

Medicare Skilled Nursing Facility Reimbursement and Upcoding

Christopher S. Brunt*

John R. Bowblis[†]

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Abstract

In 1998, Medicare implemented the Prospective Payment System (PPS) for post-acute care provided by skilled nursing facilities (SNFs). While there were many accusations of hospitals “upcoding” patients to obtain higher reimbursement after the implementation of PPS in hospitals, there are currently no studies that examine upcoding in SNFs. Using geographic variation in the generosity of Medicare reimbursement, this paper empirically tests if SNFs payment differentials across resource utilization groups (RUG) affect the probability of which RUG is selected. The results are consistent with SNFs increasing therapy minutes and varying the thresholds used to define ‘case-mix’ to obtain higher reimbursement.

Keywords Skilled Nursing Facilities, Upcoding, Medicare, Prospective Payment System, Reimbursement

JEL Classification I11, I18

*School of Business, Lake Superior State University, 650 W. Easterday Ave, Sault Ste Marie, MI 49783, (906) 635-6682, cbrunt@lssu.edu

[†]Department of Economics, 800 E. High St., Room 2054 FSB Miami University, Oxford, OH 45056, jbowlis@muohio.edu

Since the 1940s, the United States has experienced persistent rapid growth in health care spending which has out-paced growth in real gross domestic product.¹ Given the growing fiscal instability and that Medicare constitutes such a large portion of the total health care expenditures (22.5 percent), U.S. policy makers are regularly attempting to control spending through Medicare payment policy changes and refinements. Skilled nursing facilities (SNFs) which provide post-acute care for Medicare patients are often subject to these refinements as they represent 8 percent of Medicare’s total program spending (Center for Medicare and Medicaid Services, [CMS \(2010\)](#)).

During the 1980s, SNFs were reimbursed under a cost-plus reimbursement mechanism that made the provision of SNF care highly profitable ([Dummit, 2000](#)). The incentives under this reimbursement mechanism made post-acute care provided by SNFs the fast growing expenditure by Medicare in the 1990s ([GAO, 1999](#)). Specifically, between 1989 and 1996, Medicare’s real expenditures for SNFs increased from \$4.84 to \$15.45 billion dollars (2009 price level). To rein these escalating SNF costs and align the incentives of SNFs with CMS, the Balanced Budget Act of 1997 changed Medicare reimbursement for SNF care to a case-mix adjusted Prospective Payment System (PPS). Under PPS, SNFs receive compensation rates based on the Resource Utilization Group (RUG) each patient is classified. The reimbursement associated with each RUG varies positively in accordance with the intensity of the patient’s clinical complexity, requirements for special care, decreased levels of cognitive ability, limitations in physical function, and the amount of rehabilitative therapy needed.

Current research on Medicare’s PPS for SNFs has found that the movement to the PPS has directly and indirectly impacted quality and *even* the ownership structure of the nursing home industry (see [Wodchis, Fries and Hirth, 2004](#); [Konetzka et al., 2004, 2006](#); [Unruh, Zhang and Wan, 2006](#); [Bowblis, 2011](#)). If PPS impacts professional staffing and ownership patterns of SNFs, could the financial incentives provided by the PPS influence RUG selection as well? More specifically, does the higher reimbursement of more intensive RUG categories, provide SNFs with the incentive and opportunity to scale up, or “upcode,” one or more of the criteria used to determine the RUG a patient is classified into in an attempt to increase Medicare reimbursement?

Even though there is a growing literature on the effects of PPS on the amount of therapy patients receive and their average length of stay, which is discussed in the next section, little is known about the financial incentives of RUG selection and the potential for SNFs to upcode. Upcoding has been studied in the Medicare Part A (hospital) ([Silverman and Skinner, 2004](#)) and the Part B (outpatient) settings ([Brunt, 2011](#)), but there is yet to be a study that directly analyzes SNFs’ incentive to upcode. In this paper, we evaluate the

¹Between 1970 and 2009 the average difference between the growth rates of real gross domestic product and health care spending was 2.2 percent ([Chernew, 2010](#)).

profit opportunities associate with imperfections in the Medicare hospital wage index used as the basis for the SNF wage index, and exploit the geographic variation in Medicare reimbursement for post-acute care to determine SNFs response to financial incentives to upcode.

One important caveat of this estimation strategy is that identification is contingent on geographic variation in Medicare generosity. Theoretically, Medicare adjusts RUG payments to reflect the differences in prevailing wages and capital costs geographically. However, these adjustments are imperfect and this variation has been exploited in the past (Escarce, 1993; Yip, 1998; Hadley, Mitchell and Mandelblatt, 2001; Kaestner and Guardado, 2008). To verify that geographic adjustments Medicare uses are imperfect and that Medicare generosity varies with region, we first estimate the relationship between SNF profit margins and the geographic adjustment factors used by Medicare to determine reimbursement. We find that profit margins are positively correlated with geographic adjustment factors that result in higher reimbursement. Subsequently, we exploit this payment imperfection by evaluate the upcoding hypothesis for SNFs through a comparison of RUG payment differentials for separate SNF samples of stroke and hip fracture patients. The results find that SNFs with more generous Medicare reimbursement rates respond to payment differentials in such a manner that is consistent with upcoding.

1 Background

1.1 RUG reimbursement

Under the PPS, Medicare reimburses SNFs a fixed amount for each patient day that varies based on the RUG that a patient is classified. Each RUG k can use different intensity of staffing and non-labor inputs. The total payment from Medicare is broken into a labor and non-labor component to reflect these differences in intensity. CMS determines the reimbursement rate for both components by using the average cost of care reported in the Medicare Cost Reports for SNFs in prior years. The base labor and non-labor components are the same across the entire country, however they are adjusted to account for variation in the cost of providing care using geographic adjustment factors. The first geographic adjustment factors dichotomizes the base components for urban and rural SNFs. The second geographic adjustment alters the labor component to account for differences in the prevailing wages across the country. Specifically, the labor component is multiplied by a wage index that is a derivation of the Medicare Hospital wage index.² For two SNFs in the same wage index area j , the wage index can be different for urban and rural SNFs.³ In whole, if s denotes the urban/rural continuum, the per diem reimbursement Medicare pays is given by:

²The SNF wage index is developed for each core-based statistical area based on hospital average hourly earnings in comparison to the national average. The SNF wage index differs from the hospital wage index through a lack of hospital occupational weights.

