accumulations is different.

Table 2: Predictions for Inspection Rating, Deficiency, Inspection and Fine

	Inspection	Inspection Rating	Deficiencies	Log Fine	
	Logit	Ordered Logit	Poisson	Hurdle	Selection
Lag IR = 2	-0.666***	4.256***	-0.171***	-0.023**	-0.047
	(0.028)	(0.070)	(0.013)	(0.007)	(0.031)
Lag IR = 3	-1.254***	8.353***	-0.314***	-0.032***	-0.019
	(0.030)	(0.084)	(0.013)	(0.008)	(0.034)
Lag IR = 4	-1.887***	12.669***	-0.528***	-0.032***	-0.114**
	(0.034)	(0.105)	(0.014)	(0.009)	(0.038)
Lag IR = 5	-2.871***	18.021***	-0.846***	-0.030*	0.018
	(0.057)	(0.168)	(0.019)	(0.015)	(0.063)
Δt	0.323***	0.579***	0.101***	-0.006**	-0.052***
	(0.008)	(0.034)	(0.003)	(0.002)	(0.009)
Investment = 1		0.123*	-0.096***	-0.015*	-0.048
		(0.058)	(0.023)	(0.007)	(0.031)
Lag Investment = 1	0.103*	0.227***	-0.095***	-0.004	0.003
	(0.045)	(0.054)	(0.023)	(0.008)	(0.034)
Deficiencies				0.002***	0.021***
				(0.000)	(0.000)
Observations	293,095	104,559	104,559	104,464	
Pseudo R-squared	0.1037	0.7282	0.0352	0.0496	

Robust standard errors in parentheses

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Marginal Effects to be added later?

May not be able to run the hurdle regression with the full data set, may not converge.

Table **??** is the marginal effect of the transition process. We estimate the transition by a multinomial logit regression. Each column is the marginal effect on the probability to being the new star rating given an inspection occurs. The results suggest that current investment significantly decreases the probability of being 1-Star and increases the probability of other star ratings. The previous quarter's investment also helps with a better star transition, though the effect is not statistically significant. Overall, the effect of investment is small in magnitude.

Add Transition Matrix Marginal Effect? Or summary stat of the predicted values on the grid?

Table 3: Transition for IR Conditional on Inspection and Lag IR

Lag IR	**IR = 1**	**IR = 2**	**IR = 3**	**IR = 4**	**IR = 5**
1	94.62%	5.34%	0.05%	0.00%	0.00%
2	8.77%	82.93%	8.23%	0.07%	0.00%
3	0.10%	10.43%	82.56%	6.90%	0.01%
4	0.00%	0.08%	8.33%	89.03%	2.56%
5	0.00%	0.00%	0.02%	9.57%	90.41%

Table 4: Conditional Probability of Inspection (Only showing the first 99% of Δ_t)

Inspection	**Lag IR**				
Δ_t	**1**	**2**	**3**	**4**	**5**
1	0.37	0.25	0.17	0.11	0.05
2	0.43	0.34	0.27	0.20	0.13
3	0.50	0.44	0.40	0.35	0.29
4	0.56	0.55	0.54	0.54	0.54
5	0.62	0.65	0.68	0.71	0.76
6	0.68	0.74	0.79	0.84	0.90

Table 5: Predictions for Deficiencies (Only showing the first 99% of Δ_t)

Deficiencies	**Lag IR**				
Δ_t	**1**	**2**	**3**	**4**	**5**
1	8.28	7.17	6.42	5.45	4.01
2	9.16	7.93	7.11	6.02	4.43
3	10.13	8.77	7.86	6.66	4.91
4	11.21	9.70	8.69	7.37	5.43
5	12.40	10.73	9.62	8.15	6.00
6	13.72	11.86	10.64	9.02	6.64

Table 6: Predictions for Fine (Only showing the first 99% of Δ_t)

