Case Management: Effects of Improved Risk and Value Information

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Purpose: The purpose of this study was to determine the impact on resource use of providing case managers with information on the potential for patients to benefit from home care services. Design and Methods: Twenty-four case managers working in the Arizona Long Term Care System (ALTCS) were randomized into treatment and control groups. Members of the treatment group were given patient assessments for 25 ALTCS clients, estimates of the patients’ risks for various adverse outcomes, and estimates of the aggregate potential benefit for each patient. Members of the control group were given only patient assessments (as is usual practice) for the same sample of 25 clients. Both groups were asked to independently write nonbinding care plans for each patient. The cost of each case manager’s care plans was computed by multiplying standard costs per service times the mix and volume of services prescribed for each patient. Results: Treatment group care plan costs were, on average, lower than control group costs and closely tracked variation in estimated patient risks. Comparison group care plan costs were unrelated to risks. Implications: Information about risk and potential benefit can improve targeting of services to long-term-care clients. A prospective study using such an approach is warranted to see if provision of risk and potential benefit information would produce better clinical and economic outcomes.

Key Words: Case management, Long-term care, Risks, Value, Effectiveness, Randomization

Home- and community-based care services have been shown, in some settings, to reduce hospital costs (Hughes et al., 1997) and enhance life satisfaction (Kemper, Applebaum, & Harrigan, 1987). However, evaluations of these services have been equivocal about whether these services reduce overall costs, and they indicate the services are often unsuccessful in achieving sustained improvements in traditional measures of health status change, including longevity and physical function (Hedrick, Koepsell, & Inui, 1989; Weissert, Cready, & Pawelak, 1988; Weissert & Hedrick, 1994). One important reason for these results might be poor choices in selecting clients to receive home care. Despite the earnest efforts of assessment teams to select patients at high risk of adverse outcomes, the case mix of most home care programs shows that false positives are a very frequent result: Most home care patients face low risks of nursing home placement, death, and even decline in activities of daily living (ADL), and frequently they have a low risk of hospital entry (Weissert & Hedrick, 1994; Weissert et al., 1988). Because low-risk patients have little potential to benefit from home care services provided to mitigate their risks, expenditures on their behalf are hard to offset with savings from reduced utilization of other services.

However, the problem goes beyond the selection of a substantial number of low-risk patients into the home care pool. We believe that case management programs often suffer from a serious lack of patient-specific information about risks and effectiveness. Abrahams, Capitman, Leutz, and Macko (1989) observed more than a decade ago that long-term care programs allocate their resources in two phases, starting with choosing who should be served (usually referred to as targeting) and then making care planning decisions (i.e., deciding what range and quantity of services to allocate to each client, part of what is called case management; see Applebaum &
outcome is thus equal to expected cost, before home care, of a given adverse suffering the adverse event without home care, with each adverse outcome equals the risk of reduced risks for adverse outcomes. For simplicity, we outline the model only in the cases of in the probability of nursing home admission. For treated analogously to home-care-induced reductions ability that satisfaction would be increased would be example, home-care-induced increases in the probability. For outcomes. A similar approach could be taken for outcomes. We posit that the expected benefits (pecuniary and nonpecuniary) associated with risk reduction across all adverse outcomes. Total benefit will be the aggregation of the benefit (and associated costs) of various adverse outcomes. The benefit of home care is assumed to be the reduction in the risk (and associated costs) of various adverse outcomes. Total benefit will be the aggregation of the benefit associated with risk reduction across all adverse outcomes. A similar approach could be taken for positive outcomes home care might achieve. For example, home-care-induced increases in the probability that satisfaction would be increased would be treated analogously to home-care-induced reductions in the probability of nursing home admission. For simplicity, we outline the model only in the cases of reduced risks for adverse outcomes.

Without home care, the expected cost associated with each adverse outcome equals the risk of suffering the adverse event without home care, $R_i$, multiplied by the value (pecuniary and nonpecuniary) associated with avoiding the outcome, $V_j$. The expected cost, before home care, of a given adverse outcome is thus equal to $RV_j$.

