

The Effect of Generalist Care Management on Expenditures for Medicare Beneficiaries

David A. Dorr
K. John McConnell
Steven Donnelly
Cherie P. Brunker
And the Care Management Plus Team

Supported by a grant from the
John A. Hartford Foundation

Case study

Ms. Viera

a 75-year-old woman with diabetes, systolic hypertension, mild congestive heart failure, arthritis and recently diagnosed dementia.

She comes to her primary care provider (1 of 13 amb physicians) with 5 medical and 2 socioeconomic issues.

Patients like her account for 70% of Medicare spending. Some utilization seems to be due to lack of care management / coordination of care.



Care Management Plus attempts to fill in core gaps in many clinics through a proactive, flexible system.

In 7 primary care clinics at Intermountain Healthcare

Referral

- For any condition or need
- Focus on certain conditions

Care management

Care manager

- *Assess & plan*
- *Catalyst*
- *Structure*

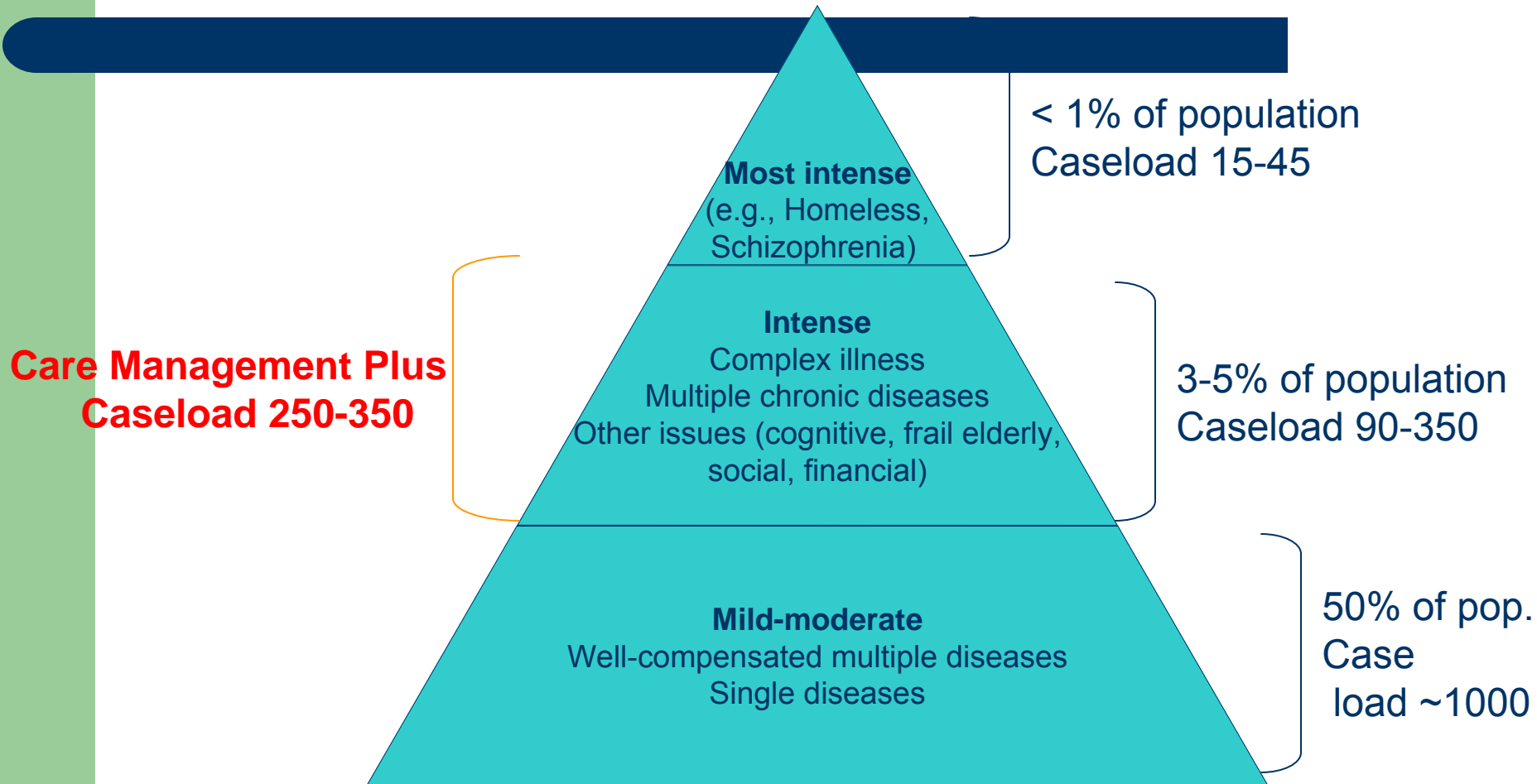
Technology

- *Access*
- *Best Practices*
- *Communication*

Evaluation

- Ongoing with feedback
- Based on key process and outcome measures

Care management varies by intensity and function for different populations and needs.



