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Evaluating Potential Proxies for Patient Functional Status in a Unified Post-Acute Care Payment System for Medicare

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Evaluating Potential Proxies for Patient Functional Status in a Unified Post-Acute Care Payment System for Medicare

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The Improving Medicare Post-Acute Care Transformation Act of 2014, or IMPACT Act, required the Medicare Payment Advisory Commission (MedPAC) to recommend design features for a unified prospective payment system (PPS) for post-acute care (PAC). In response, MedPAC issued a report on the design (MedPAC 2016) and has issued subsequent reports on implementation issues (MedPAC 2017) and other possible considerations for a unified PAC PPS. The risk models of MedPAC's demonstration PAC PPS, described below, adjust for patient age, diagnoses (reason for treatment), and comorbidities but avoid including direct measures of a patient's functional status because of concerns about the quality of the function data PAC providers collect.

Until recently, each PAC setting collected measures of patient function that were not similarly defined or directly comparable across settings. The IMPACT Act also required the four PAC settings—skilled nursing facilities (SNFs), home health agencies (HHAs), inpatient rehabilitation facilities (IRFs), and long-term care hospitals (LTCHs)—to collect and report consistent measures of patient function. But even with consistency in how the measures are defined, concerns about the misreporting of function remain. In its June 2019 report, MedPAC described the ways in which PAC providers' assessments of patient function could be responsive to payment incentives and provided evidence suggesting there is substantial miscoding of patient functional status that is typically in ways that would boost provider payments or improve performance measures (MedPAC 2019).

The current version of MedPAC's PAC PPS model intentionally excludes functional status as a risk adjustment factor in its payment model, but this results in payment-to-cost (P/C) ratios that are substantially higher for high-functioning patients. This is because the model without functional status leads to predicted costs substantially below actual costs for low-functioning patients and substantially above costs for high-functioning patients (Wissoker and Garrett 2016). If functional status is well measured and patient costliness varies with functional status after adjusting for age and diagnoses, not adjusting payments for functional status could lead providers to avoid predictably more costly patients, who would be relatively unprofitable. However, if functional status is subject to systematic misreporting or gaming, observed functional status would not reflect a patient's true expected cost, and payment weights for functional status would be distorted. Such distortions would persist even if the payment weights were periodically updated. Providers that systematically misreport patients' functional status could profit unfairly at the expense of providers that do not.

That P/C ratios vary by measured functional status does not, by itself, imply that misreported measures should be included in or excluded from a unified PAC PPS. However, there is not a clear solution. Excluding functional status from the risk adjustment would result in over- and underpayments for some patients, which could encourage providers to selectively admit certain types of patients. Including functional status in the risk adjustment would encourage providers to misreport the information if it raised payments without incurring higher costs. Such behavioral responses would require regular recalibration of the payment weights and the level of payments to keep payments aligned with the costs of care.

In this report, we consider whether it is possible to find variables with available administrative data that may serve as proxies for functional status in a unified PAC PPS. If there were proxies for functional status that were not as subject to misreporting by providers, including them in the PAC PPS risk models could allow payments to better reflect true patient functional status. To find potential proxies for functional status, we first reviewed research literature on predictors of functional status. We then examined how stay-level payments and costs vary with levels of patient functional status using Medicare PAC claims data from 2017 and modeled payments under MedPAC's unified PAC PPS design. After finding that patients with higher levels of function would be substantially more profitable under the unified PAC PPS without a direct measure of functional status, we explored whether there are feasible proxies for functional status. We conducted analyses showing how well alternative sets of proxies predict functional status and how including such proxies in the PAC PPS risk models affected P/C ratios by patient functional status. Our overall finding is that proxies of functional status offer some ability to improve the predictive ability of the PAC PPS payment models, none of the options come close to equalizing P/C ratios across patient function groups.

Potential Predictors of Functional Status

At the start of this work, we conducted a scan of academic literature on potential proxies of functional status. Six avenues of investigation appeared promising, based on background discussions with experts. These included: frailty indexes, comorbidity and multimorbidity indexes, durable medical equipment (DME) claims, prescription drug claims, outpatient claims, and International Classification of Diseases, 10th revision, clinical modification (ICD-10-CM) diagnosis codes. We generally focused on studies that attempted to predict or explain contemporaneous functional status. We summarize the key findings from our review and implications for our analysis in this section and include a full review in appendix A.

Several studies describe frailty indexes based on administrative data and use them to predict Medicare patient cost. Overall, there is some evidence that a claims-based frailty index, developed from a mix of diagnosis codes and claims to assess likely comorbidities and functional status, could improve prediction of Medicare costs when added to standard diagnosis groupings (Johnston, Wen, and Maddox 2020; Kim et al. 2018). But such indexes may require services and devices recorded outside the hospital and PAC settings, like wheelchair use, ambulance transport, and home hospital beds (Kim et al. 2018). We did not pursue using pre-PAC outpatient data, as the literature suggests most of the factors strongly associated with functional status are already included in hierarchical condition categories (HCCs; Kurichi et al. 2017) or would require unique procedures for each diagnosis (Gilden, Kubisiak, and Zbrozek 2011). Instead, we incorporated into our modeling ICD-10-CM indicators of frailty from a recent paper (Gilbert et al. 2018).

Some studies suggest comorbidity indexes and HCCs have very modest ability to predict patient functional status (Kumar et al. 2015; Kumar, Graham, Resnik, Karmarkar, Deutschby, et al. 2016; Kumar, Graham, Resnik, Karmarkar, Tan, et al. 2016; Noyes, Liu, and Temkin-Greener 2008; Wallace et al. 2016). One study found incremental ability of some specific multimorbidity pairs (e.g., heart failure and osteoporosis) to predict Medicare patient costs after controlling for HCCs (Noyes, Liu, and Temkin-Greener 2008). Therefore, we reflect these findings in our work by using Classification and Regression Tree (CART) analyses to identify combinations of diagnoses and other factors already included in our base model that could improve prediction of functional status.

Patient use of DME indicated in claims can predict functional status, according to some studies (Davidoff et al. 2013; Faurot et al. 2015; Kim et al. 2018). Overall, DME claims for wheelchairs, home hospital beds, and home oxygen therapy appear to be consistently associated with functional status across studies, but how such claims would be incorporated into a unified PAC PPS is unclear, given that such equipment is primarily used at home, after discharge from PAC. In addition, tying PAC payments to post-institutional PAC DME use could create adverse incentives to modify DME use. Relying solely on pre-PAC DME use would not control for any change in function associated with the reason for treatment. Accordingly, we did not pursue adding DME use to the base model.

Research on the predictive ability of prescription drug use (e.g., summarized as a drug burden index or used as an alternative to diagnosis codes) is limited and focused on quantifying risks to community-dwelling older adults without controlling for diagnoses (Byrne et al. 2019; Dubois et al. 2010). We did not pursue collecting data or constructing measures of prescription drug use as proxies for functional status given the challenges it would present: predictors of function based on drugs would be specific to a diagnosis and thus difficult to construct across the board, and they would need to be based on data up through, but not after, the PAC stay.

Studies using outpatient claims or electronic health records to predict functional status suggest some possible additions to risk models, such as ambulance use, neurology evaluation and management, hearing impairment, vision impairment, living arrangement, and proxy use (Davidoff et al. 2013; Faurot et al. 2015; Gilden, Kubisiak, and Zbrozek 2011; Kurichi et al. 2017; Zucchelli et al. 2019). However, it is unclear how much predictive value such additions will have beyond the HCC groupings, the JEN Frailty Index components, and other controls already in use, and we did not pursue constructing further measures from outpatient claims data.

The additional detail on patient condition potentially available in ICD-10-CM codes, including the Z codes, offer some opportunities to code functional status in hospital and outpatient settings. There is little published work, however, examining how well ICD-10-CM items predict functional status, and we found no published work assessing the use of Z codes. We investigate the potential value of such items for predicting functional status in the analyses described below.

Data and Methods

The central question of this study is whether the strong positive relationship between patient ability to function and the modeled P/C ratios of the PAC PPS demonstration payment model can be weakened or flattened by including proxies for function in the regression models used to establish payments under a unified PAC PPS. To address this question, we analyze 2017 Medicare fee-for-service claims and associated data from assessments for stays across the four PAC settings.

We use data files originally constructed for a 2019 study of PAC PPS payments to episodes of post-acute care conducted for MedPAC and described more fully below (Wissoker and Garrett 2019). The goal of the 2019 study was to understand the trade-offs involved in modifying the PAC PPS to pay for episodes of care rather than individual stays. A stay is defined by a discharge in IRFs and LTCHs, an episode in HHAs, and days on Medicare-covered claims within a SNF stay. A care episode is the aggregation of PAC stays that occur within seven days of each other. For the current study, we include all stays in care episodes that began between January and June 2017.

In this section, we first describe the data sources and the exclusions for our analysis. We then describe our approach to estimating costs per stay using claims and cost report data and provide an overview of the model used to predict costs and the construction of model-based PAC PPS payments. Next we describe the construction of the measure of function based on comparable assessment information for the four PAC settings. Finally, we describe three main approaches to developing proxies for function in the cost model: (1) diagnosis group indicators from the beta version of the Clinical Classifications Software Refined (CCRS), (2) indicators from a CART modeling approach, and (3) frailty indicators based on ICD-10-CM codes and Z codes (a group of codes in ICD-10-CM for reporting factors influencing health status and contact with health services).

Data Sources

We constructed the file using PAC claims for 2017 from the Medicare Standard Analytic File. In total, there were 8.3 million PAC stays in 2017. Of these, we combined 257,000 with a prior stay because they appeared to be partial SNF or home health stays.[1] Of the remaining 8 million stays, approximately 10 percent of home health episodes and 14 percent of institutional stays had missing data and were dropped (table A.1). We excluded stays from the analysis if they were

- for patients enrolled in a health maintenance organization (e.g., Medicare Advantage);
- missing provider data from cost reports, such as cost-to-charge ratios for institutional providers or costs per visit for home health;
- missing data on charges;
- outside the 50 states and District of Columbia (e.g., from Puerto Rico);
- problematic for other reasons, such as missing risk scores, missing an area wage index, having institutional stays with end dates that overlap with other stays, or having stays for a beneficiary with the same start day; and
- exceptionally long (SNF stays of more than 101 days and IRF and LTCH stays longer than three standard deviations above the mean of the logged distribution).

In addition, because the original purpose of the analytic file was to construct care episodes, stays were excluded if a beneficiary had a stay dropped for any reason (in such cases, we dropped all stays for the beneficiary). Altogether, we dropped approximately 907,000 stays. We used the resulting file of 7,110,982 stays to construct care episodes.

We next restricted the sample to stays that were part of care episodes begun between January 1, 2017, and June 30, 2017, to ensure most care episodes were completed during 2017. This allowed us to observe each episode for 6 to 12 months. The resulting file contained 4,740,394 stays.

Finally, we restricted the file to stays for which a patient assessment of initial condition could be obtained. Across all settings, 61 percent of stays were matched to an assessment, with a match rate of 54 percent for home health episodes, 77 percent for SNF stays, 94 percent of LTCH stays, and 95 percent for IRF stays. The final file contains 2,879,329 stays (1,891,289 stays in home health, 773,862 SNF stays, 161,611 IRF stays, and 52,567 LTCH stays).[2]

The stays were from 8,545 HHAs (36 percent of PAC providers), 14,043 SNFs (59 percent of PAC providers), 995 IRFs (4 percent of PAC providers), and 392 LTCHs (2 percent of PAC providers). Overall, 11 percent of stays were with hospital-based providers.[3]

Estimating the Cost of 2017 PAC Stays

Costs per stay include routine and ancillary costs, overhead costs, and, for IRFs, the costs associated with teaching programs and treating low-income patients.[4]

For institutional stays, we estimated routine costs as the average routine cost per day from the 2017 Medicare cost report times the stay's covered length of stay from the claims. We estimated both therapy and nontherapy ancillary costs by converting eligible charges on the PAC claims to costs using facility- and department-specific cost-to-charge ratios from each provider's 2017 Medicare cost report.

For HHAs, routine and ancillary costs are calculated by aggregating the estimated cost for the episode over six resource types. The cost of any resource type is the product of the number of visits and the cost per visit provided on the 2017 Medicare cost report. Routine costs are the sum of the costs of the three nontherapy resource types (skilled nursing, home health aides, and medical social services). Therapy costs are the sum of the costs of the three therapy resource types (physical therapy, occupational therapy, and speech language pathology services). A maximum cost per visit for each resource type was set at the 95th percentile of the distribution of costs per visit across facilities, and a minimum cost per visit was set at the 5th percentile; percentiles were calculated separately for hospital-based and freestanding agencies. Nontherapy ancillary (NTA) costs for HHAs are not calculated because they are not included in the unit of service paid for by the PPS for HHAs.

All costs were standardized using the setting-specific labor share and area wage index.