Average of Field1	**Lag IR**				
Δ_t	**1**	**2**	**3**	**4**	**5**
1	8.41	5.74	5.05	4.06	4.19
2	7.76	5.12	4.26	3.41	3.02
3	7.18	4.59	3.59	2.86	2.14
4	6.69	4.12	3.03	2.40	1.50
5	6.26	3.72	2.55	2.02	1.04
6	5.91	3.37	2.16	1.70	0.71

5.2 Dynamic Parameters

Table **??** presents the dynamic parameters. The first two columns are the structural parameters and the explanations. The third column is the estimate of parameters, and the last column is the inferred cost in thousand dollars, where we calculate the cost through $\frac{\theta}{\theta^{fine}}$ for each row.

Estimated Structural Parameters here

The results suggest the investment is costly, approximately \$31.12 thousand per quarter. On the other hand, the cost of deficiency correction is not costly, i.e., the magnitude of the estimate is small and even with an opposite sign. Hence, the incentive of investment is not due to deficiency correction. Instead, the incentive results from the fine itself and the transition of star ratings.

The disutility of being 1-Star is especially high, about $265.6 thousand. As presented above, the inspection probability conditional on 1-Star is high, and the expected fines are also high to facilities with 1-Star. Moreover, although we do not model the competition and profitability in the market, the lowest star rating is supposed to be inferior to consumers.

2-Star and 3-Star are not far different from each other, and even 3-Star sole seems worse than 2-Star. The disutilities are respectively $143.43 thousand and $172.81 thousand. On the other hand, 4-Star is strongly better than 2- and 3-Star and not quite different from 5-Star.

6 Discussion

6.1 Welfare Analysis

In this section, we mainly estimate the consumer welfare changed due to the investment. First, we show how an investment increases the quality and revisit Hackmann, 2019, in which the author estimate a model that links the nursing hours to dollar-valued welfare. Second, we estimate the change in the number of patients and refer Ching et al., 2015 to calculate the welfare change due to patients' change. In this section, we only consider the change in social welfare from the quality of care but omit the fines and disutilities of nursing homes.

Quality Change: Figure ?? presents the histogram of quality distribution. The quality metrics is the logarithm with skilled nursing hours (registered nurse plus licensed practical nurses). We use this measurement of quality to follow Hackmann, 2019 for welfare calculation. Panel (a) is the distribution of log skilled nursing hours per patient-day, and panel (b) is the distribution of the change of the log terms by a quarter.

Histogram for log(SN) distribution and distribution of the change

Table 7 is a regression of the change of quality on the investment. Column 1 and 2 are the AR1 process with investment controlled, where Column 1 is the OLS regression and Column 2 is the FE regression. Both columns suggest a 10% increase in skilled nursing hours due to current investment. Column 3 and 4 are the regression of the percentage change of nursing hours, respectively through OLS regression and FE regression. The results also indicate a 11% increase in quality of care. Hence, in this section, the welfare analysis is based on a 10% increase in skilled nursing hours.

regression table

Table 7: Investment and Skilled Nursing Hours

	$\log(SN_{j,t})$		$\Delta\log(SN_{j,t})$	
	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
$I_{j,t}$	0.104***	0.0982***	0.108***	0.114***
	(0.000858)	(0.000841)	(0.000945)	(0.000989)
$I_{j,t-1}$	0.0251***	0.0385***	0.0189***	0.0246***
	(0.000573)	(0.000624)	(0.000553)	(0.000585)
$\log(SN_{j,t-1})$	0.907***	0.742***		
	(0.00208)	(0.00449)		
Observations	268111	268111	268111	268111
adj. R^2	0.837	0.836	0.112	0.112

standard errors are clustered at facility level.