The benefit of home care is conceptualized to be the reduction in risk attributable to home care. This will depend on the effectiveness of home care, $E_j$, defined as the percentage reduction in the risk of the adverse outcome attributable to home care. Effectiveness is a function of home care spending and the specific services delivered. However, because the literature lacks evidence on the dose response associated with home care, we assume a single effectiveness of home care, independent of spending. In practice, with appropriate information, the marginal benefit of home care spending should be equated to its marginal cost. Effectiveness is also likely to be a function of patient characteristics. However, without convincing evidence on effectiveness, we assume for expository purposes that all patients would experience the same relative risk reduction from home care. More advanced models would recognize the variation in effectiveness.

The expected cost associated with the risk of adverse outcomes after home care is thus $(1 - E_j)RV_j$. Subtracting the after home care expected cost from the before home care expected cost yields the expected benefit of home care associated with mitigating the risk of any given adverse outcome, which we term the effectiveness and risk weighted value (ERV):

$$ERV_{ij} = E_j R_{ij} V_j,$$

where $ERV_{ij}$ is the effectiveness and risk weighted value of adverse outcome $j$ for patient $i$, $E_j$ is the effectiveness, defined as the average percentage change in the risk of adverse outcome $j$ for patient $i$ attributable to home care, $R_{ij}$ is the risk of adverse outcome $j$ for patient $i$ if no home care is given, and $V_j$ is the average value of avoiding adverse outcome $j$.

Once an ERV has been estimated for each patient for each identified adverse outcome, the total expected benefit of home care for that patient is calculated by summing the ERVs for the patient across all of her or his risks. This allows the benefit to reflect the value of home care in mitigating the risk of each outcome. In practice, the ERV will also be a function of home care spending because effectiveness is a function of home care spending.

A major benefit of this approach is the information it conveys to the case manager: the patients’ risks and how they compare with each other and with other patients. The approach also forces providers to think about the likelihood home care can mitigate specific risks and the value of avoiding adverse outcomes.

**Methods**

**Risk Estimation**

This study builds on previous research assessing the risk that home care clients faced for each of four adverse outcomes: death, hospitalization, nursing home admission, and functional decline (Chernew et al., 2001). In that study we used logistic regression models to estimate the monthly risk of these outcomes as a function of patient demographic and clinical characteristics. Our sample consisted of over 26,754 clients of the Arizona Health Care Cost Containment System (AHCCCS) program who were observed between December 1992 and April 1998. Patient descriptors and measurement of change in functional status came from comprehensive nurses’ assessments. These assessments, totaling 32,246, were conducted by state employees to determine program eligibility initially and annually for most
patients, more frequently when there was a major change in health status, or every other year for a small percentage of patients whose health status changed little from year to year. The data have been extensively tested in previous evaluation studies for reliability and usefulness in producing risk models that closely track in the aggregate actual annual occurrence of events being predicted.

An extensive effort was undertaken to profile risks of four adverse outcomes in the population. We focus on only four adverse outcomes (death, hospitalization, nursing home placement, and decline in physical functioning). Conceptually, the set of outcomes examined could be extended to any set of outcomes for which risk can be calculated, a value assigned, and a level of home care effectiveness assumed or empirically derived. Incidence of these adverse events in this population came from encounter data files provided by each managed care plan contractor to the state’s program administrators who pay the plan contractors their capitated monthly payments.

Risk modeling was undertaken on the entire data set, and potential correlation of risks was recognized. Our statistical model was a discrete-time hazard model that allowed for time-varying covariates. From these models, we computed a predicted risk for each patient, for each outcome, for each month that a client started in home care. Major covariates of risk of adverse outcome identified in the models were found to be physical limitations, age, some diseases, and recent discharge from the hospital or nursing home. Our findings were generally consistent with the existing literature (which itself is quite equivocal). We are generally not concerned with coefficients on specific covariates, but instead we focus on predicted risks for groups of home care clients. Tests of model fit using split sample techniques and comparisons of actual to predicted outcomes for subsamples of the population indicated that the models fit very well for each outcome. Because of space concerns, more details regarding risk estimation and findings are not given here (but are available from the authors). Because the sample is composed of individuals receiving home care, adjustments based on effectiveness estimates (discussed above) were made to our risk predictions to yield an estimate of pretreatment risk. We used the coefficients from these models to estimate client risk.