Study Objectives

- Identify the impact of a generalist care management protocol on Medicare patient expenditures

Methods

- Pre/Post difference-in-differences
- “Treated” group: Medicare enrollees assigned to Care Management Plus
- Comparison group: Medicare enrollees without Care Management Plus
- Goal: Estimate Average Treatment Effect on Treated (ATT)

Estimating ATT: what are the options?

- Regression
 - Can be misleading if you don't have common support
- Covariate matching
- Propensity score
 - Matching
 - Weighting
 - Blocking/subclassification
 - Regression
- Combinations

- We focus on matching

We focus on covariate matching

- Why not propensity score?
 1. Administrative
 - Working with Medicare QIO
 - We write the code, they give us the output
 - Code must be simple; limited ability to “shape” the model as we move forward
 2. No dominance between covariate matching and propensity score (Heckman & others); in fact:, Zhao (2004) shows
 - Covariate matching robust under a number of different setting
 - Covariate matching better when sample size is small
 - Covariate matching superior when correlation between covariates and treatment is low
 - VERY IMPORTANT: we want to analyze effect on diabetes patients; almost no ability to predict CMP enrollment in these patients

We need a string theory



You are a
puny idiot.

Other unresolved issues: defining “common support”

- Typically defined through propensity score, e.g.
 - $P(T|x_{\text{treated}}) \geq \min \{P(T|x_{\text{control}})\}$
 - $P(T|x_{\text{treated}}) \leq \max \{P(T|x_{\text{control}})\}$
 - $P(T|x_{\text{control}}) \geq \min \{P(T|x_{\text{treated}})\}$
 - $P(T|x_{\text{control}}) \leq \max \{P(T|x_{\text{treated}})\}$
- Heckman & others suggest “trimming” or perhaps even focusing only on areas with “thick support”
- But, King and Zeng (2007) suggest support should be defined not by the propensity score but by pruning observations from the control group that are outside of the convex hull of the treatment group.

Other unresolved issues: how much does “balance” matter?

- Common to use t-test or other bivariate test to show no difference between matched treated & control groups
- Some research (Diamond & Sekhon 2005) suggests that p-values of 0.05 or 0.1 are too lenient to obtain reliable causal inference
 - Matching works but only if you achieve a really high standard of balance
- But, King (2006) says balance tests are misleading and notes that as you drop observations, statistical tests for balance may be incorrect because you have no power

Our approach?

- We use covariate matching
 - Find 1-1 nearest neighbor matches through distance measure (Mahalanobis)
 - Outcome variable is pre-post *change* in expenditures
 - Bias-correction through regression

Results



Baseline characteristics

	Non-CMP	CMP	Matched Controls
Female	54%	66%	67%
Age	76	75	75
Comorbidity score	2.4	1.7	2.2
Previous admission	21%	22%	20%
Diabetes	20%	51%	47%
CHF	14%	20%	18%
Depression	12%	26%	24%

Results: Matching

	All potential controls (N=7,687)	Control Mahalanobis (N=930)	CMP (N=930)
All Patients	Mean	Mean	Mean
Cost – Baseline	\$5,325	\$4,824	\$5,608
Cost – Post	\$5,981	\$5,988	\$7,304
Difference	\$656	\$1,164	\$1,695
DID		+\$433 (-\$653, \$1,519)	
Patients with diabetes	(N=1561)	(N=480)	(N=480)
Cost – Baseline	\$7,790	\$5,792	\$6,001
Cost – Post	\$8,960	\$7,869	\$7,088
Difference	\$1,170	\$2,077	\$1,781
DID		-\$991 (-\$2,511, \$530)	

Conclusions for Care Management Plus intervention

- Previous analyses have shown substantial results in improving quality (disease status, satisfaction, utilization)
- What about cost?
 - Suggestive of savings, but...
- Other issues:
 - Cost profiles differ between patients, apparently more savings for
 - Patients with diabetes (especially if previously hospitalized, sicker, or older)
 - Younger patients
 - Patients with previous admissions
 - Males

The Next Phase...Dissemination

- Care Management Plus Dissemination
- New 4-year \$2.5M grant from John A. Hartford Fund
 - Focus on seniors and those with complex chronic illness
 - Pays for assessment, training, and IT consulting (how to better use tools)

Thank you!

The Care Management Plus Team

- OHSU

- David Dorr, MD, MS
- K. John McConnell, PhD
- Kelli Radican
- Hanh Tran
- Rachel Burdon
- John Welte

- Intermountain Healthcare

- Cherie Bruncker, MD

- Columbia University

- Adam Wilcox, PhD

Advisory board

- Larry Casalino
- Tom Bodenheimer
- Cheryl Schraeder
- Heather Young

www.caremanagementplus.org