* p<0.1 ** p<0.05 *** p<0.01

Specifically, Hackmann, 2019 estimates the discrete choice model in the nursing home industry with a similar measure of quality to the paper. The quality proxy is skilled nursing hours per patient (with logarithm), and the coefficient estimate is 2.166.[3] And the coefficient estimate of the price in dollars is -0.019 (for self-paid patients only). Hence, an 1% increase in the skilled nurses is equivalent to an increase of $\frac{\$2.166}{0.019} \times 0.01 = \$1.14$ per patient-day. According to the results, the skilled nursing hours per patient-day increase by about 10.96%, while the average patient counts of nursing homes with investment is about 98. Hence, the overall gain of consumer surplus of all existing patients in a quarter is \$1.14 $\times$ 10.96 $\times$ 98 $\times$365/4 = 111.73\$ thousand.

According to the coefficient estimate of $I_{j,t-1}$ in Table 7, the gain of consumer surplus in the next period of an investment increases by about 2.54%. As a result, an investment boost the consumer surplus by \$1.14 $\times$ 2.54 $\times$ 98 $\times$365/4 = \$25.89 thousand. while the consumer surplus gains, \$137.62 thousand.

Patient Change: Although an investment boosts the nursing hours per patient-day, it is still unclear how the quality of care improves. There are two ways to improve quality: hiring more skilled nurses or decrease patient admissions. This part suggests the latter pattern also exists in

[3] In his paper, the quality interacts with a one-dimensional individual case-mix index (CMI). The coefficient estimates of quality term and the interaction term are 1.923 and 0.221, respectively. The mean of CMI is 1.1, and so the corresponding coefficient of quality is 1.923+0.221×1.1=2.166.

quality improvement.

Figure ?? shows the distribution of patient counts, and Table 8 shows the regression results of patient counts on investment. The four columns follow the same specification in Table 7. All of the results suggest that an investment makes patient counts decrease about 1.2 in current quarter and 0.3 in the next quarter. Hence, at bi-year level, the overall decrease in patient counts is about 1.5 patient.

Histogram of patient distribution and patient change distribution

Regression table for the two variables above. Once we have the counterfactual, can get rid of these regressions.

Table 8: Investment and Patient Counts

	$Patient_{j,t}$		$\Delta Patient_{j,t}$	
	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
$I_{j,t}$	-1.199***	-1.165***	-1.256***	-1.305***
	(0.0303)	(0.0283)	(0.0341)	(0.0345)
$I_{j,t-1}$	-0.124***	-0.322***	-0.173***	-0.219***
	(0.0200)	(0.0233)	(0.0193)	(0.0201)
$Patient_{j,t-1}$	0.996***	0.807***		
	(0.000728)	(0.0156)		
Observations	275339	275339	275339	275339
adj. R^2	0.994	0.994	0.0126	0.0126

standard errors are clustered at facility level.

* p<0.1 ** p<0.05 *** p<0.01

Then we revisit literature to calculate the drop of consumer surplus by losing patients. Ching et al., 2015 estimate a discrete choice model in the nursing home industry. In their research, an additional 7,186 patient-days switching from the out-side option increases social consumer surplus by \$1.23 million, approximately \$172 consumer surplus per patient-day. Hence, connecting to the estimate of 1.5 patients decrease, the total loss of consumer surplus is $\$172 \times 1.199 + 0.124) \times 365/4 = \$20.76$ thousand.

Overall Change: Since only 2.7% of observations in the sample invest in continuous two quarters, we conclude that an investment indicate no investment in the next quarter. Thus, the bi-year cost is still the same, \$31.12 thousand. The change in consumer surplus is the gain in quality for current patients minus the loss in the number of patients, where the dollar-valued welfare is about \$137.62−\$20.76 =\$116.86 thousand. Hence, the overall change in social welfare in a nursing home (at bi-year mean level) is −\$31.12+\$116.86=\$85.74 thousand.

6.2 Future Work

Future work involves two parts: 1) to include more state variables and 2) analyze counterfactuals. Adding more state variables is important here, as we discussed in the previous part. It captures more variation, especially the variation across time-invariant state variables that help identify the investment cost. Plus, adding a budget shock as an explanatory variable makes the prediction of inspection probability more accurate.