Description of the Base Unified PAC PPS

PREDICTING THE COST OF STAYS USING PATIENT CHARACTERISTICS

Under a PAC PPS, the payment for a stay would be based on the stay's predicted cost (MedPAC 2016). Patient and stay characteristics are used to predict the actual cost of the stay. Below, characteristics marked with (*) were taken from the hospital claim when the PAC stay had a hospital stay within 30 days, or they were proxied from PAC claims for stays without a preceding hospitalization. We used measures and indicators of the following to predict the cost of stays:

- patient age and disability status
- primary reason to treat (Medicare Severity Diagnosis Related Group, aggregated into "reason to treat" groups)*
- patient comorbidities (observed in a prior hospital stay and the PAC stay)
- the number of body systems involved with a patient's comorbidities
- days spent in the intensive and coronary care units during the prior hospital stay
- the patient's severity of illness using the All Patient Refined Diagnosis Related Groups*

- beneficiary's risk score based on patient diagnoses for the prior year
- impairments and treatments (including bowel incontinence, severe wounds or pressure ulcers, use of certain high-cost service items, and difficulty swallowing)
- proxies for a patient's frailty
- the patient's cognitive status

All risk adjustors are based on administrative data and do not use patient assessment information. We used claims information from PAC stays and the preceding hospital stays, demographic information from the Medicare enrollment files, and beneficiary risk scores. Information on diagnoses and the primary reason for treatment was collected from prior hospital stay claims and from PAC stay claims for patients admitted from the community. Comorbidities data were collected from hospital stay claims, where available, and from the PAC stay claims. Indicators of ventilator care and severe wound care needs were obtained from the PAC stay claims.

We used claims-based diagnoses and procedure codes for measures of frailty, cognitive function, and select PAC service use. We used ICD-10-CM codes in the PAC claims to indicate bowel incontinence and the presence of ventilator care.[5] We calculated a JEN Frailty Index for each stay and included the 13 components of that index as predictors.[6] As proxies for cognitive function, we used ICD-10-CM codes for coma, dementia, Alzheimer's disease, schizophrenia, and depressive disorders. We used ICD-10-CM codes for dysphagia as a proxy for swallowing difficulties. More detailed definitions of the predictors are described in Wissoker and Garrett (2019).

We avoided including in the model indicators of service use that might be manipulated by providers (e.g., the amount of rehabilitation therapy, the number of therapy disciplines, or the use of oxygen without a link to a respiratory diagnosis). However, we included indicators for ventilator care, tracheostomy care, and continuous positive airflow pressure, because the costs of those services are significant, and use is much less likely to be influenced by payment policy. The measure for continuous positive airflow pressure captures use only within institutional settings, because home health claims do not provide the procedure codes needed to identify its use in home health.

As in our earlier work, we included in the model an indicator for care provided by HHAs. HHAs do not incur the same kinds or levels of costs as institutional providers, so we adjust for this with an indicator in the model for home health. Including this indicator ensures that costs for home health cases are predicted correctly on average.

Costs were predicted using generalized linear models with a log link (Poisson regression models). Compared with ordinary least squares regression, the Poisson regression gives less emphasis to infrequent but exceptionally high cost stays. In addition, Poisson models can more easily handle dependent variables with zero values (such as institutional stays with no NTA costs).

Our approach uses two models to predict each stay's actual costs: one for routine and therapy costs and another for NTA costs. The routine and therapy model is based on stays from both HHA and institutional PAC settings. The NTA model is based on stays from just the institutional PAC settings. The two models use the same set of patient and stay characteristics as predictors, except for inclusion of an indicator of a home health stay mentioned above. We combined the cost estimates generated by the models and evaluated the results by comparing total actual costs (including zero NTA costs for HHA stays) with the total predicted costs (including zero predicted NTA costs for HHA stays). Under a PAC PPS, relative weights for each stay would be based on total predicted costs.

COMPARING PAYMENTS AND COSTS

To compare what estimated payments would be under PAC PPS with the costs of and payments for stays, all costs and payments were standardized for variation in wages across geographic areas. This ensures the comparison of costs, actual payments, and modeled PAC PPS payments takes place on an equal basis. Payments from PAC claims were standardized by each provider's area wage index. Recall that costs were also standardized by the provider's area wage index. Because estimated payments under the new systems were based on standardized costs, they did not need to be further adjusted for wage differences.

Model-based payments are then adjusted to be budget neutral so the total dollars paid out equal total actual payments. Actual payments include any relevant adjustments for rural location, teaching, low-income share, outliers, and the amounts paid by the beneficiary (any coinsurance and deductibles).

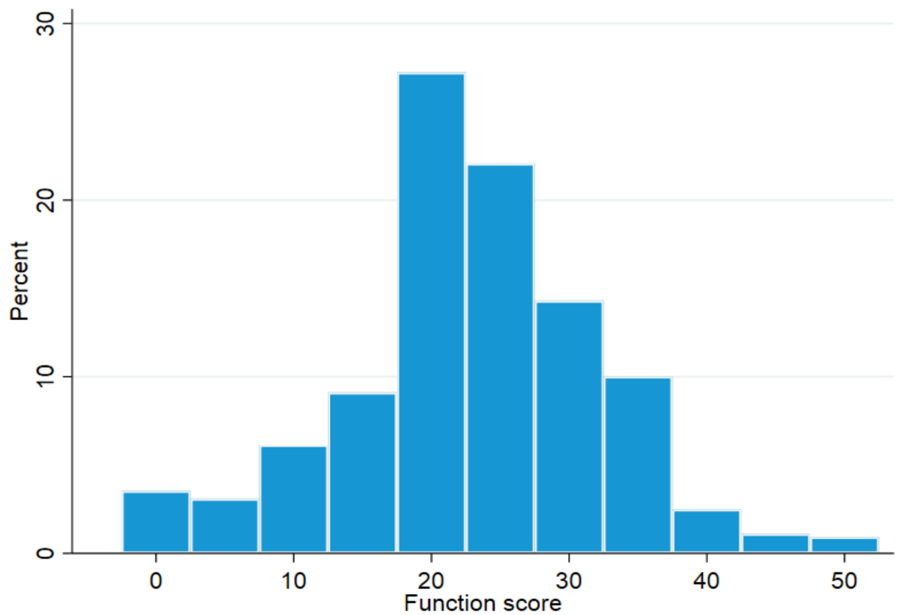
In our original modeling, we modeled both a low-utilization payment policy and a high-loss outlier system, but for simplicity we focus on model-based payments without outlier adjustments. The outlier adjustments reduce the differences in P/C ratios by level of function, but large differences remain between low- and high-functioning patients. Without the outlier adjustment, P/C ratios are 1.10 overall, ranging from 1.02 for very low– and low-functioning patients to 1.35 for high- and very high–functioning patients. With the adjustment for outliers, the range narrows, with P/C ratios of 1.03 to 1.04 for lower-functioning patients and 1.25 to 1.30 for very high- and high-functioning patients. [7]

A PAC-Setting-Consistent Function Index

All PAC providers record the functional ability of patients, but until recently and for the 2017 stays we examine, each provider type used its own definition and rating scale, as MedPAC has described in detail (MedPAC 2019). Although the four setting-specific instruments collected information on common domains (e.g., ability to walk, transfer), the way each domain was defined and the length of the observation period differed, making it difficult to compare differences in patient functioning status across settings. To allow comparisons across settings, MedPAC designed an approach for creating common levels of function based on the setting-specific instruments. The procedure defines broad function levels for four domains: eating, toileting, walking, and transferring. From each assessment tool, recorded levels of function for each domain are mapped to a typically coarser set of groupings. The eating and toileting domains are mapped into three groups (low, medium, and high functioning) scored with 0, 5, and 10 points, respectively. The walking and transferring domains are mapped into four groups with 0, 5, 10, and 15 points. The scores from the four domains are then totaled to produce an overall function score (index). Figure 1 shows the distribution of function scores, which ranges from 0 to 50 points with a mode of 20 points.

FIGURE 1

Distribution of Function Scores for PAC Patients



Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute care settings and hospital claims data, cost report data, and matched assessment data.
Notes: PAC = post-acute care. *N* = 2,879,329.

The overall function level is then categorized into five groups based on total points: very low (0 to 10 points), low (11 to 20 points), medium (21 to 30 points), high (31 to 40 points), and very high (41 to 50 points). See MedPAC (2019) for a full description of the approach to constructing the common levels of function.

Proxies of Functional Status Used in Analyses

We considered three sets of proxy measures for functional status to include in the PAC PPS payment regression model in place of including function itself. The proxy measures are based on diagnoses from patients claims and are expected to be more reliable and less manipulable than the measures of function from patient assessments. We evaluate the sets of proxy measures by first assessing their contributions to predicting functional status and costs. We next assess whether these proxies' inclusion in the payment regression model substantially flattens the relationship between modeled P/C ratios and patient function.

CCSR

To assess whether more detailed patient diagnoses could account for the observed relationship between patient function and the cost of PAC stays, we used the Clinical Classification Software Revised, v2019.1, from the Heath Care Utilization Project at the Agency for Healthcare Research and Quality. CCSR is a detailed diagnostic categorization system, assigning each ICD-10-CM code to one of 538 mutually exclusive groups associated with 1 of 21 body systems. We observe 505 diagnosis groups occurring in at least one case in our data.

For each PAC stay, we constructed a complete set of indicators for the CCSR groups by classifying all primary and secondary diagnoses from the PAC stay and from the most recent prior acute hospitalization, for those with a hospitalization within 30 days of admission. The resulting set of indicators are not mutually exclusive, because an individual may have as many positive indicators of as many CCSR groups as they have diagnoses.

CART MODEL

To take a systematic approach to identifying interaction effects that could most powerfully improve the prediction of functional status, we estimated CART models of total function points. We then used the patient groups CART produces as additional proxies for functional status. The CART algorithm partitions data into mutually exclusive groups that lead to the best prediction of the outcome, total function points. The measures used for grouping are the CCSR indicators and the predictors from the base models described above. The algorithm first splits the data into two groups based on the predictor that leads to largest share of variance explained; it adds further subpartitions if further splits of a previously determined group sufficiently improve the predictive ability. The resulting groups are those combinations of the cost-model predictors that best predict function, subject to a stopping rule that penalizes further groupings.

We then included indicators of the CART groups as additional predictors in our cost models. Recall that our Poisson regression model estimates the main effects of the included controls; given the model's log-linear form, the percent effect of one predictor variable does not depend on the values of the other predictor variables. Including the indicators of the CART groups effectively relaxes this assumption by allowing groups formed from interactions of our predictor variables to serve as proxies for function in our models of cost.

We estimated two models of total function points that differ in the number of mutually exclusive groups: a minimalist version with 13 groups and a more expansive version with 42 groups. We estimated the models using the RPART implementation of the CART algorithm in R, as we describe in detail in appendix B.

ICD-10-CM VARIABLES AND Z CODES

Finally, we explore whether use of the coding available in the ICD-10-CM can improve our ability to account for patient function in the cost models. The current PAC PPS model was designed using measures based on codes from ICD-9, which we subsequently updated to use ICD-10-CM codes using a crosswalk between the two versions of the coding. Given that the ICD-10-CM provides more detailed coding, there might be an advantage to capturing function by using the ICD-10-CM diagnoses directly as proxies of functioning.

For this exploratory analysis, we used 39 indicators based on ICD-10-CM codes to serve as proxies for function. Our starting point is a set of more than 30 ICD-10-CM codes suggested as being correlated with frailty in (Gilbert et al. 2018). We summarize the codes in the literature review (appendix A). Gilbert and colleagues (2018) generally define the codes at a somewhat broader level than the ICD-10-CM system allows, using the leading character and the first two or occasionally three digits out of up to four digits in a code. These codes indicate multiple types of dementia, different aspects of problems of the respiratory and circulatory systems, strokes, and many other diseases that could also be measured using the ICD-9 coding system. The indicators also include W codes (leading character W), indicating types of falls, and Z codes (leading character Z), indicating “Factors influencing health status and contact with health services” such as Z75 “problems related to medical facilities and other health care” and Z993, “dependence on wheelchair.” We supplement these indicators with (1) other Z codes that might be related to frailty or disability, such as history of falling, dependence on a wheelchair, problems related to care (e.g., provider dependence, bed confinement), and (2) family history of disability and chronic disease leading to disablement. We also include an indicator of one of a list of codes indicating a fall. The list of ICD-10-CM function proxies is reported in appendix table B.2.

For each PAC stay, we constructed these 39 indicators using all diagnoses from the PAC stay and from the most recent prior acute hospitalization for those with a hospitalization within 30 days of admission. To be used in practice, these measures would need to account for the relationship between cost and function, not be easily gameable, and have the potential to be consistently reported across PAC settings. Our focus here is on the initial question of whether these measures add to the ability to account for a substantial portion of the relationship between cost and patient function.

Findings

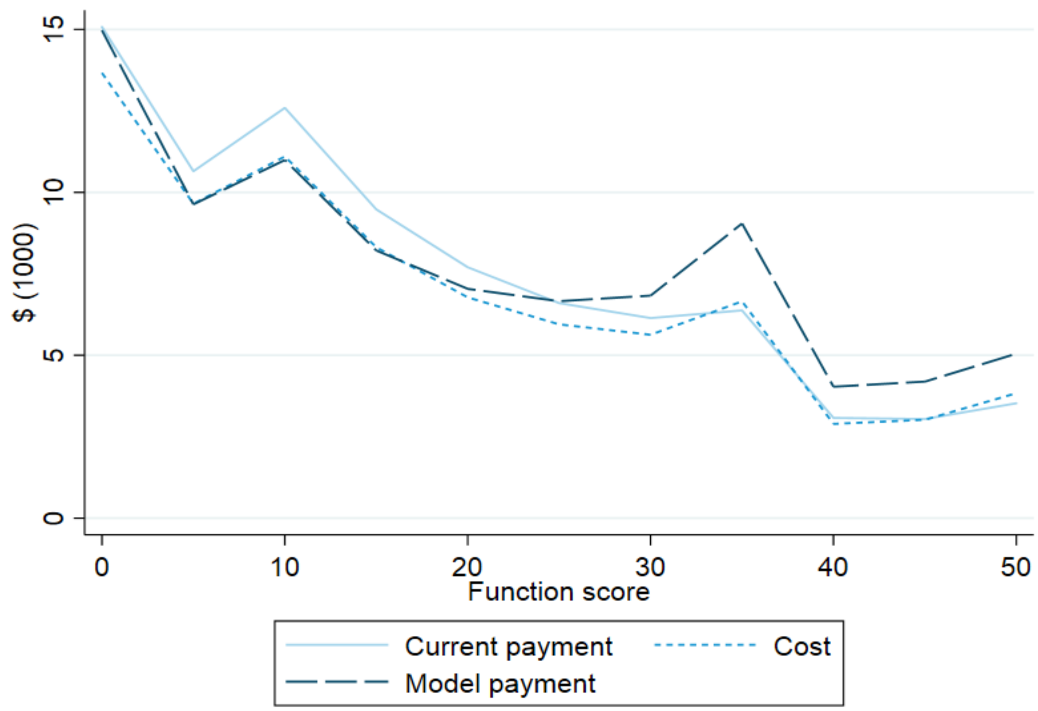
How PAC Payments and Costs Vary with Patient Functional Status

Figure 2 shows how simulated payments under the PAC PPS compare with actual payments to PAC providers and estimated costs in 2017. Estimated costs decline from more than $10,000 per stay at lower levels of function to less than $5,000 at higher levels of function. Similarly, both payment variables track the decline in costs with function. Actual payments exceed costs somewhat at lower levels of function, whereas the PAC PPS model-based payments exceed cost at higher levels of function.