³It should be noted that a wage index area can include urban and rural SNFs.

$$\text{Payment}_{k,sj} = \text{Labor}_{ks} \times \text{Wage Index}_{js} + \text{Non-Labor}_{ks} \quad (1)$$

While equation 1 determines the amount a SNF will be paid for a given RUG k , a SNF still needs to determine which RUG a patient is classified. Under the RUG-III system, patients receiving rehabilitative care can be classified into 14 different RUGs that are broadly categorized as “low”, “medium”, “high”, “very high”, and “ultra high” rehabilitation. As illustrated in Table 1, patients move from the “low” rehabilitative category to the “ultra high” rehabilitative category based on the number of therapy minutes they receive each week. Once the number of therapy minutes is determined, the Activities of Daily Living (ADL) index score of the patient determines the specific RUG.⁴ The last column of Table 1 shows that Medicare per diem rates increase either through increases in the ADL index score or the number of therapy minutes. The key facet of the PPS is that the marginal revenue for an additional therapy minute is zero except when moving into a higher broad rehabilitative category. Since only nodal therapy minutes have positive marginal revenue, this may provide SNFs with a financial incentive to increase the number of therapy minutes if a patient is close to the cut-off to be classified into a higher reimbursed RUG.

1.2 Existing Studies

Prior to the passage of the Balanced Budget Act of 1997, SNFs were reimbursed under a cost-plus reimbursement mechanism for post-acute care paid for by Medicare. This cost-plus regime reimbursed the actual cost of services provided and had few caps on the amount services a SNF could provide. To reign in costs, the PPS was phased-in from 1998 to 2002 and changed reimbursement to reflect the average cost of care within each RUG category.

The implementation of the PPS changed the financial incentives for SNFs in terms of the amount of therapy minutes they provided to patients. [White \(2003\)](#) compared the number of therapy minutes patients received pre- and post-PPS and found that the number of therapy minutes provided by freestanding SNFs underwent compression. Specifically, SNFs had a higher percentage of residents in moderate therapy minute categories with fewer residents receiving low and high levels of therapy minutes. [Murray et al. \(2005\)](#) also found evidence of compression in the number of therapy minutes in stroke patients while [Wodchis, Fries and Pollack \(2004\)](#) found declines in the number of weekly minutes of both occupational and physical therapy. In addition to compression, the implementation of the PPS increased the likelihood of patients receiving nodal therapy minutes. These nodal therapy minutes corresponded to Medicare’s cut-off for classifying patients

⁴The ADL index score is a measure of the functional limitations of the patient. Each patient is given a score in bed mobility, transferring, toilet use, and eating/fluid intake based on their level of need. This score is summed together and ranges from 4 to 18 with higher scores indicating more need.

into higher reimbursed RUGs (Wodchis, 2004).

More recently, Grabowski, Afendulis and McGuire (2011) examined the impact of the implementation of PPS and subsequent adjustments to PPS reimbursement rates that occurred in 1999 and 2000 using data from New York State. They found the initial implementation of PPS increases the number of therapy minutes patients received. The subsequent changes to PPS reimbursement rates in 1999 and 2000 did not statistically change the average number of therapy minutes received but they did effect the probability of having over 500 minutes of therapy per week.

These studies find that PPS and subsequent changes to PPS reimbursement rates affect the number of therapy minutes patients receive. They provide an important foundation that suggests SNFs change the number of therapy minutes they provide in response to reimbursement, but they do not test if SNFs upcode patients to increase reimbursement. By using cross-sectional geographic variation in reimbursement directly from an exogenous payment schedule, this paper makes an important contribution to our understanding of how health care providers respond to financial incentives by testing if SNFs upcode in geographic areas with more generous reimbursement rates.

2 Theoretical Model

In this section, a theoretical model that illustrates the incentives of SNFs to upcoding into higher reimbursed RUGs is adapted from earlier work by Brunt (2011). Specifically, assume that SNFs maximize the daily profit per representative patient. SNFs provide the case-mix factors (i.e. number of rehabilitative minutes and ADL index) to CMS for each patient in order to classify the patient into a RUG. Let τ represent the case-mix factors documented and provided to CMS. The SNF faces a daily per patient fixed costs of C_0 and variable costs $C(\tau)$ with $C(\tau)$ and $C_0 > 0$. For simplicity, assume there are only two RUGs, RUG_1 and RUG_2 which require a minimum of τ_1 and τ_2 , respectively.⁵ The payments of RUG_1 and RUG_2 are p_1 and p_2 , respectively, with $p_2 > p_1$ and $\tau_2 > \tau_1$. Let τ^* represent the true case-mix factor. For example, τ^* might represent the cost-effective amount of therapy minutes. If $\tau^* < \tau_2$, then the SNF could classify the patient into RUG_1 and will receive payment p_1 . In this situation, a SNF knows it will receive the following profit with certainty:

$$\pi_1 = p_1 - c_0 - c(\tau) \text{ if } \tau_1 < \tau < \tau_2$$

The SNF has an opportunity to upcode the patient by either using more therapy minutes or by overstating

⁵The model can be extended to allow for more RUGs, but this case doesn't any provide more insight into the incentive to upcode than the two RUG case.

the number of ADLs in order to get the patient classified into RUG_2 . However, there is a chance the SNF will be caught by CMS and would face a penalty C with probability $1 - \gamma$. If the SNF chooses to upcoding, the profit it receives is:

$$\pi_2 = p_2 - c_0 - c(\tau) \text{ if } \tau > \tau_2 \text{ with probability } \gamma$$

and

$$\pi_3 = p_2 - c_0 - c(\tau) - C \text{ if } \tau > \tau_2 \text{ with probability } 1 - \gamma.$$

The expected utility of upcoding is:

$$(\gamma)u(\pi_2) + (1 - \gamma)u(\pi_3).$$

The SNF will choose to upcode if $(\gamma)u(\pi_2) + (1 - \gamma)u(\pi_3) - U(\pi_1) > 0$ and if this equation is totally differentiating yields:

$$\partial\gamma u(\pi_2) + \gamma u'(\pi_2)[\partial p_2 - \partial c_0 - c_\tau \partial \tau] - \partial\gamma u(\pi_3) \tag{2}$$

$$+(1 - \gamma)u'(\pi_3)[\partial p_2 - \partial c_0 - c_\tau \partial \tau - \partial C] - U'(\pi_1)[\partial p_1 - \partial c_0 - c_\tau \partial \tau].$$