The second one is common for the analysis based on a structural model. To this paper, we propose several possible counterfactuals. The most straightforward policy is to subsidize investment. We can simulate the dynamic equilibrium where the government subsidizes 20% of the investment cost. The other counterfactual policy can be a more frequent inspection. We can also simulate the dynamic equilibrium where the inspection probability is 1.1 times than before, though in this case, the welfare of government spending is not feasible to simulate. The last counterfactual is to propose a more strict penalty rule and simulate the model with 20% higher fines.

7 Conclusion

This paper investigates nursing homes quality investment under a dynamic enforcement. We construct a dynamic discrete choice model to analyze nursing homes' incentive to bear an instant investment cost versus an incremental cost of inspection and future values. Using a nationwide facility-quarter level data, the estimate results suggest that investment is costly, approximately \$31.12 thousand per quarter. The main investment incentive is to avoid a low star-rating, where the rating is revealed to consumers and is strongly inferior for nursing homes.

We link the analysis to literature and calculate the welfare change due to the quality change through an investment. At a bi-year level in a typical nursing home, the better quality is worths\$137.64 thousand for existing patients. On the other hand, the nursing home improves the quality also by decreases patient admission. And the dollar-valued welfare change by decreasing utilization is about \$20.76 thousand. So the overall change due to a quality investment is

\$116.86 thousand, suggesting that an investment boosts the social welfare extensively.

