Understanding Variation in Chronic Disease Outcomes

[RUNNING TITLE: Understanding Variation]

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Abstract

We propose an explanation for variation in disease outcomes based on adaptation to the conditions of chronic disease. We develop a model of patient adaptation using the example of Type 2 Diabetes Mellitus and assumptions about the process entailed in transforming self-care behaviors of compliance with treatment, compliance with glucose monitoring, and patient’s knowledge of their disease process into health outcomes of glycemic control and patient satisfaction. Using data from 609 adults with diagnosed Type 2 diabetes we develop an efficiency (fitness) frontier in order to identify best practice (maximally adapted) patients and forms (archetypes) of patient inefficiency. Outcomes of frontier patients are partitioned by categories of returns to scale. Outcomes for off-frontier patients are associated with disease severity and patient archetype. The model implicates strategies for improved health outcomes based on fitness and self-care behaviors.
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Introduction
Managing variation is at the heart of current efforts to improve quality and control cost in health care. Improvement strategies are typically based on the presumed benefits of reducing variation in a product or service. However, the healthcare system has the important characteristic that services must often be individually tailored to a specific patient’s condition. To respond to variation in individual patient needs, variation in services is not only desirable, it may be necessary for maintaining quality of care.

One of the targets of research on health outcomes is variation in use of resources. Efforts in this area have focused on documenting variation in resource utilization at the level of the region [1, 2, 3], the hospital [4, 5], the clinic [6], and the individual provider [7, 8, 9]. A common health industry response to variation in use of resources is the attempt to direct the delivery of patient care services through the development of clinical practice guidelines [10, 11, 12, 13]. Such guidelines are intended to be evidence-based, but often include expert opinion on best practice for a given disease or condition. As these efforts progress, healthcare organizations have implemented data collection at the health plan, clinic and provider levels to track the extent to which guidelines reduce variation in clinical practice.

An important extension of research on practice variation is to determine why such variation exists and what aspects are at the heart of optimal health care. Chassin et al. [14] emphasize the need to discover the combination of factors that produce variation in the use of health services. Studies investigating specific factors that contribute to practice variation include Chilingerian, [9]; Gatsonis, et al. [15]; and Nyman, et al [16].

Much of the work done to date suggests that to understand the significance of variation in health outcomes, the question of interest must be deeper than simply which provider (HMO, physicians, clinics) characteristics result in optimal care, once patient characteristics are taken into account [17]. Rather, the focus must expand to examine how variation in processes of care delivery combine with variation in patient characteristics to produce targeted health outcomes. Effective management in the healthcare industry will require understanding how variation in patient as well as provider and organization level processes contribute to variation in outcome measures [18].
In this paper, we examine variation in health outcomes for a defined population of patients with Type 2 diabetes mellitus. Chronic disease is a particularly suitable choice for the study of variation in health outcomes since it accounts for a significant proportion of healthcare expenditures and also involves health related behaviors at multiple levels of the healthcare system (patient, provider and clinic).

**Background**

The research we describe is directed towards developing a theory based on the proposition that variation in health outcomes reflects adaptation by patients to the conditions of chronic disease. We suppose that chronic disease comprises an environment consisting of (1) the patient’s disease process, (2) the healthcare system experienced by the patient (including providers, clinics, and organizational policies), and (3) the patient’s personal psychosocial context (including lifestyle, family resources, work setting and cultural background). The variation we examine reflects differences in patients’ adaptation to this environment.

We can think of adaptation as a process through which patients achieve improved performance in response to features of their environment. We assume this process is based on the progressive modification of cognitive, behavioral and biological structures [19, 20]. In the present research we conceptualize each patient’s adaptation by means of attributes which specify physical and psychosocial states that constrain the process of transforming self-care behaviors into health outcomes. Patient and provider decisions as well as health-system policies influence many of these attributes. In this context, adaptation and transformation are different processes: the first modifies the attributes that parameterize the transformation process; the second produces health outcomes (as outputs) from self-care behavior (as inputs).

We represent each patient’s adaptation in relation to the adaptation of those patients in the population who are most successful in transforming their self-care behaviors into health outputs. We use the concept of fitness to represent the correspondence between the attributes that parameterize the transformation process and the level of outputs achieved. Differences in fitness are a result of differences in attributes not differences in outputs *per se*, although differences in output are a necessary consequence.
For a given environment, we express outputs of the most successful adaptations as a function $F_e$ of inputs $x^1$, where for $n$ outcomes

$$F_e(x) = \begin{pmatrix} f_{1e}(x) \\ \vdots \\ f_{ne}(x) \end{pmatrix}$$ (1)

In the work presented here, we consider two functions $f_{1e}$ and $f_{2e}$ representing the outputs of patient satisfaction with care and percent change in glycosylated hemoglobin ($\Delta$HbA$_1$C). These, in turn, are functions of three inputs: compliance with treatment, compliance with monitoring and patient’s knowledge of the interaction between their self-care behaviors and their disease process. For a given level of self-care behavior we assume that patients vary with respect to the level of outputs they achieve: not all adaptations are successful. This reflects variation in the attributes that comprise parameters of the transformation process.