Equation 2 is increasing in γ and p_2 , decreasing in C , τ , and p_1 , and ambiguous on τ . Equation 2 implies that an increase in the payment differential between RUG_1 and RUG_2 , $(p_2 - p_1)$, will increase the likelihood that a patient is classified into the higher reimbursed RUG, in this case, RUG_2 . This result is a function of the absolute difference between p_2 and p_1 and it doesn't matter if p_1 or p_2 is the payment that changes.⁶

It can easily be shown that if the number of RUG groups increases, the RUG chosen will be a function of the payment differentials between the RUG associated with the true case-mix factor appropriate RUG and the higher and lower reimbursed RUGs. Thus if there are three RUGs and RUG_2 is the true RUG, the incentive to upcode is a function of the difference in payment between RUG_1 and RUG_2 , called the lower payment differential, and RUG_2 and RUG_3 , called the upper payment differential.

⁶It should be noted that once a payment group is achieved the marginal revenue associated with changes in τ is zero while the marginal cost is increasing. This provides the profit maximizing SNF with incentive to provide nodal therapy minutes at the lower cusp of a payment group. Given that payment is made based on average costs, a SNF could actually earn losses on residents with above average case-mix requirements, providing them with an incentive to upcode. The resident in this case, may actually be provided with more therapy minutes than clinically necessary.

3 Data

The empirical analysis combines four distinct databases in order to complete two separate sets of analyses. The first of these databases is from [CMS \(2004\)](#). The CMS Update provides the information needed to determine the payments a SNF receives for each RUG in calendar year 2005 in accordance with Equation 1.

In the first analysis, SNF profit margin is compared to geographic adjustment factors to determine if variation in RUG payments provides a larger incentive to upcode in certain geographic areas. The primary dataset in this analysis is the Medicare Cost Reports for SNFs. The cost reports were created to provide CMS information on SNFs to determine how to adjust RUG payments. The Medicare Cost Reports contains data on the number of patient days billed for each RUG and the average per diem cost for free-standing SNFs. The cost reports used in the analysis include all reports with fiscal year start date on or after January 1, 2005 and fiscal year end data on or before December 31, 2005, have a fiscal year with at least 360 to 365 days, have a positive number of Medicare patient days, and report per diem cost data. The Medicare Cost Reports are merged with data on facility structure, case-mix, and staffing levels from the Online Survey Certification and Reporting (OSCAR) system.⁷

In the second set of analyses, information on individual SNF patients is used to determine how geographic variation in payments affects the probability of upcoding for all SNFs (freestanding and hospital-based). The primary database in this analysis is the Minimum Data Set (MDS). MDS is a federally mandated assessment of all nursing home residents and includes information on demographics, physical and cognitive functioning, diagnoses, treatment received, and the specific RUG classification for each Medicare SNF patient ([Hawes et al., 1995](#)). Medicare SNF admission assessments in calendar year 2005 were merged with OSCAR to obtain facility characteristics.

One concern with using all Medicare SNF admission assessments is that patients can be admitted for a variety of medical conditions. Including patients with different medical conditions can lead to confounding between the incentive to upcode and patient heterogeneity from clinical factors associated with each medical condition. To control for this heterogeneity, we restricted the sample to two groups, patients that have a rehabilitative SNF visit for a hip fracture and patients that have a rehabilitative SNF visit for a stroke.

⁷OSCAR is a uniform database of state nursing home regulatory reviews of all CMS certified nursing homes, including SNFs. OSCAR has been validated and is found to be appropriate for research purposes ([Feng et al., 2005](#)).

4 Methodology and Empirical Results

4.1 Geographic Adjustments Factors Analysis

Medicare adjusts RUG payments by having different payments for rural and urban SNFs. It also adjusts the payments by multiplying the labor component of the payment by a wage index that is different for each geographic area. We test if these adjustment factors are correlated with total profit margins. Holding efficiency constant, these factors should not be correlated with profit margins if geographic adjustments are perfect. However, if these factors are correlated with profit margins then geographic payments are imperfect and the incentive to upcode will vary across geographic areas.

Profits margins are constructed using the average per diem payment and per diem cost of each SNF. Average per diem payment it is calculated using the number of billed patient days for each RUG and the SNF's payment for each RUG. That is, the number of patients for each RUG is multiplied by the RUG payment to obtain the revenue the facility received for each RUG. Next, the revenue across each RUG is summed to obtain total payments. Finally, the average per diem payment is calculated as total payments divided by total number of Medicare days. Profit margins are defined as the logged difference in the average per diem payment and cost.⁸ One concern with the Medicare Cost Reports is that some SNFs report improbably high or negative profits margins. To account for potential data errors, the data is restricted to only observations with profit margins within the 1st and 99th percentile, leading to a sample of 9,124 SNFs.

As per Equation 1, the geographic adjustment factors that CMS uses to adjust Medicare payments are different payment rates for rural and urban SNFs, and a wage index that adjusts the labor component of the payment for prevailing wages in the area. This implies the profit margin regressions should include the wage index associated with each SNF, denoted WI , an indicator variable for identifying if the SNF is considered rural, denoted R , and an interaction of the wage index and the rural indicator variable. This interaction captures the potentially different effect of the wage index for rural SNFs.

The key to this test is that profit margins across geographic areas should be the same. However, if Medicare revenues are standardized, then profit margins could still vary if efficiency of SNFs vary with geographic region. Following the literature on variation in medical spending, there is no reason to believe that inefficiency is likely to be based on geography once differences in state regulatory structure, facility characteristics, and patient case-mix are taken into consideration (Zuckerman et al., 2010). Therefore, profit margins are adjusted for facility characteristics that may impact costs and state indicator variables that account for differences in the regulatory structure of each state that may affect the cost of providing care.

⁸Additional specifications defined profit margin as the dollar difference between per diem payments and costs. These regressions confirmed the results that used logged differences.

The facility characteristics can be generally broken down into facility structure, patient payer mix and case-mix, and facility staffing levels. Facility structure could affect profit margins through differences in objective by ownership (e.g. for-profit, not-for-profit, government), economies of scale through the size of facility, managerial efficiency associated with being part of a multi-facility organization, and occupancy rates. Occupancy rate is included in the regression because it has been used as a measure of operating efficiency with lower occupancy indicating less efficient production of services (Sloan, Ostermann and Conover, 2003).