Figure 3 shows how P/C ratios vary by patient functional status under the payment systems that existed in 2017 (referred to as “current”) and under the PAC PPS model, based on the same patterns shown in figure 2. P/C ratios under actual payments are around 1.1 or above for patient scores up to 30. The ratios then fall below 1.1 and are below 1.0 at some higher levels of function. That is, though relatively uniform, profitability declines as a patient's functional status increases. Conversely, under the PAC PPS model, profitability increases as a patient's functional status increases. P/C ratios for the lower-functioning patients are between 1.0 and 1.1 for function scores of 25 or less, and they rise above 1.2 at a score of 30 and reach nearly 1.4 at a score of 40. Though P/C ratios under actual payments are not uniform, they are substantially less uniform under the model-based PAC PPS payments than under the current payment systems.

FIGURE 2

Actual PAC Payments, Model-Based PAC PPS Payments, and Estimated Costs for PAC Patients in 2017

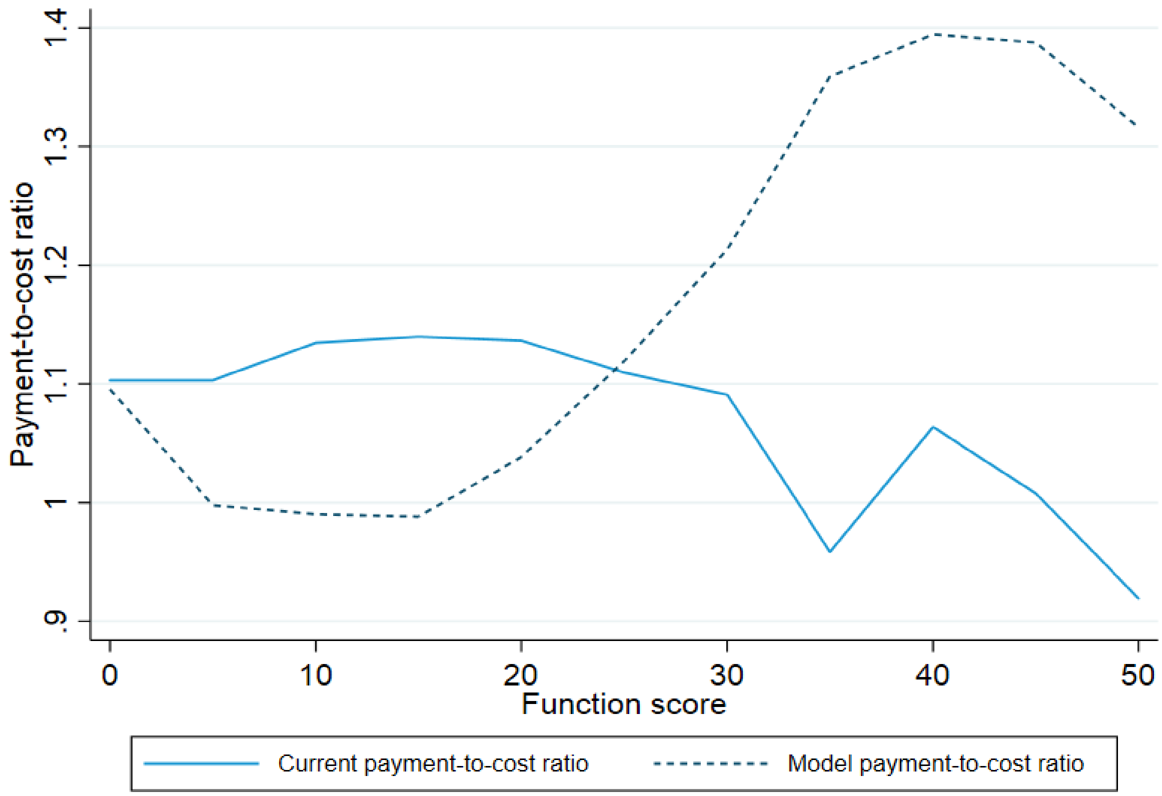


Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data, and matched assessment data.

Notes: PAC = post-acute care. PPS = prospective payment system. *N* = 2,879,329.

FIGURE 3

Payment-to-Cost Ratios under Actual PAC Payments and Model-Based PAC PPS Payments for PAC Patients in 2017



Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data, and matched assessment data.
Notes: PAC = post-acute care. PPS = prospective payment system. *N* = 2,879,329.

Characteristics of PAC Patients by Functional Status

Table 1 reports how patient characteristics differ by levels of function. Beneficiaries in the low-functioning groups tend to be older than those in the high-functioning groups, though the share ages 50 and under is higher in the very low–functioning (3.5 percent) and very high–functioning (6.9 percent) groups than in the median-functioning group (1.8 percent). Patients in the very low–functioning group are more likely to have dementia; be stroke patients; have medical neurological, kidney, or septicemia primary diagnoses; require ventilation therapy in the post-acute stay; have high risk scores; have high severity of illness; have diagnoses affecting five or more body systems; and be treated in IRF and LTCH settings.

Very high–functioning patients are most likely to have a PAC primary diagnosis of schizophrenia (3.5 percent), have chronic obstructive pulmonary disease (COPD) or cardiac primary diagnoses, have a nonhealing wound in the PAC stay, be disabled, be in home health, and be in voluntary (nonprofit) and hospital-based PAC settings. Medium-functioning patients are most likely to have an orthopedic surgery primary diagnosis.

TABLE 1

Characteristics of PAC Patients in 2017, by Functional Status

	Very low	Low	Medium	High	Very high	All
Age						
Capped at 95	77.9	78.7	77.7	75.8	71.7	77.7
Whether <=50	0.035	0.017	0.018	0.027	0.069	0.022
Cognitive function						
Dementia	0.343	0.206	0.146	0.115	0.077	0.188
Schizophrenia	0.015	0.011	0.012	0.019	0.035	0.014
Depressive	0.075	0.072	0.071	0.084	0.081	0.074
Primary Dx						
Stroke	0.047	0.023	0.022	0.026	0.015	0.026
Neurological, surgery	0.013	0.008	0.008	0.010	0.008	0.009
Neurological, medical	0.124	0.093	0.080	0.064	0.058	0.088
Vent or tracheostomy	0.016	0.006	0.005	0.006	0.006	0.007
COPD	0.019	0.033	0.036	0.039	0.045	0.033
Cardiac, medical	0.082	0.118	0.125	0.128	0.134	0.117
Ortho, surgery	0.070	0.122	0.132	0.117	0.043	0.117
Ortho, spine	0.009	0.014	0.018	0.018	0.007	0.015
Skin, medical	0.060	0.032	0.029	0.031	0.048	0.035
Kidney, medical	0.074	0.058	0.049	0.049	0.046	0.056
Infection, surgery	0.019	0.011	0.009	0.010	0.013	0.011
Septicemia	0.074	0.047	0.041	0.044	0.041	0.048
Post-acute services						
Vent	0.027	0.001	0.000	0.000	0.000	0.004
Stage 4 wounds	0.032	0.004	0.002	0.001	0.001	0.006
Nonhealing wounds	0.015	0.014	0.014	0.017	0.031	0.015
Risk score	**2.95**	**2.49**	**2.25**	**2.16**	**2.11**	**2.41**
Severity of illness						
3	0.326	0.295	0.271	0.289	0.260	0.289
4	0.187	0.089	0.073	0.078	0.063	0.094
Number of body systems involved						
>=5	0.230	0.106	0.077	0.091	0.039	0.108
Number of systems	3.7	2.8	2.5	2.5	2.2	2.8
Disability status						
Disabled	0.270	0.221	0.219	0.252	0.334	0.233
PAC setting						
Home health	0.532	0.680	0.698	0.568	0.846	0.657
SNF	0.268	0.271	0.239	0.371	0.122	0.269
IRF	0.122	0.040	0.055	0.049	0.001	0.056
LTCH	0.078	0.009	0.008	0.012	0.032	0.018
Facility/ownership type						
Urban	0.888	0.873	0.880	0.840	0.803	0.872
Voluntary	0.217	0.253	0.268	0.310	0.338	0.263
Proprietary	0.754	0.723	0.703	0.644	0.602	0.708
Hospital based	0.100	0.092	0.120	0.157	0.218	0.114

Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data, and matched assessment data.

Notes: PAC = post-acute care. Dx = diagnosis. COPD = chronic obstructive pulmonary disease. SNF = skilled nursing facility. IRF = inpatient rehabilitation facility. LTCH = long-term care hospital. *N* = 2,879,329.

Explanatory Power and P/C Ratios of Function Groups for Alternative PAC Cost Models

Table 2 examines the explanatory power of six alternative PAC cost models and how payment-to-cost ratios vary by patient functioning group under each model. The base model (1) explains 48.3 percent of variation in routine and ancillary costs and 36.6 percent of variation in NTA costs for institutional care, based on the R^2 statistics for the two cost components.[8] P/C ratios are lowest for the lower-function groups (1.027 for very low function and 1.024 for low function) and high for the high function groups (1.363 for high function and 1.351 for very high function). Thus, the base model would result in relative overpayments for high-functioning patients and relative underpayments for low-functioning patients.

TABLE 2

Explanatory Power of Alternative PAC Cost Models and Resultant Payment-to-Cost Ratios, by Function Group

	R^2 Statistics		Model Payment-to-Cost Ratio				
Model	Routine and therapy cost	Non-therapy ancillary cost	Very low function	Low function	Medium function	High function	Very high function
1. Base model (unified PAC PPS MedPAC demonstration model)	0.483	0.366	1.027	1.024	1.155	1.363	1.351
2. Base model + indicators of total function points	0.497	0.386	1.103	1.103	1.103	1.103	1.103
3. Base model + four function measures (walking, toileting, transferring, eating)	0.500	0.403	1.115	1.085	1.103	1.144	1.089
4. Base model + PAC setting indicators	0.507	0.500	1.074	1.005	1.151	1.341	1.425
5. Base model + urban status and facility/ownership type	0.493	0.366	1.027	1.017	1.158	1.376	1.376
6. Base model estimated with OLS instead of Poisson regression	0.473	0.414	1.030	1.025	1.151	1.367	1.309

Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data and matched assessment data.

Notes: PAC = post-acute care. PPS = prospective payment system. MedPAC = Medicare Payment Advisory Commission. OLS = ordinary least squares. *N* = 2,879,329; *N* = 988,040 for nontherapy ancillary cost equation. Nontherapy ancillary cost model excludes home health episodes.

Including indicators for the level of patient function in the cost equation, as we do in model 2, eliminates differences in P/C ratios by function group, as we would expect. Patients in each group would have identical P/C ratios of 1.103. R^2 for the routine and therapy cost equation increases to 0.497 from 0.483 in the base model. R^2 in the NTA cost equation increases to 0.386 from 0.366. Although this would equalize P/C ratios according to measured function status, because there is evidence that functional status is mismeasured to a substantial degree, the implied payment adjustments for functional status may not track differences in expected patient costs that reflect true patient condition.

Another way to reduce variation in P/C ratios by level of patient function would be to include indicators for the four individual function domains used to construct the common PAC function levels (walking, toileting, transferring, and eating), as we do in model 3. R^2 statistics are somewhat higher in model 3 than in model 2. P/C ratios range from 1.085 for low function to 1.144 for high function, which is much closer to uniform than in the base model. Like model 2, however, this model would depend on subjective provider-reported measures that are subject to misreporting.

In the remaining models of table 2, we sought to explore some possible alternative explanations for the pattern of P/C ratios in model 1. The models answer, in turn, whether PAC setting, provider characteristics, or regression model functional form (Poisson versus linear) explain the function-profitability relationship. A design feature of the base model is that it does not include indicators for each institutional PAC setting but, rather, only includes an indicator for home health to distinguish it from the others and reflect the very different cost structure of home health. In model 4, we include indicators for each PAC setting (less one for the reference group), which improves R^2 values relative to the other models but results in even greater spread in P/C ratios by function group.

Model 5, which adds urban status and indicators for PAC facility type (hospital-based versus freestanding) and ownership type, produces results similar to the base model. Model 6 checks whether it makes any difference to estimate the base model equation using standard linear regression rather than Poisson regression. The alternative estimation approach results in a somewhat lower R^2 for routine and therapy cost and a higher R^2 for NTA costs, but it results in findings for P/C ratios by function group similar to those in the base model.