We represent fitness as a scale factor $\varepsilon \in [0,1]$ which modifies the function $F_e$ such that adaptations achieving the outcome of those who are most successful (i.e. have the best performance) have fitness equal to 1. Adaptations with fitness indices less than 1 are less successful. We assume that for each adaptation with fitness less than 1, there exists a corresponding successful adaptation (i.e. an adaptation with $\varepsilon = 1$) having the same inputs. An adaptation with fitness $\varepsilon$ and inputs $x_o$ has outputs $y_o$ such that

$$y_o = \varepsilon F_e(x_o)$$ (2)

We assume that patients adopt a level of self-care behavior that locally optimizes the benefit they receive from their outputs relative to the costs of compliance (inputs). We represent the benefit each patient receives relative to a unit of output by the values $v_{sat}$ and $v_{dghb}$, for satisfaction and percent change in HbA$_1$C respectively. The combined value of these outputs is the sum of weighted outputs $y^Tv = \varepsilon F^Tv$ where $v = (v_{sat}, v_{dghb})^T$. We represent the cost associated with a unit of input as the value $w_{tx}$, $w_{mtr}$, and $w_{conf}$ for compliance with treatment, compliance with monitoring, and knowledge of disease respectively. The value of a combination of self-care behaviors is the sum $x^Tw$ where $w = (w_{tx}, w_{mtr}, w_{conf})^T$. The values $v$ and costs $w$ are attributes of each patient’s adaptation.
We express the adaptive problem facing patients with a given attribute structure as one of finding a level of self-care behavior $x_o$ such that the marginal benefit is equal to the marginal cost:

$$\frac{\partial (\epsilon \cdot F^T v)}{\partial x} \bigg|_{x=x_o} = \frac{\partial (x^T w)}{\partial x} \bigg|_{x=x_o}$$

Equation (3) represents self-care behaviors (inputs) that locally optimize the benefit (output) achieved for effort expended. We assume patients locate $x_o$ by employing a search strategy using local information based on a comparison of the marginal change in output for a marginal change in input (i.e. $r_i = \frac{\partial y^T}{\partial x}$); we call this comparison (matrix of ratios) the outcome gradient of patients’ adaptation.

Differentiating equation (2) with respect to inputs $x_i$ for adaptation $i$, and noting that $\frac{\partial F_e(x_i)}{\partial x_i}$ is the outcome gradient $(R_i)$ of a successful adaptation having the same inputs, we find that a given adaptation’s outcome gradient is equal to the gradient of its corresponding successful adaptation scaled by fitness:

$$r_i = \epsilon_i R_i$$

Using the preceding analysis we describe patient adaptation to the conditions of a specific chronic disease using three characteristics: (1) patient self-care behaviors ($x_o$), (2) outputs of the most successful adaptations in a particular environment ($F_e$), and (3) the fitness ($\epsilon$) of the adaptation. In the next sections we examine the relationship between specific patient adaptations and these characteristics. From these relationships we develop a model that provides an account of variation in health outcomes for patients with Type 2 diabetes.

**Research Methods and Data**

To examine the relationship between variation in patient adaptation and health outcomes we must operationalize the fitness scale factor $\epsilon$ represented in equation (2). Accordingly, we employ a technique that describes each patient’s adaptation relative to the adaptation of the most successful patients with similar characteristics. We refer to individuals with the most successful adaptation (i.e. $\epsilon = 1$, the highest level of fitness) as best practice patients.
1.1 Fitness Model Specification

To determine the best practice individuals (i.e. those with maximum fitness) in our population of patients we use an empirical approach referred to as frontier analysis. At an intuitive level, a frontier represents the locus of extremal observations in a body of data. The phrase ‘best practice frontier’ refers to the maximal output that can be attained, given a set of input quantities with respect to a sample of decision-making units that use a similar process to convert inputs to outputs [21]. The decision-making units can be individuals (patients, physicians) or organizations (clinics). Regardless of the unit of analysis, a frontier gives the maximal output (e.g. health outcomes) that can be attained, given a set of inputs (e.g. patient self-care behaviors).

We use the patient as a unit of analysis for two reasons. First, to understand sources of variation in outputs we must inquire into the interaction between practices of the healthcare system at various levels (physician, clinic) and variation in patient adaptation. This inquiry requires understanding individual patient-level characteristics that motivate variation in healthcare practices. Studies based on aggregated patient measures cannot accomplish this task because relevant patient information is lost.

Second, aggregation of patient-level information obscures the influence of physician and organization-level decision polices on specific characteristics of patient adaptation. Using summary statistics that reflect only aggregate properties of patients as a group does not permit an assessment of the relationship between variation in patient characteristics and variation in the clinical policies and practices upon which the outputs of patients are based [22].