Payer mix and case-mix are included to capture the average difference in patient characteristics across SNFs. Payer mix is defined as the percentage of residents paying through Medicare, Medicaid, and other sources. Since Medicaid reimbursement is the least generous of all payment sources, facilities with a greater proportion of Medicaid residents may need to be more efficient to operate profitably. However, the ability of the SNF to control costs is constrained by the case-mix of the residents in the SNF. While the payment rates are adjusted for case-mix, there can be some variation in case-mix within a RUG that is not captured by the payment. Therefore, the average facility acuity level, measured by the Acuindex, and the percentage of residents with dementia are included as controls.

Finally, the primary cost of care is staffing and a facility may voluntarily choose to employ more staff. Since staffing levels can impact per diem costs, the level of staffing for registered nurses, licensed practical nurses, and certified nurse aides are controlled for in the regression analysis. These staffing variables are measured in terms of hours per resident day.⁹

The total profit margin variable (M) is regressed against the wage index (WI), a dummy variable for rural SNF as defined for Medicare payment adjustments (R), and an interaction of the wage index and rural indicator variable. This implies the empirical model, which has a SNF as the unit of observation, is as follows:

$$M = \alpha + \beta_1 WI + \beta_2 R + \beta_3 WI \times R + X\delta + \epsilon$$

where X is a set of facility control and state indicator variables discussed above. The regression is estimated using ordinary least squares with standard errors robust to clustering within states.

The beta parameters identify if the geographic payment factors are correlated with profit margin. If geographic adjustment factors are perfectly determined, then the coefficient estimates of the betas should not be statistically different from zero. However, if any of the betas are found to be statistically significant, it

⁹Nurse staffing variables are used in the empirical analysis, occasional improbable staffing levels are identified and controlled for using the same method as Bowblis (2011). Improbable staffing values for each type of staff type are identified using the following criteria: (1) more than twenty-four hours of staffing; (2) zero staffing; and (3) among facilities that do not fall into first two categories, those that are outside three standard deviations of the mean. Next, for each staff type, an indicator variable for an improbable staffing value is created and the staffing level for that staff type is coded as zero.

suggests that profit margins are imperfect and different geographic areas have varying incentives to upcode.

The first column of Table 2 reports the summary statistics of the sample and the other columns report the regression results. Overall, SNFs have a positive profit margin of 1.1 percent. Nearly 4 out every 10 SNFs is in a rural Medicare reimbursement area, and the average facility has a wage index of 0.964 with a range of 0.729 to 1.522.

Three regressions are reported, each with additional control variables included in the model. As more controls are added, the coefficient estimates of the geographic adjustments have similar magnitude and are statistically indistinguishable. SNFs in rural areas have lower profit margins compared to urban SNFs. Further, a higher wage index is also found to be associated with higher profit margins, with the effect being larger for rural SNFs. For urban and rural SNFs a one standard deviation change in the wage index results in higher profit margins of 4.2 and 7.6 percentage points, respectively. These results suggest that geographic adjustment factors are not perfect and some areas may have a larger incentive to upcode.

4.2 Upcoding Analysis

In this section, two separate analyses are performed to determine if geographic variation in RUG payments provide a financial incentive for SNFs to upcode. In the first analysis, an empirical model is estimated to determine if SNFs increase the number of therapy minutes patients receive to obtain higher payments from Medicare. This is done by restricting patients to predefined ADLs in which higher payments can only be received by the SNF through increasing the number of therapy minutes provided. Since SNFs may also upcode by varying the thresholds they use to determine the ADL index score, the second analysis allows for SNFs to potentially upcode using therapy minutes and the ADL index score.

Both empirical analyses model the probability that RUG k is chosen for patient i . This probability is determined by a set of Medicare reimbursement covariates that are specific to each RUG, MR_{ik} , and a set of covariates that describe the patient and SNF, Z_i . If y_i indicates which RUG is chosen for patient i then the empirical model can be written as

$$P_{ik} = Pr(y_i = k) = f(\alpha MR_{ik} + \beta_k Z_i), k = 1, \dots, K \quad (3)$$

where α and β_k are parameters to be estimated. Since equation 3 contains alternative-specific and alternative-invariant covariates, coefficient estimates are obtained using a mixed logit specification.

The Medicare reimbursement covariates, MR_{ik} , capture the financial incentives SNFs have to classify patients into various RUGs and are the key variables in equation 3. The first variable is the payment rate of the RUG. The payment rate controls for the actual payment the facility receives for choosing RUG k and

provides a baseline for comparing the payment rate of RUG k to other RUGs. The next two variables are payment differential variables. The upper (lower) payment differential is the absolute difference between the current RUG and the higher (lower) reimbursed RUG if a patient is (downcoded) by changing either the number of therapy minutes, ADL index score, or both.¹⁰

Under the null hypothesis that SNFs do not respond to financial incentives, a patient would be classified into a RUG solely based on alternative-invariant covariates Z_i that describe the patient, their clinical characteristics, and the characteristics of the SNF.¹¹ This implies the coefficient estimates for the lower and upper payment differentials would not be statistically different from zero. However, if a positive coefficient estimate is found for the lower payment differential, then a larger payment difference between the current and lower reimbursed RUG increases the probability of the higher reimbursed RUG being chosen. This is consistent with upcoding. If the coefficient is negative, then the higher reimbursed RUG has a lower probability of being chosen and the result would be consistent with downcoding. For the higher payment differential, a positive coefficient estimate implies the current RUG has a higher probability of being chosen and a negative coefficient estimate implies a lower probability the current RUG is chosen. If there is upcoding, then the higher payment differential is expected to be negative and statistically significant.

4.2.1 Upcoding through Therapy Minutes

Holding ADLs constant, SNFs can upcode a patient into a higher reimbursed RUG by using more therapy minutes. To make sure that SNFs upcoding only on the dimension of therapy minutes, the hip fracture and stroke samples are broken into two separate groups that have ADL scores in the range of 4 to 7 and 16 to 18. For these ADL ranges, patients in the 4-7 ADL range can be classified into the RUGs of RLA, RMA, RHA, RVA, and RUA whereas patients in the ADL range of 16-18 can be classified into the RUGs of RLB, RMC, RHC, RVC, and RUC (see Table 1). This implies by restricting the sample to these ADL ranges, SNFs can only obtain higher payments by increasing the number of therapy minutes a patient receives.