Predicting Functional Status Using Proxy Measures of Function

In table 3, we examine how well we can predict patient functioning using alternative proxy measures and modeling approaches. In model 1, we predict total function points (using the PAC function index), using the set of predictor variables in the base PAC PPS cost model (102 variables). The model explains 16.2 percent of variability in total function based on R^2. Model 2 adds 503 CCSR diagnosis groups to model 1, which increases R^2 from 0.162 to 0.203. This suggests there is some, but limited, ability to better predict function using additional diagnostic details.

TABLE 3

Explanatory Power of Models of Total Function Points

Model and proxies of functional status	*N*	Number of predictors	R^2
1. OLS using base model predictors	2,879,329	102	0.162
2. OLS using base model predictors PAC PPS and CCSR indicators	2,879,329	605	0.203
3. Groups from CART model estimated with base model and CCSR predictors (13 groups)	949.535	12	0.117
4. Groups from CART model estimated with base model and CCSR predictors (42 groups)	949.535	41	0.140
5. OLS using base model predictors, CCSR indicators, 42 CART groups	2,879,329	644	0.207
6. OLS using base model predictors + ICD-10-CM frailty indicators (and Z codes)	2,879,329	141	0.200

Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings, hospital claims data, and matched assessment data.

Notes: OLS = ordinary least squares. PAC PPS = post–acute care prospective payment system. CCSR = Clinical Classification Software Revised. CART = Classification and Regression Tree. CART models were estimated using a random subsample of one-third of stays.

Models 3 and 4 use indicators from the 13-group and 42-group CART models, respectively, to predict total function points. R^2 statistics from the models are 0.117 and 0.140, respectively. Although they explain less variability in function points on their own than model 1, models 3 and 4 may add incremental value in predicting function (and ultimately costs) by capturing interaction effects among the base model variables. To test this, model 5 adds indicators from the larger CART model (model 4) to model 2 (base predictors + CCSR indicators). Model 5 has an R^2 of 0.207, which is only a slight improvement over model 2. This suggests that though there may be some meaningful interaction terms to consider, the interactions deemed most important through the CART algorithm, collectively, have a negligible effect explaining variation in total function points net of the main effects already captured in model 2.

In model 6, we add 141 ICD-10-CM frailty indicators and Z codes to model 1, which gives an R^2 value of 0.200. Including these additional predictors shows an increase in explanatory power relative to the base model, similar to what we found when we added the CCSR variables in model 2.

Explanatory Power and P/C Ratios of Function Groups for PAC Cost Models Using Proxies for Functional Status

The analyses in table 4 examine whether including the proxies of functional status in the PAC PPS cost model can improve the prediction of PAC costs. More importantly, the analyses also examine whether the proxies can narrow the spread of P/C ratios across the patient functioning groups. The overall finding is that cost model predictability can be improved somewhat, but none of the proxies for functional status we have considered can substantially narrow the differences in P/C ratios by function group.

TABLE 4

Explanatory Power of Alternative PAC Cost Models Using Proxies for Functional Status and Resultant Payment-to-Cost Ratios, by Function Group

Model	R^2 Statistics		Model Payment to Cost Ratio				
	Routine and therapy cost	Non-therapy ancillary cost	Very low function	Low function	Medium function	High function	Very high function
1. Base model (unified PAC PPS demonstration model)	0.483	0.366	1.027	1.024	1.155	1.363	1.351
2. Base model + CCSR indicators	0.502	0.427	1.057	1.027	1.142	1.329	1.343
3. Base model + 42-group CART	0.489	0.375	1.030	1.029	1.152	1.350	1.327
4. Base model + CCSR indicators + 42-group CART	0.505	0.433	1.058	1.029	1.142	1.324	1.329
5. Base model + ICD-10-CM frailty indicators (and Z codes)	0.488	0.389	1.041	1.022	1.150	1.355	1.349
6. Base model + CCSR indicators + 42-group CART + squared prediction of total points	0.507	0.441	1.059	1.031	1.141	1.317	1.317
7. Base model + CCSR indicators + 42-group CART + predicted probability of high function	0.507	0.441	1.058	1.032	1.141	1.313	1.312

Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data, and matched assessment data.

Notes: PAC PPS = post–acute care prospective payment system. CCSR = Clinical Classification Software – Revised. CART = Classification and Regression Tree. *N* = 2,879,329; *N* = 988,040 for nontherapy ancillary cost equation. Nontherapy ancillary cost model excludes home health episodes.

Model 1 is the same base model as shown in table 2, repeated for reference. Model 2 includes the CCSR indicators, which increases the R^2 of the routine and therapy cost equation from 0.483 to 0.502 and increases that of the NTA cost equation from 0.366 to 0.427. Adding the 42-group CART model (model 3) and the ICD-10-CM frailty indicators and Z codes (model 5) shows less improvement in R^2 values than model 2. Results for model 4, which adds the CCSR and CART model indicators at the same time, show little improvement over results for model 2.

Models 6 and 7 try to improve on model 4 by including nonlinear functions of the predictors. Model 6 adds the square of predicted total function points (from model 5 in table 3). Model 7 adds the predicted probability of being high or very high functioning, based on a logistic model using the same predictors. Both offer only small improvement over model 4. Model 6 raises the P/C ratio for very low–functioning patients the most (from 1.024 to 1.059). Model 7 reduces the P/C ratio for very high–functioning patients the most (from 1.351 to 1.312).

Despite adding a large number of potential proxies for functional status to the base model, some of which improve the overall prediction of PAC patient costs, none of the proxy variable models are able to substantially narrow the range of P/C ratios that result from leaving functional status out of the base model.

Conclusion

We examined whether it is possible to find variables with available claims-based data that may serve as proxies for functional status in a unified PAC PPS. If we could find proxies for functional status that were less subject to misreporting by providers, including them in the PAC PPS risk models could allow payments to better reflect true patient functional status. Using more recent data on Medicare PAC patients in 2017, we confirmed earlier findings that patients with higher levels of function would be substantially more profitable under the unified PAC PPS without including a direct measure of functional status in the risk adjustment. We explored whether there are feasible proxies for functional status based on a review of the literature on predicting functional status.

After considering a wide range of proxy measures, we find that claims-based proxy measures are unlikely to adequately account for functional status in a unified PAC PPS. Though proxies of functional status offer some ability to improve the explanatory power of the PAC PPS payment models, none of the options we explored come close to equalizing P/C ratios across patient function groups. Our findings suggest policymakers will need to either accept the potential for gaming of functional measures (if function is included in the risk adjustment) or accept allowing large differences in patient profitability (if function is excluded from the risk adjustment) that could lead providers to avoid predictably unprofitable patients in a unified PAC PPS. Our findings also highlight the importance of validating the patient assessment data.

Appendix A. Review of the Literature on Predicting Patient Functional Status

Background

We scanned the academic literature on potential proxies for functional status that may be relevant to MedPAC's work developing a unified PAC payment system. A complete annotated bibliography follows. To summarize our findings, we have organized them into avenues of investigation that appeared promising based on background discussion with experts. These include frailty indexes, comorbidity and multimorbidity indexes, DME claims, prescription drug claims, outpatient claims, and ICD-10 diagnosis codes. This summary focuses on literature that attempted to predict or explain contemporaneous function, but we also include literature predicting functional decline and other outcomes where relevant (as described in the annotated bibliography).

Frailty Indexes

The literature includes several frailty indexes based on administrative data that attempt to predict patients' current level of frailty (Segal et al. 2017), patients' current activities of daily living (ADL) dependency (Kinosian et al. 2018), morbidity and mortality among frail adults (Kim et al. 2018; Kinosian et al. 2018; Zucchelli et al. 2019), or patients' Medicare costs (Johnston, Wen, and Joynt Maddox 2020). In general, the predictive power of these frailty indexes was not tested against HCCs or other measures of comorbidity. However, Johnston, Wen, and Joynt Maddox (2020) tested whether adding a frailty index to HCCs better predicted Medicare costs.

Kim and colleagues (2018) found that a claims-based frailty index that included Healthcare Common Procedure Coding System (HCPCS) codes for home hospital beds, wheelchairs, walking aids, accessories for oxygen delivery devices, diabetes supplies and diabetic footwear, and transportation services, including ambulance, had a small but statistically significant advantage in predicting disability, mobility impairment, and falls over a comorbidity index, but the study did not include HCCs. However, frailty indexes that were tested alongside functional status performed worse than functional status in predicting morbidity and mortality (Kinosian et al. 2018).

Johnston, Wen, and Maddox (2020) assessed whether HCC-based predictions of Medicare costs could be improved with the addition of the claims-based frailty index developed by Kim and colleagues (2018). They found that a risk adjustment model including both HCCs and the claims-based frailty index better predicted annual Medicare costs for community-dwelling beneficiaries, on average, across four frailty groups (ranging from robust to severe frailty) and for dual-eligibles. However, neither the HCC model nor the model including HCCs and the claims-based frailty index captured the wide variation in observed annual Medicare costs within each frailty group, and beneficiaries in long-term care were excluded from the analysis.

Kim and Schneeweiss (2014)'s meta-analysis of studies using claims-based multivariate models to predict frailty or disability only found 3 relevant models in 152 reports, and the paper suggested all models had limitations, such as possible overestimation, as covered in the DME and outpatient sections of Davidoff and colleagues (2013), or limited generalizability and modest performance, as covered in the prescription drug section of Dubois and colleagues (2010) and in Rosen and colleagues (2000, 2001)[9].

Overall, there is some evidence that the claims-based frailty index could improve prediction of Medicare costs when added to HCCs, though it was not tested for beneficiaries in long-term care. The claims-based frailty index includes services and devices received outside the hospital and PAC settings, however, such as wheelchairs, ambulance transport, and home hospital beds.

Comorbidity and Multimorbidity

The Charlson Comorbidity Index, first discussed in Charlson and colleagues (1987), has been found to have similar performance to other comorbidity indexes in predicting mortality. In general, studies of comorbidity indexes found very modest predictive value for functional status at discharge and poor predictive value for functional decline. For example, Wallace and colleagues (2016) compared the performance of five comorbidity and multimorbidity indexes in predicting functional decline in community-dwelling adults and found poor discrimination for all five models.

In addition, three studies (Kumar et al. 2015; Kumar, Graham, Resnik, Karmarkar, Deutsch, et al. 2016; Kumar, Graham, Resnik, Karmarkar, Tan, et al. 2016) suggested comorbidity indexes and HCCs provide very modest ability to predict discharge functional status for patients with stroke, lower-extremity fracture, or joint replacement. Kumar and colleagues (2015) and Kumar, Graham, Resnik, Karmarkar, Deutschby, and colleagues (2016) also indicated that HCCs performed better than the Charlson Comorbidity Index, the Elixhauser Comorbidity Index, the tier comorbidity system, and the functional comorbidity index in predicting discharge functional status (Kumar et al. 2015) or readmission rates for stroke and joint replacement across functional status groups (Kumar, Graham, Resnik, Karmarkar, Tan, et al. 2016).

Finally, Noyes, Liu, and Temkin-Greener (2008) developed pairs of comorbidities based on prior evidence of synergy between condition pairs and ADL deficiencies to try to examine the implications of the HCC model on Medicare payments for individuals with comorbid conditions. They found underprediction of payments for patients with multiple comorbidities, including heart failure and osteoporosis, heart failure and dementia, stroke and arthritis, and stroke and hypertension. These multimorbidities were also associated with ADL deficiencies.

Overall, the literature suggests comorbidity and multimorbidity indexes have very modest predictive value and the differences among indexes are quite small. The results from Noyes, Liu, and Temkin-Greener (2008) suggest some possible additions to the model if those combinations are not already captured by the JEN Frailty Index already included in the PAC PPS model.

Durable Medical Equipment Claims

Several studies explored whether claims for particular types of DME were associated with functional status. First, Faurot and colleagues (2015) found that charges for a home hospital bed and a wheelchair were strong predictors of contemporaneous ADL dependency. They used the Medicare Current Beneficiary Survey (MCBS) in a model that also included a subset of ICD-9 codes thought to be associated with frailty (but not HCCs). Home oxygen therapy was also a statistically significant predictor of functional status.

In addition, Kim and colleagues (2018) found that a claims-based frailty index that included HCPCS codes for home hospital beds, wheelchairs, walking aids, accessories for oxygen delivery devices, diabetes supplies and diabetic footwear, and transportation services, including ambulance, had a small but statistically significant advantage in predicting disability, mobility impairment, and falls over a comorbidity index, but the study did not include HCCs.

Finally, Davidoff and colleagues (2013) developed a claims-based prediction model for disability status and found that DME use, particularly wheelchairs and hospital beds, was associated with disability status as defined in the study.

Overall, DME claims for wheelchairs, home hospital beds, and home oxygen therapy appear to be consistently associated with functional status across studies, but it is unclear how such claims would be incorporated into a unified PAC PPS, given that such equipment is primarily used at home. In addition, tying PAC payments to DME use could create adverse incentives to modify DME use.

Prescription Drug Claims

Byrne and colleagues (2019) assessed the association between a drug burden index score (a measure of exposure to medications with anticholinergic and/or sedative side effects) and functional status in community-dwelling older adults in Ireland, finding that high drug burden index exposure was significantly associated with impaired function. However, the drug burden index was not associated with health care utilization, and the study did not control for diagnoses.

Dubois and colleagues (2010) created a chronic disease score for disability in older adults using outpatient prescription drug claims, and it was modestly predictive of disability. However, the study used prescription drug claims as an alternative approach to identifying diagnoses and did not test its approach against ICD-9 or ICD-10 codes, HCCs, or other diagnosis-based indexes.