**Effectiveness Estimation**

Given the relatively poor performance of home care in the literature, and lack of dose-response information, we made optimistic assumptions based on existing literature about home care effectiveness and assumed effectiveness to be insensitive to the level of home care spending. The full results of our literature review are reported in Miller and Weisssert (2000, 2001). Our effectiveness estimates are based on a database that we assembled containing 167 multivariate analyses of longitudinal data analysis projects abstracted from close to 80 journal articles published between 1985 and 1998. We searched for all articles published since 1985 that empirically test or model the predictors or risk factors of nursing home placement, hospitalization, functional impairment, and mortality. In MEDLINE and HealthSTAR databases, we used combinations of the following key words: risk factors, predictors, models, nursing homes, institutionalization, hospitalization, function, activities of daily living, instrumental activities of daily living, mortality, death, quality of life, long-term care, and health services utilization. We limited all searches to English-language articles and the 65 and older cohort. Approximately 400 articles were identified, collected, and examined for other possible sources from their references. These too were collected, resulting in a total of 540 articles, each of which was examined carefully for appropriateness for inclusion in our analysis.

Acceptable studies shared the following criteria: they evaluated the predictors of mortality, functional impairment or decline, or the volume of hospital or nursing home use (i.e., admission or length of stay); they were published between 1985 and 1998; and they focused on the 65 and older population in the United States, utilized longitudinal data and multivariate techniques, and used sample sizes of 50 or greater. We chose 1985 as our cutoff because we wanted to update rather than overlap prior reviews and further the contemporary applicability of our findings. We eliminated cross-sectional studies, because causality is much more easily attributed with longitudinal data; opted to focus on multivariate analyses, because, unlike univariate approaches, they allow investigators to control for the confounding effects of other variables; and required samples sizes greater than 50 because larger samples increase statistical power and tend to be more representative of the populations from which they were drawn. Actual estimates used were those at the 75th percentile of ranked effect sizes that we found for each outcome among the studies we reviewed, thus setting effectiveness estimates for our budget targets at relatively high levels, certainly as high as the literature would support.

**Value Estimation**

Estimation of the value of avoiding each outcome was also based on existing literature. Because our conceptualization of value includes nonpecuniary benefits, much of our analysis was based on the literature concerning value of life, cost-effectiveness, and quality of life. Our estimate of the value of avoiding a death is $202,500. To arrive at this estimate, we used a monetary value of $50,000 per Quality Adjusted Life Year (QALY) that is fre-

<table>
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<tr>
<th>Outcome Event</th>
<th>Effectiveness (%)</th>
<th>Value ($)</th>
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<tbody>
<tr>
<td>Death</td>
<td>0.5</td>
<td>202,500</td>
</tr>
<tr>
<td>Hospitalization</td>
<td>15</td>
<td>32,624</td>
</tr>
<tr>
<td>Nursing home admission</td>
<td>20</td>
<td>18,700</td>
</tr>
<tr>
<td>Functional decline</td>
<td>5</td>
<td>38,709</td>
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The four resulting risk estimates derived as above can be converted to estimates of the potential benefit from home care services based on our estimates of effectiveness of home care in mitigating those risks and our estimates of the value of avoiding the four outcomes. To illustrate our aggregation method, one could assume, for example, that the risk of hospitalization for a particular patient is estimated to be 25%, the pecuniary and nonpecuniary value of avoiding hospitalization on average is $10,000, and the average effectiveness is 20%. Multiplying these figures, we would for this patient compute a $500 monthly expected value for avoiding hospitalization ($500 = .20 \times .25 \times 10,000$). We would then perform an analogous calculation for the other three outcomes and would then sum the outcome-specific expected values to get a total monthly expected value for home care for our example patient. These expected values of risk mitigation would then be used as suggested budget targets for home care spending. The ERV estimates in Table 1 were used in an algorithm to assign budget targets to each patient. Risk profiles for each patient and an accompanying set of budget targets were then provided to the treatment group case managers only. Two sample cases illustrate the kinds of information with which case managers were provided, and which constituted the information intervention.