Figures 1 and 2 report the distribution across therapy minutes for rehabilitative RUG-classified patients with 16-18 ADLs that had a hip fracture and stroke. As can be seen in the figures, there are large increases in the proportion of patients at certain therapy minutes. In particular, they occur at or slightly above the

¹⁰For example, assume a SNF can only upcoding based on therapy minutes and a patient is currently classified into RUG group RHC. The lower payment differential is the absolute difference in total payment of RHC and RMC whereas the higher payment differential is the difference in total payment of RUC and RHC.

¹¹Included in the regression is a set of alternative-invariant covariates that capture patient and SNF characteristics that can influence which RUG a patient is classified. Patient characteristics include gender, age, race, education, short and long term memory loss, cognitive impairment, and indicators for the following medical conditions: diabetes, heart disease, cardiac dysrhythmia, heart failure, COPD, dementia, anxiety, and depression. SNF characteristics are obtained from OSCAR and include the facility structure, patient payer-mix and case-mix, and nurse staffing variables used in the geographic adjustment factor analysis. In addition, regional indicator variables of New England, Mid Atlantic, Midwest, South, Mountain, and Western States are included.

minimum number of minutes required to classify a patient into a higher reimbursed RUG and are suggestive of upcoding.¹²

Equation 3 is estimated to formally test if SNFs are upcoding based on therapy minutes. The lower and upper payment differentials refer to the absolute difference in the payment between the current RUG and the RUG associated with only changing the number of therapy minutes. The low rehabilitative RUG categories of RLA and RLB are infrequently used, below 0.3 percent in all samples and in some cases below 0.01 percent. These RUG groups are excluded from the analysis though the results were found to be robust to their inclusion.

The estimates of parameter α are reported in Table 3 and across all four samples the results have similar signs for the coefficient estimates of the payment and payment differential variables although the effect sizes are more than double the size for the 4-7 ADL samples compared to the 16-18 ADL samples. This suggests that the general conclusion of the results is not affected by restricting the sample to certain ADL groups.

All significant coefficients in Table 3 are consistent in sign with the hypothesis of upcoding. Lower total payments in each RUG decreases the chance a specific RUG is chosen. The coefficient estimates for the lower payment differential are positive and statistically significant in each regression. For a one dollar increase in the lower payment differential, this coefficient estimate corresponds to a 1.3 to 5.2 percentage point change in the probability the higher reimbursed RUG is chosen holding all other variables constant. The effect of the higher payment differential is generally found to be negative and statistically significant, with an one dollar increase in the upper payment differential decreasing the probability of the current RUG being chosen by 0.1 to 0.7 percentage points. The only exception is the 16-18 ADL hip fracture sample with an effect that is not statistically different from zero.

The Cost Implications of Therapy Minute Upcoding

The results indicate that SNFs use more therapy minutes in order to increase their Medicare reimbursement and this upcoding can lead to wasteful spending by Medicare. Since there is no control group that did not face the incentives to upcode, it impossible to identify the total cost upcoding. However, as shown earlier, SNFs in higher wage index areas have higher profit margins, resulting in larger payment differentials than SNFs in other areas. This implies SNFs in higher wage index areas have a greater incentive to upcode. By comparing the distribution of RUG categories in highest wage index areas to those in the lowest wage index areas, an estimate of the cost of the upcoding through therapy minutes can be obtained. This cost estimate is the amount of wasteful spending caused by the additional incentive to upcode created by the wage index

¹²Although not shown, the histograms for the hip fracture and stroke samples with 4 to 7 ADLs have a similar pattern and suggest that SNFs upcode based on therapy minutes.

and can be viewed as a lower bound estimate of the cost savings to Medicare if upcoding was completely eliminated.

In order to obtain the estimate of cost savings, the predicted probability of being in each RUG category is estimated for each patient and averaged separately for patients in SNFs that are in the lowest and highest quartile of the wage index. The predicted probability is obtained using the coefficient estimates reported in Table 3. This controls for potential differences that may arise in the sample between the two quartiles. Further, the distribution of RUG categories is calculated for urban SNFs separate of rural SNFs because of the potential confounding that may arise because of variation in the wage index and base components. Next, the average cost is calculated by applying equation 1 to each RUG category using the average wage index in the quartile and averaging across RUG categories weighting by the percentage of patients predicted in each RUG category. Finally, cost savings is defined as the difference in the average cost of the highest quartile wage index group and if this group had the same distribution of RUG categories as the lowest quartile wage index group. The predicted RUG distributions, average cost, and cost savings are reported in Tables 4 and 5.

Generally, the predicted distribution of RUG categories find a larger percentage of patients in higher reimbursed RUGs in the highest quartile compared to the lowest quartile. The only exception is urban stroke patients with ADL index scores of 4-7. As expected, the lowest quartile has lower average cost, on order of \$72.62 to \$101.27 per patient day. The difference in average cost between these two groups represents the cost savings if the highest quartile had the same wage index and RUG distribution as the lowest quartile.

Cost savings due to upcoding is on order of \$-3.14 to \$10.39 (-0.90 to 3.05 percent) per patient day. If urban stroke patients with 4-7 ADLs are excluded, all the other categories find a cost savings, with the lowest being \$1.41 or 0.40 percent per patient day. With an average length of stay of 22.9 days (White, 2003), this cost savings translates into a cost savings of \$32.22 to \$237.88 per admission.

4.2.2 Upcoding through Therapy Minutes and ADL Index Scores

In this section, equation 3 is estimated using the entire hip fracture and stroke samples to determine if SNFs upcoding therapy minutes and ADL index scores simultaneously.¹³ In particular, three sets of lower and upper payment differential variables are included in the regression. The first is the unilateral ADL payment differential. It is defined as the absolute difference in the payment between the current RUG and the lower or higher reimbursed RUG if only the ADL index score is changed. The second is the unilateral therapy minute payment differential and it has the same definition as the ADL payment differential except that only therapy minutes are changed. The third differential is the joint ADL and therapy minute payment differential. It is

¹³Given the infrequent use of the “low” rehabilitative RUG category, it was excluded from this analysis.

used to determine if SNFs upcode patients by changing the ADL index score and number of therapy minutes at the same time. Regressions are reported in Table 6 that exclude and include the joint ADL and therapy minute payment differential variables.