Overall, it is unclear whether using prescription drugs to identify diagnoses is superior to ICD-9 or ICD-10 codes for MedPAC's purposes. In addition, the drug burden index score captures only exposure to drugs that can cause drowsiness, sedation, confusion, and/or delirium as side effects, rather than capturing the broader range of conditions associated with functional decline. Further, the index is focused on quantifying risks to community-dwelling older adults.

Outpatient Claims or Electronic Health Records

In addition to DME claims, Faurot and colleagues (2015) found that ambulance transport and/or CPR, stroke or brain injury, heart failure, diabetes complications, decubitus ulcers, paralysis, weakness, difficulty walking, sepsis, podiatric care, and having a prior nursing home stay were statistically significant predictors of contemporaneous ADL dependency. The authors used the MCBS in a model that also included other ICD-9 codes (not HCCs). Similarly, Davidoff and colleagues (2013) found that ambulance use, neurology evaluation and management visits, and certain procedures (e.g., minor skin procedures, major orthopedic procedures) were associated with disability status.

Kurichi and colleagues (2017) used MCBS data to attempt to predict functional deterioration and found 16 factors that increased the risk of functional deterioration. Of these, most were diagnoses already included in HCCs. However, the following were significantly associated with functional decline and could be considered for addition to the models, depending on their availability in claims or assessment data: hearing impairment, vision impairment, living arrangement, and proxy use.

To attempt to assess the economic burden of multiple sclerosis patients on Medicare, Gilden, Kubisiak, and Zbrozek (2011) used prior outpatient treatment history to classify multiple sclerosis patients as progressive versus relapsing-remitting, which had a significant effect on Medicare expenditures. Such approaches would need to be implemented on a diagnosis-by-diagnosis basis, however, likely making this approach impractical for a unified PAC PPS.

Finally, Zucchelli and colleagues (2019) found that walking speed, as measured by nurses, was a significant predictor of mortality, but this measure is not currently available on the PAC assessments.

These studies suggest some possible additions to the risk-adjustment model from outpatient claims or assessments, such as ambulance use, neurology evaluation and management, hearing impairment, vision impairment, living arrangement, and proxy use. However, it is unclear how much predictive value such additions would have beyond HCCs and the JEN Frailty Index already included in the PAC PPS model.

ICD-10 Diagnosis Codes

Sundararajan and colleagues (2004) translated the Charlson Comorbidity Index from ICD-9 to ICD-10 and found no loss of performance, suggesting that updating comorbidity indexes to ICD-10 will not significantly alter risk adjustment results.

Gilbert and colleagues (2018) used ICD-10 to create a hospital frailty risk score to predict adverse outcomes in the UK. The hospital frailty risk score included codes new in ICD-10, such as Z73 – problems related to life management difficulty. The hospital frailty risk score overlapped significantly with other measures of frailty, however, and discriminated weakly between individuals with different outcomes within hospitals.

Though ICD-10 may provide some opportunities to code functional status in hospital and outpatient settings, it is unclear whether the ICD-10 Z codes are widely used in the US. We did not find any studies assessing the use of ICD-10 Z codes in predicting functional status.

Annotated Bibliography

Impact of Drug Burden Index on Adverse Health Outcomes in Irish Community-Dwelling Older People: A Cohort Study
Byrne, CJ, C Walsh, C Cahir, and K Bennett
BMC Geriatrics (2019) 19:121. https://doi.org/10.1186/s12877-019-1138-7
Objective: To assess the association between the Drug Burden Index (DBI) tool and functional status and other health outcomes. The DBI tool produces a score quantifying use of medications with anticholinergic and/or sedative effects.
Study sample: Community-dwelling Irish adults aged 65+ from the Irish Longitudinal Study on Ageing who were also enrolled in General Medical Services.
Outcomes: Any ADL impairment, any instrumental activity of daily living (IADL) impairment, self-reported fall in the past 12 months, any frailty (Fried Phenotype measure), quality of life score (Control Autonomy Self-Realisation Measure), any hospital admission in the past 12 months, any ED visit in the past 12 months.
Methods: The study estimated multivariate logistic and linear regression models with DBI exposure as the dependent variable. DBI exposure was categorized as none (0), low (between 0 and 1), and high (1+). All models controlled for potential cofounders.
Main findings: In the year before outcome assessment, 61.3% of the study subjects had received one or more DBI prescriptions. High DBI exposure (1+) was associated with impaired function as measured by ADLs and IADLs (ADL impaired adjusted OR 1.89, IADL impaired adjusted OR 2.97), self-reported falls (adjusted OR 1.5), frailty (adjusted OR 1.74), and lower quality of life (-1.84). DBI exposure was not statistically associated with health care use.
Generalizable to PAC users in Medicare? Unclear. The age range is appropriate, but the study isn't limited to PAC patients, and differences in health systems could affect results.
Results suggest new variables to test as proxies for function? DBI index could be useful at predicting function for some patients, but prescription drug data would be required.

A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation
Charlson ME, P Pompei, KL Ales, CR MacKenzie
J Chron Dis (1987) 40 (5): 373–83
Objective: To classify comorbid conditions that might predict mortality risk.
Study sample: The model was trained on 559 patients admitted to New York Hospital-Cornell Medical Center during one month in 1984. The model was tested on 685 women with breast cancer who received their first treatment at Yale New Haven Hospital between 1962 and 1969.
Outcomes: Mortality, survival in months.
Methods: This study assessed survival rates by the life table method. The researchers coded each comorbid condition as present or not present, and condition severity on a scale from 1 to 5 (not ill to moribund). The relationship between mortality and the independent variables was assessed using Cox's regression method, controlling for other comorbid conditions, illness severity, reason for admission, and age.
Main findings: The study developed a weighted comorbidity index to assess both the number of comorbid conditions and their severity simultaneously. With each increase in this index, there were corresponding increases in the cumulative mortality attributable to comorbid disease. Age was also a

predictor of mortality. Overall, the Charlson Comorbidity Index performed similarly to the Kaplan-Feinstein Index.
Generalizable to PAC users in Medicare? This comorbidity index has been used extensively for the Medicare population (see other publications in this bibliography).
Results suggest new variables to test as proxies for function? Unclear if this index would add any predictive power beyond the HCCs already in use.

Statistical Methods to Compare Functional Outcomes in Randomized Controlled Trials with High Mortality
Colantuoni, E, DO Scharfstein, C Wang, MD Hashem, A Leroux, DM Needham, TD Girard
BMJ Open Access (2018) 36: j5748. http://dx.doi.org/10.1136/bmj.j5748
Objective: To assess three statistical approaches to evaluating likely functional outcomes for decedents in RCTs with high mortality. These three statistical approaches include: survivors analysis, survivor average causal effect, and composite endpoint.
Study sample: Meta-analysis of three RCTs.
Outcomes: Functional status.
Methods: Describe three approaches to assessing functional status changes in RCTs with seriously ill patients when some participants die prior to functional assessment. Compare how these three approaches would affect conclusions about the effectiveness of treatment on functional status using an example randomized controlled trial.
Main findings: Each approach to assessing functional outcomes in RCTs when some participants die before functional outcomes can be assessed has benefits and drawbacks. Researchers should choose the measure that best fits the expected effects of the intervention and by their target patient population. For example, in RCTs where there is no biological reason to suspect that treatment assignment will affect mortality, survivors analysis provides an unbiased estimate. In contrast, if the treatment is expected to affect mortality rates, survivors analysis would produce misleading results. In that case, alternatives like the composite endpoint approach would produce more reliable estimates.
Generalizable to PAC users in Medicare? Yes, but only in the context of RCTs for treatments to improve longevity or functional status.
Results suggest new variables to test as proxies for function? No.

A Novel Approach to Improve Health Status Measurement in Observational Claims-Based Studies of Cancer Treatment and Outcomes
Davidoff, AJ, A Hurria, IH Zuckerman, SM Lichtman, N Pandya, A Hussain, F Hendrick, JP Weiner, X Ke, MJ Edelman
J Geriatr Oncol (2013), 4 (2): 157–65
Objective: To validate and assess a multivariate, claims-based prediction model for disability status among adults aged 65+.
Study sample: 2001–2005 MCBS for Medicare beneficiaries ages 65 and older.
Outcomes: Disability status summary measure based on self-reported functional status, strength, stamina, and exercise. The summary measure was grouped into dichotomous indicators for good disability status (DS = 0–2) and poor disability status (DS = 3–4).
Methods: Independent variables were BETOS indicators from physician or hospital claims, grouped into preventive services, evaluation and management visits, other visit types, minor or ambulatory procedures, major procedures, imaging, durable medical equipment use, and other. Explanatory variables were selected using stepwise logistic regression with poor disability status as the dependent variable (a 95 percent significance level was used for variable entry and exit). The optimal model was the one with the lowest Akaike information criterion. Interactions were permitted within health care service indicators and between service indicators and region and enrollment in Medicare Savings Programs.

The study tested model fit by generating a predicted disability status measure from model results. This predicted disability status was then compared to survey-based disability status for both the estimation and validation samples.

Main findings: Nursing home stays, home care, and ambulance use were associated with a higher probability of poor disability status. In contrast, vaccinations, screenings, and cardiac monitoring and stress tests were associated with a lower probability of poor disability status. For the validation sample, the positive predictive value of the model without interactions was 48.3 percent and negative predictive value was 97.8 percent.

Generalizable to PAC users in Medicare? Yes, the study sample isn't limited to cancer patients.

Results suggest new variables to test as proxies for function? Ambulance use, DME, and certain types of evaluation and management visits (neurology) and procedures (minor skin procedures, major orthopedic procedures) were associated with poor disability status. Most of these would need to come from outpatient claims.

Assessing Comorbidity in Older Adults Using Prescription Claims Data

Dubois, MF, N Dubuc, E Kroger, R Girard, R Hebert

Journal of Pharmaceutical Health Services Research (2010), 1: 157–65

Objective: To develop and validate a new comorbidity index based on outpatient prescription claims from community pharmacies: the Chronic Disease Score for Disability in Older Adults (CDS-DOA).

Study sample: Community-dwelling Canadian adults ages 75 and older identified as at risk for functional decline who were part of the Program of Research to Integrate Services for the Maintenance of Autonomy study.

Outcomes: Disability score (based on 29 functions covering ADLs, mobility, communication, mental functions, and instrumental ADL). Alternative outcomes included number of diseases, the number of diseases included in the CDS-DOA, and the number of distinct prescription medications.

Methods: Using prescription claims over a six-month period, the researchers created a binary variable for each disease to indicate use of a medication for that condition. The study employed OLS regressions to estimate the value of each disease for predicting disability in the development sample, and the model was reduced via backward elimination (p = 0.05). The authors then constructed a weighted comorbidity score using the magnitude of the beta coefficient as a weight for each of the diseases included in the final model, where higher comorbidity scores indicated greater disability. The predictive ability of the CDS-DOA was assessed by examining the percentage of disability explained by the CDS-DOA score.

The relationship between the CDS-DOA score and disability was validated using a validation sample. The study also tested three alternative measures: number of diseases, the number of diseases included in the CDS-DOA, and the number of distinct prescription medications.

Each outcome was tested for correlation with existing measures of comorbidity, including self-reported health status, age, self-reported severity of chronic diseases, use of services, and functional decline, institutionalization, and death in the following year.

Main findings: In the development sample, the CDS-DOA explained 16 percent of the variance in disability, compared to 12 percent in the validation sample. The CDS-DOA showed high year-to-year stability, and was it correlated with alternative measures of comorbidity.

Generalizable to PAC users in Medicare? Yes.

Results suggest new variables to test as proxies for function? It is unlikely that the diseases covered in the CDS-DOA add to the HCCs and comorbidity index already in use. Prescription drugs were used as a vehicle for identifying diagnoses, which we already have.

Complementing Chronic Frailty Assessment at Hospital Admission with an Electronic Frailty Index (FI-Laboratory) Comprising Routine Blood Test Results

Ellis, HL, B Wan, M Yeung, A Rather, I Mannan, C Bond, C Harvey, N Raja, P Dutey-Magni, K Rockwood, D Davis, SD Searle

CMAJ 2020 January 6;192:E3–E8. https://doi.org/10.1503/cmaj.190952
Objective: To validate a frailty index based on routine hospital admission laboratory tests.
Study sample: A prospective cohort of 1,750 older adults representing 2,552 admissions to a large tertiary hospital in the United Kingdom between April 2015 and January 2017.
Outcomes: Days spent in hospital, discharge to a higher level of care, readmission, and mortality.
Methods: The authors created a frailty index from routine admission laboratory investigations (FI-Laboratory) linked to data on in-hospital and post-hospital outcomes. They evaluated the association between the FI-Laboratory and total days spent in the hospital, discharge to a higher level of care, and readmission and mortality, controlling for age, sex, clinical frailty scale score, presence of dementia, presence of delirium, a history of falls, and residence at admission.
Main findings: The FI-Laboratory was only weakly correlated with the Clinical Frailty Scale (CFS; R^2 = 0.09). An increase in the Clinical Frailty Scale and the FI-Laboratory, respectively, were associated with longer inpatient stays, discharge to a higher level of care (odd ratios 1.39, and 1.30), and a higher readmission rate (1.26 and 1.18). Higher Clinical Frailty Scale and FI-Laboratory scores were also associated with increased mortality (Hazard Ratios 1.39 and 1.45).
Generalizable to PAC users in Medicare? Possibly, though the outcomes do not focus on PAC specifically. Also, health systems differ.
Results suggest new variables to test as proxies for function? Laboratory test results are not available in routine Medicare claims data. It is also unclear if lab results could be consistently compared across hospitals. This study focused on within-hospital differences.