**Applying the Estimates**

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**Risk and Budget Information Provided to Treatment Group Case Managers Only**

**Sample Case One.**—Patient characteristics consisted of an 87-year-old woman with four ADL dependencies. The risk of death was 82%, the risk ranking among all ALTCS patients was 15th to 20th percentile, and the monthly budget target was $8. The risk of functional decline was 1.28%, the rank among all patients was 10th to 15th percentile, and the monthly budget target was $35. The risk of hospitalization was .86%, the rank among all patients was 15th to 20th percentile, and the monthly budget target was $42. The risk of nursing home admission was 1.71%, the rank among all patients was 0th to 5th percentile, and the monthly budget target was $64. The total monthly budget target was $149 and the rank of this budget among all patients’ budgets was 0th to 5th percentile.

**Sample Case Two.**—Patient characteristics consisted of an 82-year-old married woman with four ADL dependencies. The risk of death was 67.59%, the risk ranking among all ALTCS patients was 95th to 100th percentile, and the monthly budget target was $684. The risk of functional decline was 2.35%, the rank among all patients was 25th to 30th percentile, and the monthly budget target was $375. The risk of hospitalization was 7.66%, the rank among all patients was 95th to 100th percentile, and the monthly budget target was $375. The risk of nursing home admission was 61.86%, the rank among all patients was 95th to 100th percentile, and the monthly budget target was $2,314. The total monthly budget target was $3,419 and the rank of this budget among all patients’ budgets was 95th to 100th percentile. (If more outcomes were available for valuation and estimation, their values would be added to the patient’s expected value from home care.)

**Caveats.**—Our resulting measure of potential benefit suffers many limitations. Most notably, we estimate potential benefit for only four out-
comes. Moreover, we assumed that effectiveness is insensitive to the level of home care spending, and our estimates of value required us to make a wide variety of technical assumptions. Thus, neither the value nor the effectiveness should be viewed as a precise number, and the noise in these estimates, combined with noise from the risk models, will lead to imprecision in the estimates of potential benefit. Our purpose here is to illustrate an approach and test how well it can work despite limitations in the estimates we use.

**Setting and Study Design**

This study was conducted by use of case managers and patient profiles from the Arizona Long Term Care System (ALTCS). The ALTCS provides home- and community-based services and nursing home care to over 25,000 patients in a capitated payment system. After assessment by state employees to screen for eligibility for Medicaid services, patients are reassessed by managed care contractors’ case managers, and care plans are written to manage their care. In the ALTCS system, case management refers to a service plan developed by a case manager that involves the overall management of a patient’s care, and ongoing monitoring and reassessment of the need for services. Case managers are degree as a social worker or a licensed registered nurse or have a minimum of 2 years of experience in providing case management services to a person who is elderly and physically disabled or has developmental disabilities. Most case managers far exceed minimal requirements and receive frequent in-service training. McCall and colleagues (1991), in an evaluation of the ALTCS program for the then Health Care Financing Administration, found that ALTCS case manager selection criteria, in-service training, assessment instruments, procedures, and supervision compared favorably with other programs throughout the country.

Home- and community-based services managed by the case managers include home health care, nursing, and homemaker and aide services; personal care; ADL training, orientation training, and mobility training; medical supplies and equipment; physical, occupational, and recreational therapies; speech and audiology services; transportation to medical services; adult day health care; supervision of the patient’s care plan; preventive, therapeutic, and restorative services; hospice (if appropriate); and other services.