Regardless if the joint ADL and therapy minute payment differential is included in the regression, the coefficient estimates for the other payment differentials are similar. The ADL lower payment differential is positive and statistically significant and is consistent with SNFs having a higher probability of choosing the higher reimbursed RUG group. The effect of the ADL upper payment differential is positive but none of the coefficient estimates are statistically significant. Both coefficient estimates for the unilateral lower and upper payment differentials based on therapy minutes are statistically significant with signs consistent with upcoding. The signs of the coefficient estimates for the joint ADL and therapy minute payment differential are consistent with upcoding as well. The lower payment differential is statistically significant in both the hip fracture and stroke samples, while the upper payment differential is only marginally significant in the stroke sample.

5 Conclusion

This paper is the first to test the hypothesis that there is upcoding in the skilled nursing industry. Upcoding can occur when SNFs provide more therapy minutes than might be clinically justified or when SNFs use varying thresholds to increase the ADL index score of the patient. While Medicare payments are adjusted to reflect the difference in cost of providing care across the country, these geographic adjustments are imperfect and areas with higher wage indexes are found to have higher profit margins. In this paper, this geographic variation in reimbursement is used to empirically test the incentive to upcode by SNFs.

Histograms of the number of therapy minutes patients receive find that a significant proportion of therapy minutes occur at the nodal amounts slightly above the RUG cut-off into higher reimbursed RUG categories. To empirically test if this is consistent with upcoding, discrete choice models estimate the probability a patient is classified into a particular RUG. The key variables are the payment differences between the current RUG chosen and if the SNF changed the number of therapy minutes, ADL index score, or both to get the patient into a higher or lower reimbursed RUG. The results of the empirical analysis suggest that SNFs upcode by using more therapy minutes and varying the threshold used to determine ADL index scores.

The fact that SNFs are found to upcode has important implications for policy. While it is impossible to identify the exact extent of upcoding without having a proper control group, an estimate of the additional upcoding caused by differences in the wage index can be determined. For patients admitted to SNFs in the highest wage index areas, a lower bound of the additional expense to Medicare caused by this type of

upcoding is on the range of \$32.22 to \$237.88 per admission. Given that these areas had over 266 thousand admission in 2005, the total savings range from 8.6 to 63.2 million dollars. While these cost savings are modest, it seems that upcoding is more of a problem today compared to 2005. Of all admissions in our data for 2005, only 33.0 percent and 14.7 percent were in the “very high” and “ultra high” categories. A recent article in the *Wall Street Journal* states these categories comprise 30.2 percent and 45.4 percent of SNF admissions in the first half of fiscal year 2011, and cite this increased use in high therapy intensity RUGs as the reason CMS cut aggregate reimbursement rates for SNF care by 11.1 percent on July 29, 2011.¹⁴

The existence and subsequent expansion of upcoding may partially be caused by how patients are classified into RUGs. The two recent versions of the RUG system have large bins of therapy minutes and ADL index scores in order to classify into a specific RUG. These large bins give SNFs the incentive to upcode if the marginal cost of doing so is smaller than the marginal benefit. For example, if the clinically justified number of therapy minutes is 450, the cost of providing an additional 50 minutes of therapy may be lower than the additional reimbursement the SNF receives by upcoding the patient into the “very high” rehabilitative RUG group. This discrete jump in reimbursement at pre-defined therapy minute and ADL index score cut-offs create a perverse incentive to upcode and potential refining of the PPS for SNFs should include a larger number of groupings or a continuous scale for therapy minutes and ADL index scores. Further, CMS recertification may want to intensify their surveying of SNFs by enhancing their audits to determine how SNFs are determining the amount of therapy minutes to provide and the ADL index score of a patient.

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¹⁴The day after CMS announced the cut in reimbursement, the SNF stocks of Sun Healthcare, Skilled Health care, and Kindred Healthcare declined 52.1 percent, 42.5 percent, and 29.3 percent in one day. (Health-care firms come down with severe case of cutback jitters, Korn & Kamp (2011), *WSJ*, August 2, 2011)

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Table 1: Rehabilitation RUG-III Categories

Category	Therapy Minutes	ADL Index Score	RUG Code	Reimbursement Rate
Ultra High	$720 \geq$	16-18	RUC	\$467.21
		9-15	RUB	\$420.56
		4-8	RUA	\$397.90
Very High	$500 \geq$	16-18	RVC	\$360.21
		9-15	RVB	\$348.21
		4-8	RVA	\$317.55
High	$325 \geq$	13-18	RHC	\$330.36
		8-12	RHB	\$303.70
		4-7	RHA	\$278.37
Medium	$150 \geq$	15-18	RMC	\$325.28
		8-14	RMB	\$290.63
		4-7	RMA	\$273.30
Low	$45 \geq$	14-18	RLB	\$259.15
		4-13	RLA	\$217.83

Notes: The number of therapy minutes reflect the minimum number of therapy minutes required 5 days a week. The Federal reimbursement rate reflects the total payment, as per equation (1), for an urban SNF in a geographic area with a wage index of 1.

Table 2: Profit margin and geographic payment adjustment factors

	Summary Statistics	Overall Profit Margin (%)		
Rural Facility Adjustment	0.379 (0.485)	-0.177* (0.103)	-0.187* (0.107)	-0.167 (0.108)
Wage Index	0.964 (0.144)	0.302*** (0.046)	0.291*** (0.048)	0.295*** (0.052)
Wage Index * Rural Facility Adjustment	0.333 (0.431)	0.251** (0.119)	0.258** (0.124)	0.232* (0.126)
Regression Includes:				
State Indicator Variables		X	X	X
Facility Characteristic Variables			X	X
Staffing Variables				X
Average of Dependent Variable		0.011	0.011	0.011
Observations		9124	9124	9124
R-squared		0.354	0.449	0.467

Summary statistics are reported in the first column with standard deviations in parentheses. The summary statistics are based on the labor profit margin sample. Regression results are reported in all other columns with standard errors reported in parentheses. Standard errors are adjusted for clustering at the state level. All regressions include state indicator variables. Facility characteristic variables include ownership, number of beds, beds squared, part of multi-facility chain, payer mix, occupancy rate, acuity level, percent dementia and the proportion of days at the default payment rate. Staffing variables include registered nurse, licensed practical nurse, certified nurse aide, occupational therapy, physical therapy staff and indicators variables for improbable staffing levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Regression Results for Therapy Minute Upcoding