Using Claims Data to Predict Dependency in Activities of Daily Living as a Proxy for Frailty
Faurot, KR, MJ Funk, V Pate, MA Brookhart, A Patric, LC Hanson, WC Castillo, T Sturmer
Pharmacoepidemiol Drug Saf (2015) 24 (1): 59–66. https://doi.org/10.1002/pds.3719
Objective: To develop an algorithm to predict ADL dependency among Medicare beneficiaries to improve control for confounding frailty in population-based studies of drug effectiveness and safety among older adults.
Study sample: 2006 MCBS respondents residing in the community aged 65+ with Medicare claims appended to their MCBS record (Part A, Part B, home health, and/or hospice claims). Final sample was 6,391.
Outcomes: ADL dependency, including needing help with bathing, eating, walking, dressing, toileting, or transferring; mortality.
Methods: The authors used multivariate logistic regression to predict ADL dependency. Independent variables of interest included demographics, ICD-9 diagnosis/procedure codes, CPT codes, HCPCs codes, and durable medical equipment codes for frailty-associated conditions. The study employed Cox models to estimate mortality hazard ratios as a function of ADL dependency.
Main findings: ADL dependency was strongly predicted by charges for a home hospital bed (OR 5.44) and wheelchair (OR 3.91). Several other independent variables were statistically significant predictors of ADL dependency, including home oxygen therapy, ambulance transport and/or CPR, stroke or brain injury, heart failure, diabetes complications, decubitus ulcer, paralysis, weakness, difficulty walking, sepsis, podiatric care, and a prior nursing home stay. The overall c-statistic for the model including diagnoses and procedures was 0.845, compared with 0.70 for a model with demographics only.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? It is unclear how much predictive power the additional DME, diagnoses, and procedures would add to the HCCs already in use. Potential avenues to explore include DME claims for home-hospital beds, wheelchairs, and home oxygen therapy; ambulance transport; podiatric care claims; diagnoses for weakness and difficulty walking (if not included in HCCs); and prior SNF use.

Development and Validation of a Hospital Frailty Risk Score Focusing on Older People in Acute Care Settings Using Electronic Hospital Records: An Observational Study

Gilbert, T, J Neuburger, J Kraindler, E Keeble, P Smith, C Ariti, S Arora, A Street, S Parker, HC Roberts, M Bardsley, S Conroy
Lancet 2018; 391: 1775–82. http://dx.doi.org/10.1016/S0140-6736(18)30668-8
Objective: To assess whether frailty among older people can be identified using routinely collected hospital data.
Study sample: The study used the 2013–14 and 2014–15 Hospital Episode Statistics inpatient database, a data repository for all patients admitted to National Health Service hospitals in England. The development cohort was an 80 percent random sample of patients ages 75 and older living in Southampton, Leicester, or Nottingham and discharged from the hospital after an elective, nonelective, or day case admission between April 1, 2013, and March 31, 2015. The validation cohort included patients aged 75+ admitted to an acute hospital as an emergency between April 1, 2014, and March 31, 2015.
Outcomes: 30-day mortality; long hospital stay (>10 days); emergency readmission within 30 days.
Methods: The authors conducted a cluster analysis to identify patients with high resource use and diagnoses associated with frailty. They created a hospital frailty risk score based on ICD-10 codes that characterized this group. Then, in validation cohorts, the authors tested how well the hospital frailty risk score predicted adverse outcomes. They also assessed whether it identified similar high-risk groups as other frailty tools. In the validation sample, logistic regression models were used to estimate the association between the hospital frailty risk score and the outcomes noted above. Models were estimated with and without adjustment for age, sex, socioeconomic status, admission history, and Charlson Comorbidity Index and included hospital random effects.
Main findings: In the national validation cohort, the patients with the highest Hospital Frailty Risk Scores had higher 30-day mortality (odds ratio 1.71), longer hospital stays (6.03), and 30-higher day readmission rates (1.48) than patients with the lowest Hospital Frailty Risk Scores. The Hospital Frailty Risk Score was moderately correlated with other frailty scales.
Generalizable to PAC users in Medicare? Unclear if the index would be applicable to Medicare payment system, 65- to 75-year-olds, or community admits.
Results suggest new variables to test as proxies for function? May point to some potentially useful ICD-10 codes that are not included in HCCs, such as Z73 – problems related to life management difficulty.

The Economic Burden of Medicare-Eligible Patients by Multiple Sclerosis Type
Gilden, DM, J Kubisiak, AS Zbrozek
Value in Health 14 (2011) 61–69. https://doi.org/10.1016/j.jval.2010.10.022
Objective: To examine the variation in Medicare spending by multiple sclerosis (MS) type using a claims-based classification algorithm.
Study sample: Traditional Medicare beneficiaries with MS in 2003 to 2006. MS patients were those with an ICD-9 code from an office visit or hospitalization of 340 in the 2003–2006 US national Medicare 5 percent sample.
Outcomes: All-cause Medicare expenditures.
Methods: Patients were grouped by their 2006 status as prevalent or incident cases. The authors stratified prevalent cases into relapsing-remitting MS or progressive MS, using patterns of nursing home, home health, and rehab or DME use over time. Relapsing-remitting patients were those with periods of supportive care followed by periods of decreased or no care, whereas progressive patients were those with increasing supportive care over time. Multivariate analyses controlled for demographics, eligibility characteristics, and comorbid chronic disease and mental health conditions. The authors selected covariates using a forward stepwise approach with $p < 0.05$ required for model entry and final inclusion. The independent variable in all analyses was total 2006 Medicare expenditures.
Main findings: MS patient classifications based on claims data showed substantial differences in Medicare expenditures, with progressive cases far more expensive than relapsing-remitting cases.
Generalizable to PAC users in Medicare? No.

Results suggest new variables to test as proxies for function? Prior treatment history could be useful for certain conditions but is likely too complex to implement. MS, in particular, is a rare disease, so wouldn't be the right place to start.

The Development of a Comorbidity Index with Physical Function as the Outcome
Groll, DL, T To, C Bombardier, JG Wright
Journal of Clinical Epidemiology. (2005) 58: 595–602. https://doi.org/10.1016/j.jclinepi.2004.10.018
Box link: https://urbanorg.box.com/s/5lr5cxy87silydzrifmaomodyljqrvia
Objective: To assess and validate a self-administered functional comorbidity index to predict physical function.
Study sample: Participants in the Canadian Multi Centre Osteoporosis Study (cross-sectional random sample of 9,423 Canadian adults) and a sample of 28,349 US adults seeking treatment for spine ailments from the National Spine Network.
Outcomes: SF-36 physical function scale.
Methods: The study first identified potential predictors of function through a literature review and focus groups with patients and health care providers. The authors grouped the predictors identified through the literature review and focus groups by clinical and diagnostic similarity, and comorbidities were included in linear regression models as binary variables. The final functional comorbidity index contains 18 diagnosis groups defined by ICD-9 codes. The authors estimated multiple linear regression models with SF-36 physical function score as the dependent variable. The study used forward, backward, and stepwise independent variable entry with a cutoff p-value of 0.05.
Main findings: The functional comorbidity index was more strongly associated with SF-36-measured physical function than the Charlson Comorbidity Index or the Kaplan-Feinstein index (R^2 of 0.29, 0.18, and 0.07, respectively). In over three-quarters of cases (77%), the functional comorbidity index correctly classified patients as high or low function.
Generalizable to PAC users in Medicare? The index was developed using a younger population, with average ages of 62 for the Canadian sample and 49 for the American sample. It is unclear how the index would perform for PAC older adults.
Results suggest new variables to test as proxies for function? The 18 diagnosis groups that form the functional comorbidity index could be tested as an addition to HCCs, if there are diagnoses present in the functional comorbidity index that are excluded from HCCs (e.g., back pain, anxiety, visual impairment). The study team would need to translate these diagnosis groups into ICD-10 codes. However, see Kumar, Graham, Resnik, Karmarkar, Tan, and colleagues (2016) for a test of HCCs versus the functional comorbidity index in the Medicare population.

Relationship of a Claims-Based Frailty Index to Annualized Medicare Costs: A Cohort Study
Johnston, KJ, J Wen, KE Joynt Maddox
Ann Intern Med. 2020;172:533–40. https://doi.org/10.7326/M19-3261
Objective: To explore whether a claims-based frailty index can predict Medicare cost more accurately than current approaches.
Study sample: 2006–2013 MCBS linked to Medicare claims. The sample was limited to 16,535 community-dwelling, fee-for-service beneficiaries (26,705 patient-years).
Outcomes: Annualized Medicare costs.
Methods: The authors employed the claims-based frailty index in Kim and colleagues (2018) to assess patient frailty. The authors estimated regression models to assess the relationship between the frailty index and Medicare costs. The authors further estimated the variance between observed and predicted Medicare costs when using only the CMS-HCC model versus the CMS-HCC model in combination with the frailty index.
Main findings: Adding the frailty index to the CMS-HCC model improved Medicare cost prediction. When combined with the CMS-HCC model, the frailty index predicted an average of $2,712, $7,915, and $16,449 in additional costs for prefrail, mildly frail, and moderately to severely frail patients,

respectively. The combined model produced more accurate predictions at all four levels of frailty, though observed costs were still more widely distributed than predicted costs.
Generalizable to PAC users in Medicare? Yes, but the sample was limited to community-dwelling beneficiaries.
Results suggest new variables to test as proxies for function? Yes, the claims-based frailty index developed by Kim and colleagues (2018). See below.

Measuring Frailty in Medicare Data: Development and Validation of a Claims-Based Frailty Index
Kim, DH, S Schneeweiss, RJ Glynn, LA Lipsitz, K Rockwood, J Avorn
J Gerontol A Biol Sci Med Sci,2018, 73 (7): 980–87. https://doi.org/10.1093/gerona/glx229

Objective: To develop and validate a claims-based frailty index for Medicare and assess its ability to predict death, disability, recurrent falls, and health care use relative to a survey-based frailty index and the combined comorbidity index.
Study sample: 2006 and 2011 MCBS with appended claims
Outcomes: Survey-based frailty index, combined comorbidity index, death, disability, recurrent falls, and health care use
Methods: The authors used 2006 MCBS data to calculate a survey-based frailty index and a combined comorbidity index, and to develop a claims-based frailty index. Death, ADL disability, IADL disability, mobility impairment, recurrent falls, number of hospital bed days, and SNF days in 2007 were predicted using 2006 age, sex, and either the combined comorbidity index or the claims-based frailty index. The authors evaluated predictive power in two ways: C-statistics (for binary variables) and pseudo R^2 (for hospital days and SNF days). The study reports odds ratios for the survey-based frailty index and the claims-based frailty index that control for age, sex, and the combined comorbidity index. The 2011-2012 MCBS served as a validation sample, as it was not used to develop the claims-based frailty index.
Main findings: The claims-based frailty index and survey-based frailty index are correlated (correlation coefficient: 0.6). In both the development and validation sample, the claims-based frailty index was a better predictor of disability, mobility impairment, recurrent falls, and SNF days than the claims-based comorbidity index. Predictions were most accurate in the model that included age, sex, the claims-based frailty index, and the claims-based comorbidity index.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? The claims-based frailty index includes HCPCS codes for home hospital beds, wheelchairs, walking aids, accessories for oxygen delivery devices, diabetes supplies and diabetic footwear, and transportation services, including ambulance. Addition of these HCPCS codes could offer some predictive value, but the study found relatively small differences between the predictive value of the claims-based frailty index and the comorbidity index, suggesting the index may not significantly improve upon HCCs.

Measuring Frailty Using Claims Data for Pharmacoepidemiologic Studies of Mortality in Older Adults: Evidence and Recommendations
Kim, DH, S Schneeweiss
Pharmacoepidemiol Drug Saf. 2014 September 23 (9): 891–901. https://doi.org/10.1002/pds.3674
Objective: To assess and suggest improvements to claims-based models of frailty, with the goal of improving frailty adjustment in pharmacoepidemiologic studies.
Study sample: Meta-analysis using MEDLINE and EMBASE from inception through April 2014 without a language restriction.
Outcomes: N/A.
Methods: The authors identified studies of claims-based multivariable models that predicted frailty or disability and assessed each study for relevance and model performance.
Main findings: The authors identified 3 models out of 152 reports. One promising model (Davidoff et al. 2013, see above) predicted poor functional status using claims for both community-dwelling and

institutionalized older adults (C statistic, 0.92), but the authors observe that including institutionalized and hospice beneficiaries may have may have affected the results. The other two models, Dubois and colleagues (2010) and Rosen and colleagues (2000) and (2001), performed modestly and may not be generalizable. The authors did not identify any models that had been used in pharmacoepidemiologic studies.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? See assessments of underlying studies.

Validation of the JEN Frailty Index in the National Long-Term Care Survey Community Population: Identifying Functionally Impaired Older Adults from Claims Data
Kinosian, B, D Wieland, X Gu, E Stallard, CS Phibbs, O Intrator
BMC Health Services Research (2018). 18:908. https://doi.org/10.1186/s12913-018-3689-2
Objective: To test the JEN Frailty Index's (JFI) ability to predict ADL dependence, one-year long-term institutionalization, and mortality among Medicare beneficiaries.
Study sample: The 2004 National Long-Term Care Survey data for 12,000 Medicare beneficiaries linked to Medicare, Minimum Data Set, Veterans Health Administration files and vital statistics.
Outcomes: ADL dependence, one-year risk of long-term institutionalization, five-year community survival.
Methods: The authors tested whether JFI correctly identified whether individuals had multiple ADL deficiencies (>=2 or >=3) using binomial logistic regression. To test whether JFI correctly identified individuals with long-term institutionalization during the one-year follow-up period, the authors used multinomial logistic regression. For both analyses, the authors reported areas under the receiver operating characteristic curves (AUCs). The authors assessed community survival based on ADLs and JFI risks using five-year Kaplan-Meier curves with 95 percent Hall-Wellner bands.
Main findings: AUCs for functional dependency at 3 or greater or 2 or greater for JFI models controlling for age and sex were 0.807 (3 or more ADLs) and 0.812 (2 or more ADLs). The AUC for models predicting long-term institutionalization was 0.781 for the model including JFI and age, compared with 0.829 for the model including ADLs and age. Predictive accuracy for five-year community survival was similar between JFI and ADLs.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? Unclear if the JFI would add any additional predictive power beyond HCCs, and this study indicates that JFI predicts some outcomes more poorly than ADLs do. The JFI is proprietary and owned by Westat.