In this study, 24 case managers from one large site in the ALTCS program were randomly split into two groups of 12 for study purposes. Each case manager was asked to write a care plan for 25 clients, selected from the ALTCS patient tracking files for clients admitted in 1997. Cases were selected to represent a diverse set of patient profiles, which were identified in previous risk modeling. Case managers in the treatment group were given four types of information for 25 patients: (a) a complete assessment that included information on demographics, living environment and informal caregiver support, clinical condition and medications, functional, cognitive, and sensory impairments, continence and skin condition, formal service use, and case manager assessment of clients’ needs; (b) each patient’s profile for his or her risk of each of four adverse outcomes (estimated risk and percentile ranking of this risk among other clients in the larger ALTCS population); (c) potential benefit, presented as monthly budget target for each risk and in total, based on the expected value of mitigating the risks; (d) a price list for services reflecting ALTCS costs for each service. Case managers randomly assigned to a control group received the assessment data for the same 25 patients, but not the risk profiles and budget targets. They also received the same ALTCS price list for services. They were asked to write care plans for the same 25 cases, using ALTCS program usual care practices. Each case manager in the pilot study was asked to identify each patient’s problems and to prescribe services the manager felt would be appropriate for mitigating those problems. Services could include all those offered by ALTCS plus any additional services the case manager felt were needed, whether covered by ALTCS or not.

The treatment group case managers were encouraged to exercise discretion and ignore the budget targets if they felt justified doing so. They each received a half-day of training in how to interpret the risk and budget information.

The impact of the intervention was measured by comparing means and using multivariate regression. An analysis of means was adjusted for nonindependent responses by case managers (which yielded more conservative estimates than a comparable analysis treating observations as independent or clustering by case) by using the “cluster option” in STATA. We report results that measure spending in dollars because the coefficients are easy to interpret, though analogous models using the logarithm of spending as the dependent variable yield the same conclusions.

All analysis was performed by using STATA version 7. The base regression analysis included fixed effects for cases (binary variables for each client) and adjusted the standard errors for nonindependence within observations from the same case manager. The regression models that included covariates measuring client risk omitted the fixed effects (because they are collinear with risk measures). Case managers had information on the estimated probabilities of each of the four adverse events (nursing home admission, hospitalization, death, and ADL decline), based on applying the coefficients of the risk models reported in Chernew et al. (2001) to the patient’s observed characteristics. However, we exclude the risk of death from the statistical model.
because it is highly collinear with the risk of nursing home admission. In addition to the regression models explaining the total cost of services prescribed in the care plans, we also estimate a probit model for whether or not the care plan prescribes any medical (physician) services and a regression model for the amount of spending prescribed for medical services. The focus on medical services is potentially interesting because most traditional home care plans have not included medical services, and it is possible that one area in which care plans for high-risk patients might expand is in adding medical services. Savings from allocating less care to low-risk clients might be sufficient to pay for these expanded services with minimal impact on overall budgets. Better outcomes might result.

**Results**

Treatment group case managers identified approximately 10% more problems on average per patient than control group case managers: 5.6 problems versus 5.1 ($p = .005$). However, despite having identified more problems, treatment group case managers prescribed slightly fewer services per problem: 3.92 (treatment) versus 4.03 (control) average services per patient ($p = .51$). By prescribing fewer services, the treatment group wrote care plans that on average were approximately 22% less expensive than those of the control group: $943 (treatment) versus $1,216 (control) per month per patient ($p < .01$). As noted above, the $p$ value is conservatively adjusted for nonindependence of cases within care manager.

Next we examined the impact of the intervention on spending and on the relationship between spending and risk. Our expectation was that case managers equipped with better risk profile information and budget recommendations based on effectiveness, risk, and value would make an allocation of home care resources in a pattern more closely correlated with risk than the control group’s allocation pattern. Table 2 reports the results from these regressions. Column 2 reports the base findings, including client fixed effects. The spending in the treatment group was $273 lower than in the control group. Figure 1 reports average spending per case for each case manager. Ten of the case managers in the treatment group spent less than $1,000 on average, whereas only 2 of the 12 control group case managers spent less than $1,000 on average. Thus, the reduction in average spending seen in the treatment group was not driven by the behavior of only one or two case managers.