	Hip Fracture Sample		Stroke Sample	
	4-7 ADLs	16-18 ADLs	4-7 ADLs	16-18 ADLs
Lower Payment Differential	0.312*** (0.075) [0.052]	0.086*** (0.023) [0.014]	0.172*** -0.044 [0.030]	0.072*** (0.013) [0.013]
Payment Rate	-0.208*** (0.043) [-0.035]	-0.069*** (0.015) [-0.011]	-0.124*** -0.026 [-0.022]	-0.061*** (0.008) [-0.011]
Upper Payment Differential	-0.044*** (0.013) [-0.007]	0.000 (0.003) [0.0001]	-0.029*** -0.008 [-0.005]	-0.007* (0.004) [-0.001]
Number of Observation	14920	105736	50260	170088
Number of Patients	3730	26434	12565	42522

Notes: Standard errors adjusted for clustering at the state level are reported in parentheses. The average marginal effect evaluated at the mean is reported in square brackets. All regressions are estimated using a mixed logit model and include patient and SNF characteristics. Patient characteristics include gender, age, race, education, short and long term memory loss, cognitive impairment, and indicators for the following medical conditions: diabetes, heart disease, cardiac dysrhythmia, heart failure, COPD, dementia, anxiety, and depression. SNF characteristic variables include ownership, number of beds, beds squared, part of multi-facility chain, payer mix, occupancy rate, acuity level, percent dementia and nurse staffing levels. In addition, regional indicator variables of New England, Mid Atlantic, Midwest, South, Mountain, and Western States are included.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Predicted RUG Categories by Generosity of Medicare Payment: Therapy Upcoding (4-7 ADLs Sample)

	Predicted Distribution of RUG Categories			Cost of Predicted RUG Mix	Highest Percentile has Lowest Percentile Distribution	
	RMA	RHA	RVA		Cost Savings (\$)	Cost Savings (%)
Hip Fracture Sample (Urban)						
Lowest 25th Percentile Wage Index	12.10%	39.41%	36.01%	12.48%	\$272.04	
Highest 25th Percentile Wage Index	11.68%	34.72%	42.11%	11.49%	\$352.20	\$1.41 0.40%
Hip Fracture Sample (Rural)						
Lowest 25th Percentile Wage Index	14.63%	43.41%	31.84%	10.12%	\$257.14	
Highest 25th Percentile Wage Index	10.88%	34.48%	40.50%	14.14%	\$339.34	\$10.39 3.06%
Stroke Sample (Urban)						
Lowest 25th Percentile Wage Index	12.96%	39.22%	30.88%	16.93%	\$275.27	
Highest 25th Percentile Wage Index	15.59%	37.29%	33.13%	13.99%	\$348.97	-\$3.14 -0.90%
Stroke Sample (Rural)						
Lowest 25th Percentile Wage Index	13.29%	40.26%	29.86%	16.58%	\$269.71	
Highest 25th Percentile Wage Index	12.98%	36.32%	33.69%	17.02%	\$342.33	\$2.53 0.74%

Notes: The table reports the predicted probability of being in each RUG category using the coefficient estimates in Table 3. The cut-offs for the percentile rankings of the wage index are determined for each sample, weighted for the number of patients in the sample. The cost of predicted RUG mix is the average per diem reimbursement given the distribution of RUG categories. The cost savings is the amount of per diem cost saved if the highest 25th percentile wage index patients had a similar distribution of RUG categories as the lowest 25th percentile wage index patients.

Table 5: Predicted RUG Categories by Generosity of Medicare Payment: Therapy Upcoding (16-18 ADLs Sample)

	Predicted Distribution of RUG Categories				Cost of Predicted RUG Mix	Highest Percentile has Lowest Percentile Distribution	
	RMC	RHC	RVC	RUC		Cost Savings (\$)	Cost Savings (%)
Hip Fracture Sample (Urban)							
Lowest 25th Percentile Wage Index	11.27%	44.25%	30.41%	14.06%	\$317.68		
Highest 25th Percentile Wage Index	10.41%	37.03%	34.67%	17.90%	\$416.74	\$7.50	1.80%
Hip Fracture Sample (Rural)							
Lowest 25th Percentile Wage Index	12.27%	44.29%	29.11%	14.33%	\$311.18		
Highest 25th Percentile Wage Index	9.53%	38.84%	34.35%	17.28%	\$395.57	\$7.15	1.81%
Stroke Sample (Urban)							
Lowest 25th Percentile Wage Index	12.00%	39.23%	28.40%	20.36%	\$324.76		
Highest 25th Percentile Wage Index	11.68%	33.91%	29.37%	25.04%	\$426.03	\$7.66	1.80%
Stroke Sample (Rural)							
Lowest 25th Percentile Wage Index	12.90%	40.68%	27.24%	19.19%	\$314.36		
Highest 25th Percentile Wage Index	10.44%	34.85%	30.06%	24.65%	\$406.35	\$10.29	2.53%

Notes: The table reports the predicted probability of being in each RUG category using the coefficient estimates in Table 3. The cut-offs for the percentile rankings of the wage index are determined for each sample, weighted for the number of patients in the sample. The cost of predicted RUG mix is the average per diem reimbursement given the distribution of RUG categories. The cost savings is the amount of per diem cost saved if the highest 25th percentile wage index patients had a similar distribution of RUG categories as the lowest 25th percentile wage index patients.