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A Prediction Fit

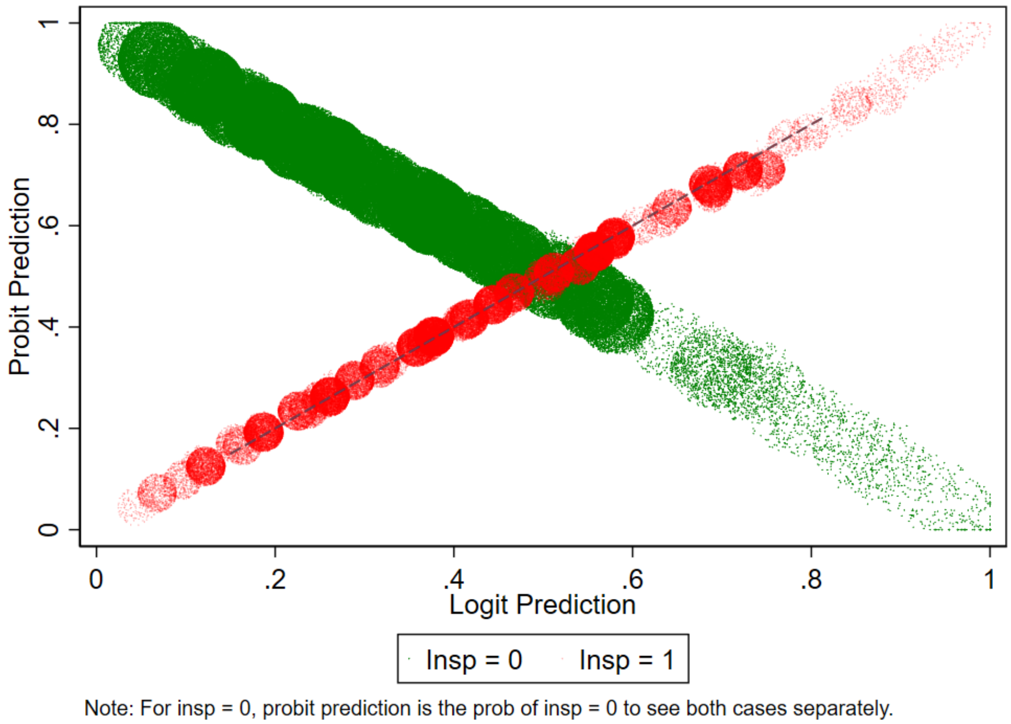


Figure A3: Prediction of Inspection

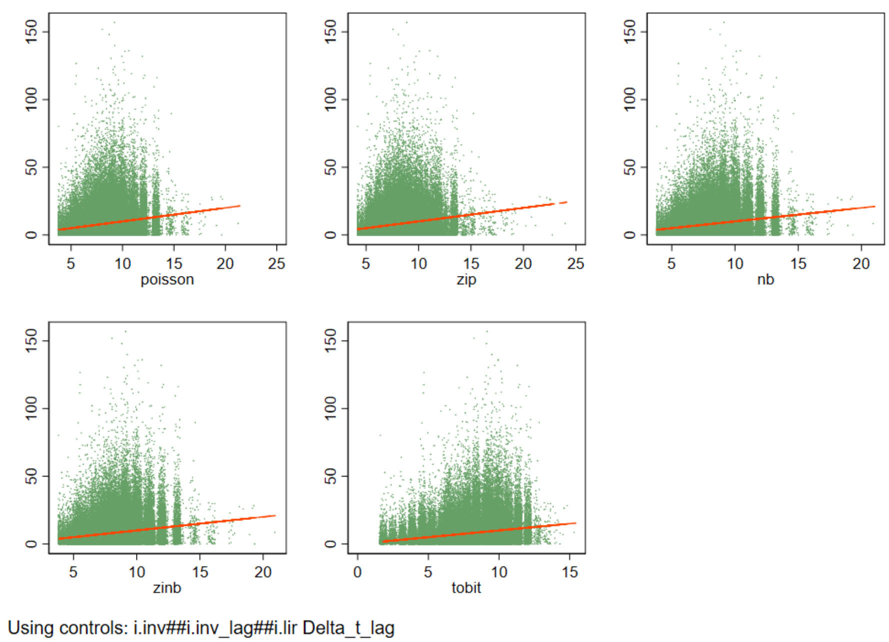