Table 2, column 3 reports analogous results, including measures of risk of ADL decline, nursing home placement, and hospitalization. The treatment group effect on spending remains negative. In contrast, in the control group (coefficients on the three risks), the effects of risk on care plans were quite limited. Higher risk of nursing home admission led to a small increase in spending, but higher hospitalization risk actually led to unexpectedly lower spending. Spending was not significantly related to risk of ADL decline. The relationship

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Total Spending$^a$</th>
<th>Total Spending$^b$</th>
<th>Any Use$^a$</th>
<th>Spending$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1,063*** (9.72)</td>
<td>1,315 (92)</td>
<td>−2.45 (−6.79)</td>
<td>−6.92 (−.86)</td>
</tr>
<tr>
<td>Group dummy (control = 0, TX = 1)</td>
<td>−273** (−2.74)</td>
<td>−525 (3.01)</td>
<td>1.98 (8.38)</td>
<td>47.76*** (5.87)</td>
</tr>
<tr>
<td>Risk of ADL decline</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk of NH admission</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk of hospitalization</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment Group × Risk of ADL Decline</td>
<td>−12 (−.79)</td>
<td>4.01 (2.72)</td>
<td>−27.75 (−2.20)</td>
<td></td>
</tr>
<tr>
<td>Treatment Group × Risk of NH Admission</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment Group × Risk of Hospital Admission</td>
<td></td>
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</table>

**Notes:** T statistics are given in parentheses (based on standard errors adjusted for clustering at the case manager level). TX = treatment; ADL = activity of daily living; NH = nursing home.

$^a$Case dummies included.

$^b$Case dummies excluded.

**p < .05; ***p < .01.**
between spending and both hospitalization and nursing home risk is much stronger and of the expected sign in the treatment group (coefficients on the interaction terms between the three risks and being in the treatment group). The risk of ADL decline was again not a significant predictor of spending. Overall, it appears that control group case managers did not allocate more resources to patients at higher risk of adverse outcomes, whereas treatment group case managers’ allocations in the pilot study reflected the expected upward slope of spending with increasing risk.

A further examination of allocations also allayed concerns that treatment group case managers might have simply reduced spending by the same amount across the board. A case-by-case analysis showed that, for some high-risk cases, treatment group case managers allocated more resources than did the control group to a given patient, on average, whereas they tended to cut low-risk spending cases. Figure 2 shows the relationship between risk of nursing home admission and case-by-case spending for treatment versus control group cases.

Our analysis of spending on medical care resources suggests that case managers in the treatment group were more likely to have some positive spending on medical services (Table 2, column 4). Moreover, the treatment group case managers, on average, spent more on medical services than control group case managers, despite spending less overall (Table 2, column 5). The spending on medical services was generally not related to risk in either group. The only statistically significant finding regarding risk and medical spending is that medical spending had an unexpected, inverse relationship to hospitalization risk.

**Discussion**

These results lend considerable weight to the view that this basic approach of equipping case managers with patient risk, value, and benefit potential information has the potential to alter care planner behavior. In a manner consistent with organizational theory, which suggests that agents’ performance can be improved by giving them better information (Moe, 1984), case managers, when they are equipped with better outcome potential information and training in how to interpret this information, appear to allocate scarce resources in ways likely to maximize patient benefits. When given information about risk, they shift resources from low-risk-benefit to high-risk-benefit potential clients.

The results of this pilot study are both disturbing and promising. Case managers face a daunting task: They work at the bottom of the organization and must make up for all the failings of the policies and systems within which they work. They must compensate for inadequate information and work within a variety of limitations. Lipsky (1980) approvingly called such employees “street level bureaucrats” because they work down at the level where ideas and policies must be translated into tough choices about public services—in this case, care plans. The lack of relationship that we found between risk and resource allocation in the control group suggests that case managers, even in a capitated system, do not get the help they need if they are to take risk into account when writing care plans. Without better information on patients’ risks and effectiveness of services in mitigating those risks, our results should not be surprising. Managed care is all about putting incentives in place to improve efficiency, yet few incentives work at the case...
manager level. They seem to have been forgotten in the way most programs are designed. Furthermore, case managers in long-term care face even greater difficulties than do those who work in single-disease management programs, where information about risks and effectiveness of interventions are much better developed.