Comorbidity Indices Versus Function as Potential Predictors of 30-Day Readmission in Older Patients Following Post-Acute Rehabilitation
Kumar, A, AM Karmarkar, JE Graham, L Resnik, A Tan, A Deutsch, KJ Ottenbacher
J Gerentol A Biol Sci Med Sci (2016). 00(0):1–6
Objective: To compare predictions of 30-day all-cause hospital readmission following community discharge from post-acute IRFs across five comorbidity indexes.
Study sample: Medicare fee-for-service beneficiaries with stroke, lower extremity joint replacement, and fracture discharged from an IRF in 2011 (75,582).
Outcomes: 30-day all cause readmissions.
Methods: The authors predicted 30-day all-cause readmissions using logistic regression models. For each impairment, the authors estimated a base model including demographic characteristics and length of stay. The authors then estimated five subsequent models for each impairment, one for each comorbidity index. The comorbidity indexes included in this study were: the Charlson and Elixhauser Comorbidity Indexes, the tier comorbidity system, the functional comorbidity index, and HCCs. All models were estimated both with and without discharge functional status.
Main findings: Thirty-day readmission rates ranged from 6.5 percent for joint replacement to 14 percent for stroke. C-statistics ranged from 0.53 to 0.56 for the demographics-only models across impairment groups and were not improved substantially by the inclusion of any of the comorbidity

indexes (the range across indexes and impairments was 0.03 to 0.09). Adding discharge functional status to the model increased the C-statistic by 0.06 to 0.09 across conditions.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? No, HCCs performed better, in general, than other comorbidity indexes in this study. However, the authors did not test HCCs in conjunction with comorbidity indexes, so it is unclear if a comorbidity index could add marginal value to a model already containing HCCs.

Comparing Comorbidity Indices to Predict Post-Acute Rehabilitation Outcomes in Older Adults
Kumar, A, JE Graham, L Resnik, AM Karamarkar, A Tan, A Deutsch, KJ Ottenbacher
American Journal of Physical Medicine & Rehabilitation 2016). 95(12): 889–98
https://doi.org/10.1097/PHM.0000000000000527
Objective: To compare predictions of community discharge and functional status after post-acute rehabilitation across five comorbidity indexes.
Study sample: Fee-for-service Medicare beneficiaries ages 66 and older with stroke, lower-extremity fracture, and joint replacement who were discharged from an IRF in 2011 (final sample 105,275). Data were from the Beneficiary Summary File, the MEDPAR, and the Inpatient Rehabilitation Facility Patient Assessment Instrument for calendar year 2011.
Outcomes: Self-care, mobility, and cognitive function; community discharge.
Methods: The authors estimated linear regression models to assess the impact of each comorbidity index (the Charlson and Elixhauser Comorbidity Indexes, the tier comorbidity system, the functional comorbidity index, and HCCs) on discharge functional status during inpatient rehab, controlling for age, gender, race/ethnicity, Medicare qualifying disability, dual eligibility, and length of IRF stay. R^2s were compared across models to assess the predictive value of each comorbidity index. Logistic regression models were used to assess the impact of each comorbidity index (and functional status) on discharge destination.
Main findings: R^2 values for discharge to self-care, mobility, and cognition increased by 0.2 percent to 3.3 percent when the comorbidity indexes were added to the base models that included sociodemographic and clinical variables. The C-statistics for community discharge in the base model ranged from 0.58 (stroke) to 0.62 (joint replacement). These increased only 1 to 2 percent with the addition of comorbidity indexes. In contrast, The C-statistics increased more than 25 percent when discharge functional status was added to the base model.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? No. This study suggests that function is a better predictor of community discharge than comorbidity indexes, and that comorbidity indexes are poor predictors of functional status in Medicare patients using IRFs.

Examining the Association between Comorbidity Indexes and Functional Status in Hospitalized Medicare Fee-for-Service Beneficiaries
Kumar, A, JE Graham, L Resnik, AM Karmarkar, A Deutsch, A Tan, S Al Snih, KJ Ottenbacher.
Phys Ther (2015). 96(2): 232–240. https://doi.org/10.2522/ptj.20150039
Objective: To examine association between functional status as assessed at IRF admission and five comorbidity indexes (the Charlson and Elixhauser Comorbidity Indexes, the tier comorbidity system, the functional comorbidity index, and HCCs).
Study sample: Medicare fee-for-service beneficiaries ages 66 and older admitted to an IRF in 2011 after a stroke, lower-extremity joint replacement, or lower-extremity fracture. Data sources included the beneficiary summary file, the Inpatient Rehabilitation Facility Patient Assessment Instrument, and MEDPAR.
Outcomes: Motor functional status, as documented by the Functional Independence Measure in the Inpatient Rehabilitation Facility Patient Assessment Instrument (as a proxy for functional status upon hospital discharge).

Methods: The authors estimated linear regression models for each impairment group with functional status as the dependent variable. In the base models, independent variables included age, sex, race/ethnicity, disability, dual eligibility, and length of stay. These base models were compared to subsequent models including one comorbidity index each using R^2.
Main findings: Base models explained between 3.8 percent (joint replacement) and 7.7 percent (stroke) of the variation in motor function rating at IRF admission. The R^2 increased by between 0.3% and 2.8% when comorbidity indexes were added to each model. HCCs had the most predictive value across impairments (an increase of R^2 between 2.1 and 2.8 percent).
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? No, HCCs are already included, and the study suggests they have only marginal value for predicting functional status at hospital discharge.

Predictive Indices for Functional Improvement and Deterioration, Institutionalization, and Death among Elderly Medicare Beneficiaries
Kurichi, JE, PL Kwong, D Xie, HR Bogner
PM R (2017). 9(11): 1065–76. https://doi.org/10.1016/j.pmrj.2017.04.005
Objective: To identify risk factors and protective factors that may predict functional deterioration, institutionalization, and death.
Study sample: 2001–2008 MCBS respondents who were ages 65 and older and were followed for two years.
Outcomes: ADL stage transitions over two years following entry into the MCBS, categorized as follows: stable or improved function, functional deterioration, institutionalization, or death.
Methods: The index was derived in a 60 percent random sample and tested in the 40 percent sample. The index was created in five steps: (1) Covariates were identified and categorized based on prior research, and included sociodemographic, health conditions, impairments, perceived facilitators to receiving health care, perceived barriers to receiving health care, and function as indicated in prior studies. Health conditions included Alzheimer's disease, angina pectoris or coronary artery disease, complete or partial paralysis, diabetes, emphysema/asthma/COPD, hypertension, mental or psychiatric disorder, myocardial infarction, other heart conditions, Parkinson's disease, and stroke or brain hemorrhage. Impairments included severe hearing impairment or deaf and severe vision impairment or blind. (2) Chi-square tests were used to assess the association between functional transition and each covariate. (3) Candidate predictors were entered into a multinomial logistic regression model if $p < 0.2$ in step 2. (4) Multinomial logistic regression coefficients were used to derive a point-scoring system. (5) The model and point system were validated using the test cohort.
Main findings: Using backward selection ($p<0.05$), the authors identified 16 factors significantly associated with functional deterioration: age, gender, education, living arrangement, dual eligibility, proxy use, Alzheimer's disease/dementia, angina pectoris/coronary heart disease, diabetes, emphysema/asthma/COPD, mental/psychiatric disorder, Parkinson's disease, stroke/brain hemorrhage, hearing impairment, vision impairment, and baseline ADL.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? Many of the variables included in this study are not available from Medicare administrative datasets or are already included in our models. However, in future work focused on inpatient rehabilitation facility patients, one could consider adding measures of hearing impairment, vision impairment, and living arrangement, which are currently available on the Inpatient Rehabilitation Facility Patient Assessment Instrument.

Comparison of Count-Based Multimorbidity Measures in Predicting Emergency Admission and Functional Decline in Older Community-Dwelling Adults: A Prospective Cohort Study
Wallace, E, R McDowell, K Bennett, T Fahey, SM Smith
BMJ Open (2016) 6:e013089. https://doi.org/10.1136/bmjopen-2016-013089
Objective: To compare predictions of emergency hospital admissions and functional decline across five count-based multimorbidity measures.

Study sample: Community-dwelling patients ages 70 and older using 15 general practices in Ireland.
Outcomes: Emergency admission; ambulatory care sensitive admission, self-reported functional decline.
Methods: The authors estimated descriptive statistics and assessed measure discrimination using C-statistics. Estimates were adjusted for age, gender, and an address-based deprivation index. Key independent variables of interest were five multimorbidity measures: disease counts, selected condition counts, Charlson Comorbidity Index, RxRisk-V, and medication counts.
Main findings: Multimorbidity prevalence rates ranged from 37 to 91 percent, depending on the measure used. All multimorbidity measures showed poor discrimination across the outcome variables. C-statistics ranged from 0.55 (functional decline) to 0.68 (ambulatory care sensitive admission).
Generalizable to PAC users in Medicare? Unclear. The age range is appropriate, but the study isn't limited to post-acute patients, and differences in health systems could affect results.
Results suggest new variables to test as proxies for function? No.

Medicare Capitation Model, Functional Status, and Multiple Comorbidities: Model Accuracy
Noyes, K, H Liu, H Temkin-Greener
Am J Manag Care. 2008 October 1; 14(10): 679–90
Objective: To examine the effect of the CMS-HCC risk adjustment model on Medicare payments for individuals with comorbidities.
Study sample: 1992–2000 MCBS with appended claims.
Outcomes: Medicare cost ratio (ratio of individual's annualized costs to mean annual Medicare costs of entire sample).
Methods: The authors developed pairs of comorbidities based on prior evidence of a relationship between the conditions and needing assistance with ADLs. The pairs of comorbidities included in this study are as follows: heart disease and cancer, lung disease and cancer, stroke and hypertension, stroke and arthritis; congestive heart failure and osteoporosis, diabetes and coronary artery disease, and congestive heart failure and dementia. The authors compared Medicare cost ratios for each ADL level to HCC ratios from the CMS-HCC payment model. The study used multivariate regression models to examine whether including ADLs and the identified pairs of comorbidities improved accuracy of the CMS-HCC model predictions.
Main findings: For patients with hypertension, lung disease, congestive heart failure, and dementia, the CMS-HCC model underpredicts costs. Patients with multiple comorbidities had larger discrepancies between predicted and actual costs, particularly among those with congestive heart failure and osteoporosis (costs underpredicted by 30.02 percent). The number of ADLs explained some of the variation between actual and predicted costs. ADL deficiencies were particularly prevalent among patients with CHF and dementia, CHF and osteoporosis, stroke and arthritis, and stroke and hypertension.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? Perhaps add comorbidity pairs, particularly those that include conditions not accounted for in HCCs, to the model. Unclear if this approach will add any predictive value beyond current approaches to comorbidity. Combinations of CHF and dementia and CHF and osteoporosis appear particularly important.

Risk Adjustment for Measuring Health Outcomes: An Application in VA Long-Term Care
Rosen, A, J Wu, BH Chang, D Berlowitz, C Rakovski, A Ash, and M Moskowitz
American Journal of Medical Quality (2001), 16(4): 118–127
Objective: To predict functional decline among patients residing in US Department of Veterans Affairs (VA) long-term care facilities.
Study sample: VA long-term care patients with both an initial and final functional assessment occurring between April 1, 1996, and October 1, 1996. Patients with initial ADL scores high enough that decline was impossible were excluded from the sample.

Outcomes: An ADL summary score was based on eating, toileting, and transferring scores (ranging from 3 to 15). Functional decline was defined as an increase in a patient's ADL summary score of 2 or more between the baseline and semiannual assessments.
Methods: Independent variables were drawn from the literature and recommendations from clinical experts, including age, time in weeks between the baseline and follow-up assessment, baseline functional status, pressure ulcers, multiple sclerosis, terminal illness, hemiplegia, quadriplegia, and 9 diagnostic categories (heart, endocrine, musculoskeletal pulmonary, neurologic, cancer, sensory, psychiatric, and other). The authors grouped ADLs into 4 categories (ADLs 3–7, ADLs 8–9, etc.). The authors considered variables that were significantly associated with decline ($p < 0.05$) in bivariate models, as well as clinically relevant variables, for inclusion in the multivariate model. Age, baseline ADLs, and time between assessments were included in all models. Predictive ability of each model was measured using R^2 and discrimination using the C-statistic. The authors then used the model to risk adjust estimated rates of functional decline across facilities.
Main findings: Age, time between assessments, baseline functional status, terminal illness, pressure ulcers, pulmonary diseases, cancer, arthritis, congestive heart failure, substance use disorders, and various neurologic disorders were all statistically significant predictors of functional decline. The model C-statistics were 0.7 for the development sample and 0.68 for the validation sample. When the authors ranked facilities by rates of functional decline, the risk-adjusted rankings differed from the unadjusted rankings.
Generalizable to PAC users in Medicare? Perhaps for patients in long-term acute care hospitals, IRFs, and SNFs. However, long-term care populations differ substantially from those in home health.
Results suggest new variables to test as proxies for function? No. This study focused on predicting decline using baseline functional status. The conditions included in the model are likely covered by HCCs and the comorbidity index already in use.