Figure A4: Prediction of Deficiencies

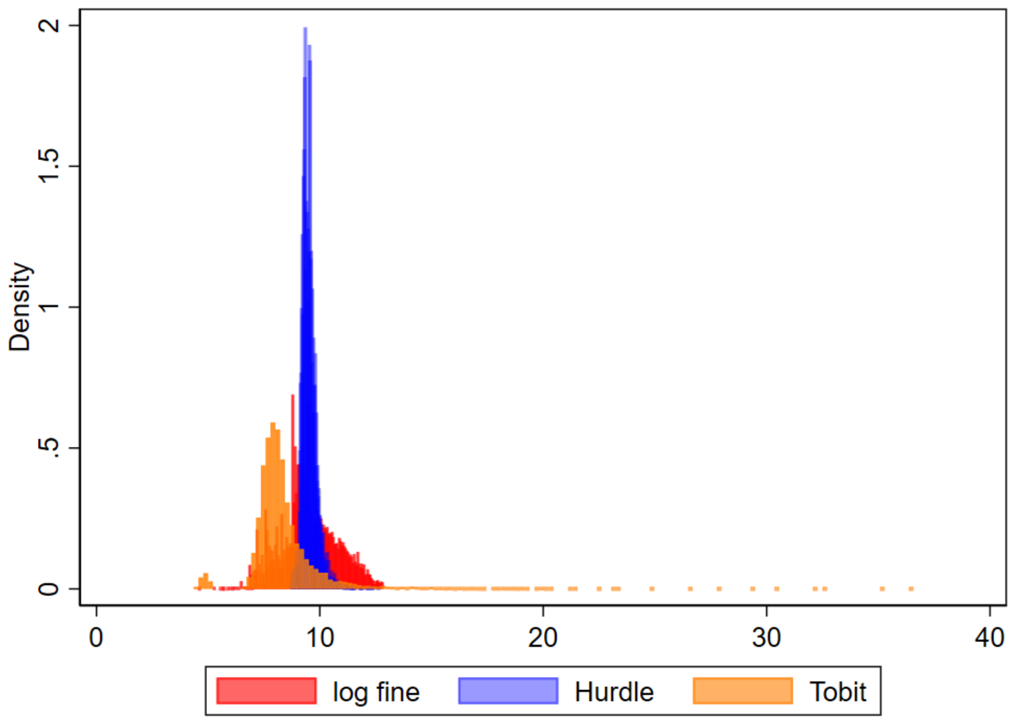


Figure A5: Prediction of Fine

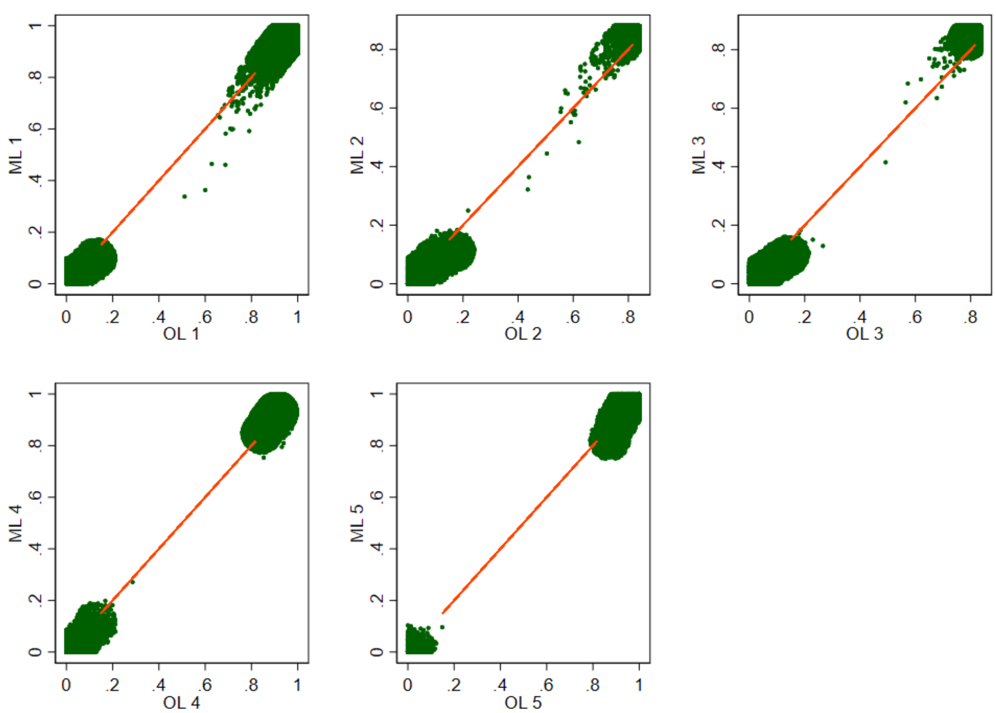
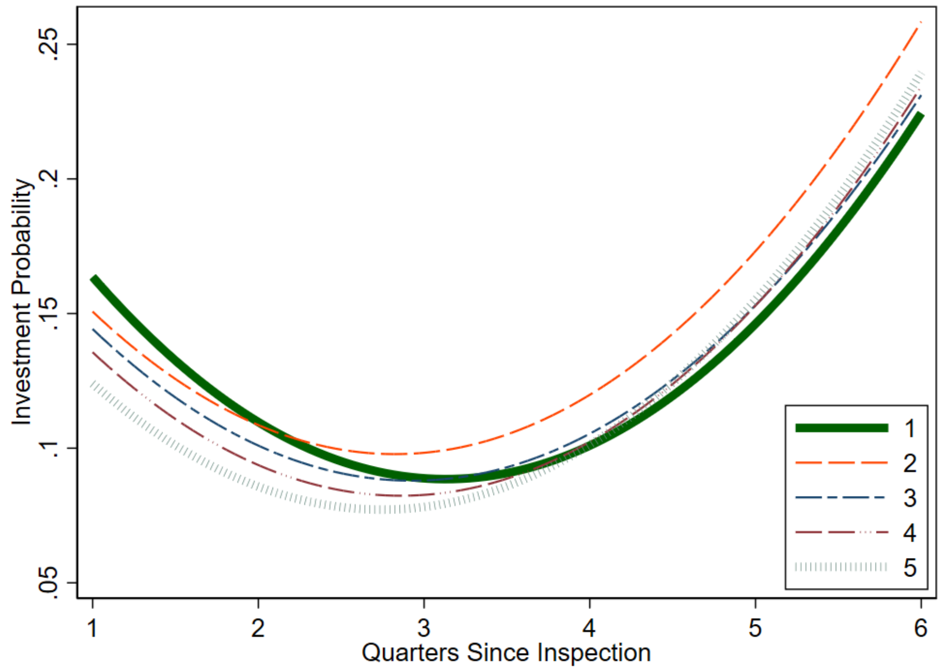