The response by the treatment group is promising in that it indicates that at least some case managers, with limited additional training, were willing and able to use the provided information in guiding their prescriptions. The approach here introduces a systematic analysis of risk, weighting each patient condition against each risk, and adjusts them for both benefit potential from the service being allocated—in this case home care—and for the economic value of the risk being avoided. This approach recognizes the “bounded rationality” (Moe, 1984; Simon, 1945) of human decision making: We are simply not equipped to calculate in our heads how much risk one patient faces versus another with any degree of accuracy for even one risk, let alone several. Furthermore, proper resource allocation suggests that risk is but one factor to consider in allocating resources. Other factors are benefit potential and the economic value of that benefit (multiple benefits for most patients). More systematic resource allocation methods are needed.

That said, there are several limitations to our study. As in many clinical trials, the results are not necessarily generalizable beyond the intervention site. For example, clinical trials conducted in academic medical centers may not be generalizable to other settings, and trials conducted on a narrowly defined patient populations may not be generalizable to other populations. In our case we had only one site, with a relatively small number of clients and case managers. Despite the small size, we were able to detect an effect, even when accounting for non-independence of decisions by case managers. Nevertheless, the apparent success of the pilot intervention has to be confirmed in a larger implementation on which real care decisions, not just hypothetical plans, are based. Moreover, our randomized controlled trial was not able to examine the duration of any effects. We cannot assess whether the impact demonstrated in this study would persist over time or whether care plans would revert back to baseline after the novelty of the information subsided.

Practical issues that must be addressed in a larger implementation include training, feedback, monitoring, and incentives. Case managers in the pilot received very limited training—approximately 4 hr—and there was no group review and feedback of case managers’ decisions, either during the training or during study implementation. Further, there were no performance incentives built into the intervention. Case managers were immune to cost consequences of their decisions, and they suffered no adverse effects if their care planning decisions did not capitalize on patients’ benefit potential or because they prescribed more care than might be needed to achieve a given outcome in low risk patients. Nor were their decisions closely monitored or exposed to peer review, and no one was praised for “getting it right.” Important next steps might include testing an intervention that places case managers at risk for the outcomes of patients, rewarding them if their resource allocations were responsive to risk, value, and benefit potential and if the patient did indeed improve or avoid adverse outcomes. Consistent with agency theory, this would create strong incentives, which, added to the additional information provided to them and reinforced with peer review, monitoring, and feedback, might produce even broader and stronger responses to the intervention. Another limitation of this study is that creation of the budget targets provided to case managers required many assumptions and was limited by available data and in many cases inconclusive research. This issue arises in any evaluation of many managerial interventions such as guidelines. It is clear that improvements could be made in our budget target-generation process, and we hope that this study will motivate researchers to address this issue. However, the “appropriateness” of the budget targets is not crucial to the central message of this study. In our case, if the targets were horribly flawed, we would expect less case manager response. The fact that we observed a response suggests some reasonableness of the budget targets and certainly indicates the potential for budget targets in general to change behavior. We are not advocating for these targets per se; we state only that the idea of using a system of resource allocation that balances costs and benefits should be considered.

Implementation of this system would require consensus regarding the risk, value, and effectiveness estimates. The estimates need not be perfect, because the budget targets are not binding, but better estimates would add credibility and improve the effectiveness of the system. Moreover, implementation would encourage development of better estimates. In addition, our analysis was focused on costs. In a next study, outcome effects should be evaluated.

Thus, a third limitation is that we were not able to investigate outcomes because of the hypothetical nature of our pilot. The impact of this system on outcomes is critically important. We believe that information about risk would act to improve outcomes because it will help target interventions to the most salient outcomes, but we could not test this.

Despite these limitations, we have nevertheless demonstrated that when such information is provided to case managers—none of whom had special training in statistics or decision-making methods—they can use the information to improve their decision making. Coupled with incentives designed
to reward or bite at the level of the case manager, better training in resource allocation methods, monitoring, peer feedback, and more research into the relationship between marginal services and marginal benefits for a given type of patient, case management may indeed offer the promise of improved patient care outcomes at low cost that its proponents have hoped it would. Without these techniques for making it much more systematic, it is likely to fall quite short of its potential.

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