Table 6: Regression Results for Therapy Minute and ADL Upcoding

	Hip Fracture Sample		Stroke Sample	
	(1)	(2)	(3)	(4)
Payment Rate	-0.047*** (0.008)	-0.074*** (0.009)	-0.041*** (0.006)	-0.061*** (0.006)
ADL Lower Payment Differential	0.034*** (0.010)	0.033*** (0.012)	0.033*** (0.006)	0.034*** (0.008)
ADL Upper Payment Differential	0.013 (0.010)	0.004 (0.012)	0.008 (0.008)	0.001 (0.009)
Therapy Minutes Lower Payment Differential	0.053*** (0.014)	0.069*** (0.015)	0.041*** (0.014)	0.055*** (0.010)
Therapy Minutes Upper Payment Differential	-0.010*** (0.003)	-0.010*** (0.003)	-0.014*** (0.003)	-0.014*** (0.003)
ADL & Therapy Minutes Lower Payment Differential		0.028*** (0.010)		0.019*** (0.006)
ADL & Therapy Minutes Upper Payment Differential		-0.010 (0.006)		-0.008* (0.004)
Number of Observation	1151700	1151700	1774296	1774296
Number of Patients	95975	95975	147858	147858

Notes: Standard errors adjusted for clustering at the state level are reported in parentheses. All regressions are estimated using a mixed logit model and include patient and SNF characteristics. Patient characteristics include gender, age, race, education, short and long term memory loss, cognitive impairment, and indicators for the following medical conditions: diabetes, heart disease, cardiac dysrhythmia, heart failure, COPD, dementia, anxiety, and depression. SNF characteristic variables include ownership, number of beds, beds squared, part of multi-facility chain, payer mix, occupancy rate, acuity level, percent dementia and nurse staffing levels. In addition, regional indicator variables of New England, Mid Atlantic, Midwest, South, Mountain, and Western States are included.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

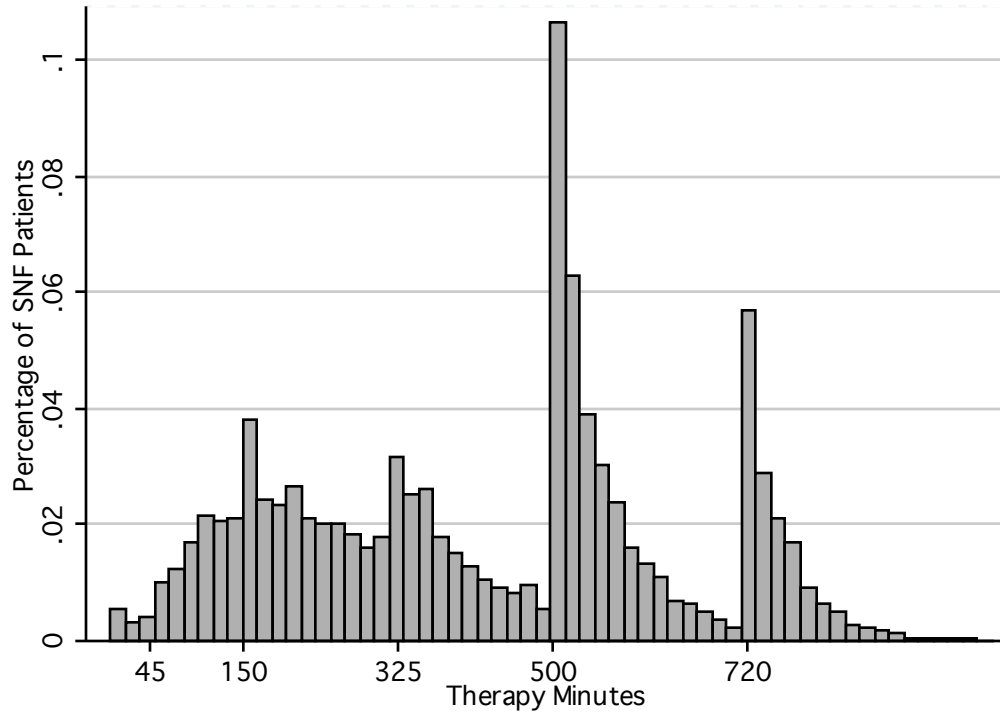


Figure 1: Histogram of Therapy Minutes for 16-18 ADLs Hip Fracture Sample

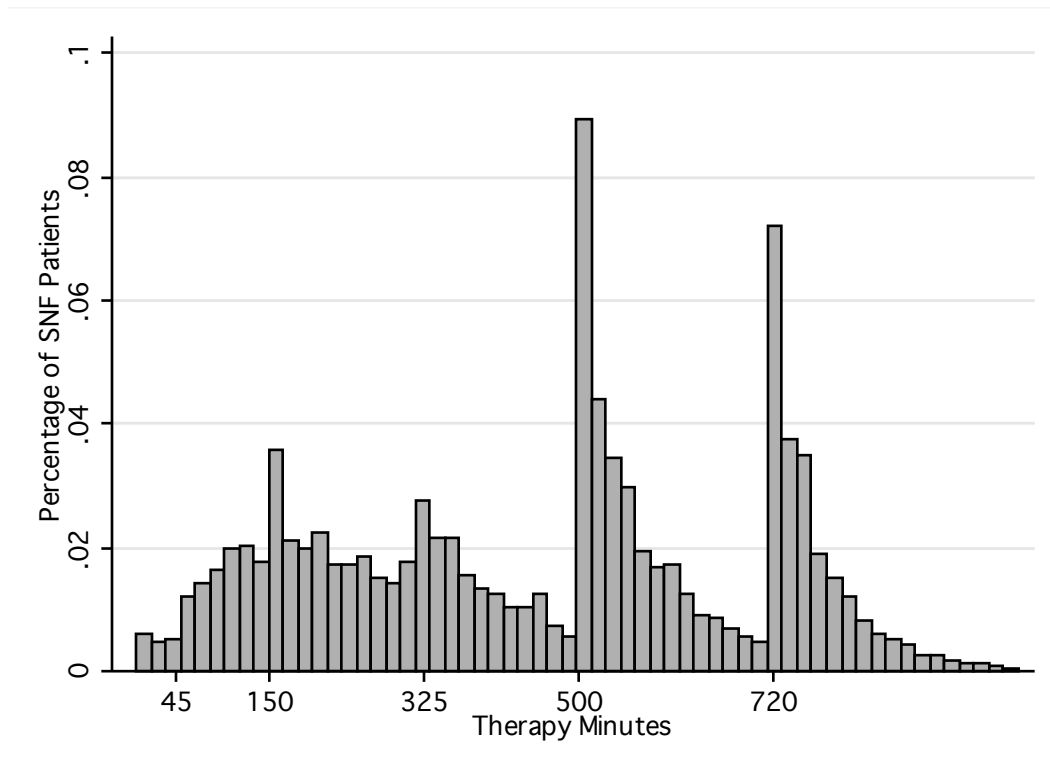


Figure 2: Histogram of Therapy Minutes for 16-18 ADLs Stroke Sample