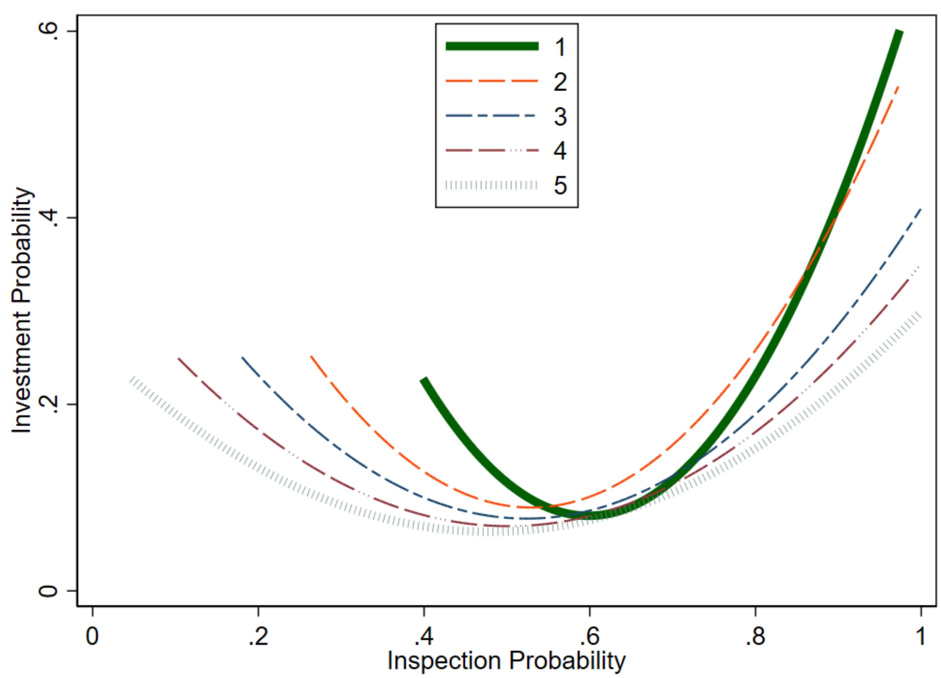
Figure A6: Prediction of Inspection Rating

B Correlation

Without adding controls:



(a) Quarters from Inspection



(b) Predicted Inspection Probability

Figure B7: Investment Frequency by Inspection Rating: Quadratic Fit

C Supporting Tables in Dynamics

Table **??** resents probit results conditional inspection probability. The high positive coefficient estimate of $I_{j,t}$ does not mean the causality. Instead, it reflects that nursing homes are more like to invest when predicting inspection likely to occur. Hence, it is inappropriate to include $I_{j,t}$ to predict inspection probability.

As for the appropriate lagged term of investment, Table **??** actually supports to include the two-period lag-investment into the conditional inspection prediction. However, Table **??** suggests the one-period lagged term of investment is appropriate. Especially for fines, adding the second lagged term disturbs the result a lot.