Does Diagnostic Information Contribute to Predicting Functional Decline in Long-Term Care?
Rosen A, J Wu, BH Chang, D Berlowitz, A Ash, and M Moskowitz
Medical Care (2000), 38(6): 647–59
Objective: To determine whether ICD-9-CM diagnosis codes can be used to predict functional decline among long-term care patients.
Study sample: 15,693 VA long-term care residents in 1996.
Outcomes: Increase of >=2 in ADL summary score from baseline to semiannual assessment.
Methods: The authors estimated a base regression model predicting functional decline and compared it to a full model that included ICD-9-CM codes. An independent cohort was used to validate.
Main findings: The full model including ICD-9 codes predicted the decline modestly better than the baseline model ($R^2 = 0.06$ and $R^2 = 0.05$, respectively) and discriminated better (C-statistic 0.7 and 0.68, respectively).
Generalizable to PAC users in Medicare? Perhaps for patients in long-term acute care hospitals, IRFs, and SNFs. However, long-term care populations differ substantially from those in home health.
Results suggest new variables to test as proxies for function? No. This study focused on whether ICD-9 codes could predict decline in function, which is already covered in our use of HCCs.

Development of a Claims-Based Frailty Indicator Anchored to a Well-Established Frailty Phenotype
Segal, JB, HY Chang, Y Du, J Walston, M Carlson, R Varadhan
Med Care (2017) 55(7): 716-722. https://doi.org/10.1097/MLR.0000000000000729
Objective: To develop a proxy for frailty phenotype using administrative claims data.
Study sample: 4,454 participants in the Cardiovascular Health Study from four clinical sites with linked Medicare claims.
Outcomes: Frailty phenotype (low grip strength, slowed walking speed, low physical activity, or unintentional weight loss), mortality, time to mortality, number of hospital admissions, and nursing home admission.

Methods: The authors estimated penalized logistic regression models to predict frailty phenotype using a combination of claims-based diagnoses, age, and sex. The study also examined the predictive value of the frailty index for outcomes including mortality and hospital admissions.
Main findings: The claims-based frailty index was associated with frailty phenotype (area under the ROC curve of 0.75). The CFI was also significantly associated with death (OR 1.84), time to death (HR 1.71), number of hospital admissions (incidence-rate ratio 1.74), and nursing home admission (OR 1.47), after adjusting for age and sex.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? Unclear if the claims-based frailty index would add any predictive power beyond the HCCs already in use.

Functional Status Predicts Acute Care Readmissions from Inpatient Rehabilitation in the Stroke Population
Slocum, C, P Gerrard, R Black-Schaffer et al.
PLOS One (2015). 10 (11): e0142180. https://doi.org/10.1371/journal.pone.0142180
Objective: To determine whether functional status better predicts acute care readmissions among IRF stroke patients than comorbidities.
Study sample: Data were from the Uniform Data System for Medical Rehabilitation, which includes IRF-PAI assessments from 70 percent of IRFs nationally. Patients were included in the sample if they had a Medicare-established Impairment Group Code for IRF admission of 01.1 to 01.9, which indicates right, left, or bilateral body involvements in stroke, no paresis, or other stroke. Patients who died in the IRF setting were excluded. The final sample was 803,124 patients.
Outcomes: Acute care readmission within 3, 7, and 30 days.
Methods: The authors estimated a basic logistic regression model with acute care readmission risk as the independent variable. The base model included age and functional status as predictors. The authors compared the base model to models incorporating functional status and medical comorbidity indexes (the Elixhauser Comorbidity Index, Deyo adaptation of the Charlson Comorbidity Index, and CMS comorbidity tiers) or age and medical comorbidities alone. Functional status was derived from the IRF-PAI, and measures of motor skills and cognitive skills were included in the models separately. Comorbidities were also from the IRF-PAI assessment. The authors evaluated model performance by comparing C-statistics.
Main findings: All models that included only age and comorbidity indexes performed worse than the base model (age plus functional status). The best-performing model included age, the Elixhauser comorbidity index, and functional status.
Generalizable to PAC users in Medicare? Yes.
Results suggest new variables to test as proxies for function? No, this study suggests comorbidity indexes are worse than functional status at predicting readmissions for IRF patients.

New ICD-10 Version of the Charlson Comorbidity Index Predicted In-Hospital Mortality
Sundararajan, V, T Henderson, C Perry, A Muggivan, H Quan, WA Ghali
Journal of Clinical Epidemiology (2004), 57(2004): 1288–94
Objective: To develop and validate an ICD-10 version of the Deyo adaptation of the Charlson Comorbidity Index.
Study sample: Population-based hospital data from Victoria, Australia.
Outcomes: Mortality.
Methods: A mapping algorithm was used for initial translation of ICD-9 to ICD-10, which was manually examined by coding experts and a general physician. For generalizability, the study kept as many translated codes as possible at the three-digit level.
Main findings: The ICD-9 and ICD-10 CCI scores show similar distributions. Increasing CCI scores are strongly associated with mortality in both the ICD-9 and ICD-10 versions.
Generalizable to PAC users in Medicare? This study included all ages in Australia, so it isn't clear whether ICD-10 Charlson Comorbidity Index would perform similarly in the Medicare population.

Results suggest new variables to test as proxies for function? No, but they suggest updating to an ICD-10-based comorbidity index will likely have little effect on results.

Comparing the Prognostic Value of Geriatric Health Indicators: A Population-Based Study
Zucchelli, A, DL Vetrano, G Grande, A Calderon-Larranaga, L Fratiglioni, A Marengoni, D Rizzuto
BMC Medicine (2019) 17: 185. https://doi.org/10.1186/s12916-019-1418-2
Objective: To compare predictions of health and health care use outcomes among five geriatric health indictors: frailty index, frailty phenotype, walking speed, multimorbidity, and a summary score including clinical diagnoses, functioning, and disability (the Health Assessment Tool).
Study sample: Swedes aged 60+ enrolled in the Swedish National Study on Aging
Outcomes: Three- and five-year mortality, one- and three-year unplanned hospitalizations, contacts with health providers in the six months before and after baseline evaluation.
Methods: The authors assessed predictive accuracy for each geriatric health indicator via areas under the receiver operating curve (AUC). Each indicator was included in the analysis as a continuous variable, and the analyses were repeated stratified by age. The multimorbidity index was calculated exclusively from diagnoses, whereas all other predictors were calculated from a combination of self-reported functioning data, nurse-reported functioning data (e.g., walking speed), and/or diagnoses.
Main findings: Frailty index, walking speed, and the Health Assessment Tool were the most accurate predictors of mortality, and the frailty index and Health Assessment Tool were also the most accurate predictors of unplanned hospitalizations. Multimorbidity was the most accurate predictor of multiple provider contacts but otherwise performed worse than other measures that included patient or nurse-reported functioning. All predictions were less accurate for individuals under age 78.
Generalizable to PAC users in Medicare? Probably, though health systems vary.
Results suggest new variables to test as proxies for function? Probably not. Results suggest multimorbidity, which is the only measure possible with currently available Medicare data, is a poor predictor of mortality and unplanned hospital use.

Appendix B. Additional Tables

We estimated two CART models of total function points: a minimalist version with 13 groups and a more expansive version with 42 groups.

The 13-group version is presented in detail in table B.1. An X indicates a condition is required to be present to be in the group, and a 0 indicates the condition must be absent within the group. The first split is based on presence of dysphagia. Those with dysphagia are further split into four groups, according to presence of pressure ulcers, gastrointestinal and liver problems, and dementia. As can be seen in the rightmost column of the table, these four groups differ considerably in their function scores, ranging from an average of 11 for the group with dysphagia and pressure ulcers to 20 for the group with dysphagia but without pressure ulcers, gastrointestinal and liver problems, or dementia. The group without dysphagia is then divided into nine groups, four with and five without pressure ulcers.

The 42-category CART model includes almost all indicators from the 13-category model but also includes 2 measures of stroke, residual effects of stroke, neurology excluding stroke, hematology, 2 measures of fractures of lower limbs (except hip), hematology and immunology, orthopedic/medical primary diagnosis, JFI indicators of minor ambulatory problems, age, a home health indictor, and post-acute use of a ventilator.

APPENDIX TABLE B.1

CART Model of Total Function Points with 13 Groups

Dysphagia	Pressure ulcer	Non-pressure ulcer of skin	HCC for GI and liver	Dementia	Paralysis (other than cerebral palsy)	Severe ambulatory (from JFI)	Risk score	*N*	Average total function points
X	X							12,523	11.24
X	0		X					14,768	14.43
X	0		0	X				23,097	16.73
X	0		0	0				46,904	20.40
0	X	0		X				10,520	12.74
0	X	0		0	X			4,001	10.76
0	X	0		0	0			33,328	18.41
0	X	X						18,613	21.80
0	0			X				134,398	20.94
0	0			0		X		111,245	22.52
0	0			0	X	0		6,472	17.15
0	0			0	0	0	>1.732	250,755	24.29
0	0			0	0	0	<1.732	282,911	25.76

Source: Urban Institute analysis of data from 2017 fee-for-service Medicare post-acute settings and hospital claims data, cost report data, and matched assessment data.

Notes: CART = Classification and Regression Tree. HCC is hierarchical condition category. GI is gastrointestinal. JFI is JEN Frailty Index. X indicates the condition is present; 0 indicates it is not present. Blank cells indicate that presence or absence of the condition does not influence the assignment of CART group. CART model estimated using a subsample of one-third of stays in care episodes that began in January to June 2017. The nontherapy ancillary cost model excludes home health episodes. R^2 = 0.117; N = 949,535.

APPENDIX TABLE B.2

ICD-10-CM and Z Code Proxies of Frailty Used in Models of Function and Cost

ICD-10 CM and Z Code Proxies
B96: Other bacterial agents as cause of disease
E46: Unspecified protein malnutrition
E86: Volume depletion, including dehydration, hypovolemia, and other
F01: Vascular dementia
F02: Dementia in other diseases
F03: Unspecified dementia
F05: Delirium, not induced
G30: Alzheimer's
G31: Other degenerative
I67: Other cerebrovascular disease
I69: Sequalae cerebrovascular disease
L89: Decubitus ulcer
N39: Other urinary system disorders
R15: Fecal incontinence
R26: Abnormalities of gait and mobility
R262: Difficulties in walking, not elsewhere classified
R268: Other/unspecified abnormalities of gait and mobility
R29: Other symptoms involving nervous/musculoskeletal
R32: Unspecified urinary incontinence
R40: Somnolence, stupor, and coma, excluding diabetic, etc.
R41: Other symptoms and signs involving cognitive function and awareness
R45: Symptoms involving emotional state
R460: Low level personal hygiene
R54: Senility
S00: Superficial head injury
W00 - W17, falls
W18: Other fall on same level
W19: Unspecified fall
Y95: Nosocomial condition
Z73: Problems related to life-management difficulty
Z739: Unspecified life-management difficulty
Z74: Problems related to care-provider dependency
Z7401: Problems related care-prov dep: Bed confinement
Z7409: Problems related care-prov dep: Other reduced mobility
Z75: Problems related to med facilities and other health care
Z82: Family history of disabilities and chronic disease leading to disablement
Z89: Acquired absence of limb
Z9181: History of falling
Z993: Dependence on wheelchair

Sources: ICD-10-CM measures of frailty are drawn from Thomas Gilbert, Jenny Neuburger, Joshua Kraindler, Eilis Keeble, Paul Smith, Cono Ariti, Sandeepa Arora, et al., "Development and Validation of a Hospital Frailty Risk Score Focusing on Older People in Acute Care Settings Using Electronic Hospital Records: An Observational Study," *Lancet* 391, no. 10132, 1775–82. Z codes were selected by the authors.

Notes

[1] Partial SNF stays were indicated when a SNF stay began three or fewer days after the previous SNF stay. Partial home health episodes were indicated when an episode was discharged or transferred with a plan to readmit and the end of its 60-day episode overlapped with the start of the subsequent home health episode.

[2] Ninety-three percent of the stays began between January and June 2017.

[3] Hospital-based facilities (i.e., those based in acute-care hospitals) account for 6 percent of SNF stays, 11 percent of home health stays, and 43 percent of IRF stays. No LTCH stays are considered hospital based.

[4] Because the overhead share of the total cost of a stay was similar across settings (though the levels differed), we did not model fixed and variable costs separately.

[5] Severe wound care includes care for nonhealing surgical wounds, a wound for a patient who is morbidly obese, a fistula, osteomyelitis, or stage III, stage IV, or unstageable pressure wounds.

[6] The JEN Frailty Index is an algorithm developed by JEN Associates Inc. to identify frail older adults who may be at risk of institutionalization. The algorithm is based on 13 grouped categories of diseases or signs found to be significantly related to the need for long-term care services, either concurrently or in the future. The algorithm uses diagnoses codes from claims.

[7] The inclusion of outlier payments reduces the payment-to-cost ratios for high-functioning cases from 1.36 to 1.30 (N = 360,001) and reduces those ratios for the small group of very high–functioning cases from 1.35 to 1.25 (N = 58,308). Among very low function cases, the P/C ratio is stable (1.02 to 1.03; N = 367,600). Among low-functioning cases, the P/C ratio increases modestly from 1.024 to 1.045 (N = 1,046,043).

[8] The R^2 statistics are based on a regression of cost on predicted values from the corresponding Poisson regression.

[9] These studies are available in the annotated bibliography, but they are excluded from this summary because they focus on predicting functional decline using baseline functional status as an independent variable.

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