Based on the definition of fitness ($\varepsilon$) in the preceding section, the measure used to operationalize fitness must have four characteristics: (1) $\varepsilon$ relates multiple inputs and multiple outputs; (2) $\varepsilon$ ranges between 0 and 1; (3) $\varepsilon$ is equal to 0 if outputs are 0, and is equal to 1 on the frontier where outputs are highest for given inputs; and, (4) $\varepsilon$ operates as a multiplicative factor as required by equation 2. Data envelopment analysis (DEA) is a non-parametric method for frontier analysis that calculates a measure (labeled efficiency) having these characteristics.
DEA has two further advantages for the work described here: (1) invariance with respect to the scales of input and output variables (allowing variables to be represented in their natural units), and (2) a non-parametric frontier that allows the specific form of the frontier to be unspecified. DEA has been used in the healthcare field in studies of hospital efficiency [4, 5], nursing homes [16], area agencies on aging [23], and physicians [8, 9].

DEA employs mathematical programming to obtain empirical relations between a given set of inputs and outputs. Instead of trying to fit a regression plane through the center of the data, DEA floats a piecewise linear surface on top of the observations (i.e. using the highest values) —i.e. DEA *envelops* the observations. DEA calculates an interpretable scalar measure of efficiency using multiple inputs and outputs. This is accomplished by assigning weights that maximize a ratio of the weighted sum of outputs to the weighted sum of inputs, subject to the constraint that the set of weights not assign an efficiency greater than 1 when applied to any patient in the sample. Formally, for an individual (indexed by \( i \)) with output vector \( y_i \) and input vector \( x_i \), efficiency is expressed as the weighted ratio

\[
\varepsilon_i = \frac{p_i^T y_i}{q_i^T x_i}
\]

where \( p \) is the weight vector associated with the outputs and \( q \) is the weight vector associated with the inputs. The weight vectors are computed by DEA as

\[
\max_{p,q} \left( \frac{p_j^T y_j}{q_j^T x_j} \right) \text{ subject to } \frac{p_j^T y_j}{q_j^T x_j} \leq 1 \ \forall j \in N \text{ and } p_j, q_j > 0
\]

where \( j \) is an index over the sample \( N \) [24]. The constraints \( \{p, q\} > 0 \) are a formal requirement for the linear programming evaluation. Each of the inputs and outputs may be stated in different units of measurement.

We employ DEA methodology to determine best practice patients using inputs of: (1) reported patient compliance (adherence) with treatment, (2) reported patient compliance with home glucose monitoring, and (3) reported patient confidence in their knowledge of the interaction between compliance and the
disease process. As outputs we use two health outcomes: (1) reported patient satisfaction (see below),
and (2) percent change in patient glycosylated hemoglobin ($\Delta \text{HbA}_1c$), a measure of glycemic control,
over a twelve-month period. We assume patients adopt self-care behaviors in response to physician
prescribed treatments and features (e.g., nurse educators) of the healthcare system. Patient self-care
behaviors in this sense are part of the satisfactory management of chronic illness [25].

We use the percent change in patient glycosylated hemoglobin ($\Delta \text{HbA}_1c$) as an outcome variable based on
evidence which suggests that glycosylated hemoglobin levels strongly correspond with the physiological
health status of patients with Type 2 diabetes mellitus [26]. The outcome variable of patient satisfaction
is important to both patients and healthcare providers as indicated by its influence on patient enrollment
and disenrollment with health plans [27, 28, 29, 30]. Patient satisfaction has also been related to
compliance with medical regimes as well as cooperation with healthcare providers [31, 32, 33, 34].

To adjust for disease severity we block patient data into nine severity groups labeled with the letters A
through I (see Table 1) based on reported duration of diabetes from time of diagnosis (< 5, 5-10, > 10
years) and HbA1c levels at the time of data collection (< 8%, 8-10%, > 10%). A separate DEA is used to
compute efficiency scores for each patient severity group [24].

<table>
<thead>
<tr>
<th>Initial HbA1c</th>
<th>Disease Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (Cell)</td>
</tr>
<tr>
<td></td>
<td>Duration &lt; 5 years</td>
</tr>
<tr>
<td>HbA1c &lt; 8%</td>
<td>126 (A)</td>
</tr>
<tr>
<td>HbA1c 8-10%</td>
<td>63 (D)</td>
</tr>
<tr>
<td>HbA1c &gt; 10%</td>
<td>41 (G)</td>
</tr>
</tbody>
</table>

To specify the returns to scale characteristics of the production (frontier) function we test the hypothesis
that the frontier is represented by constant returns to scale (i.e. a single hyperplane in the input/output
space) in each of the nine severity groups shown in Table 1. Tests were performed using both test
statistics proposed by Banker [35]: one statistic assumes inefficiency has a chi-square distribution, the
other assumes inefficiency has a half-normal distribution. For each severity group, both test statistics were significant at the 0.01 level. The hypothesis of constant returns to scale was therefore rejected in favor of variable returns to scale.

The final DEA model used to analyze the data in each severity group is specified as the maximization of the outcomes of patient satisfaction and ΔHbA\textsubscript{1c} relative to a frontier with variable returns to scale, where the maximization is conditioned on the three self-care behaviors as inputs. Output maximization rather than input minimization was used in order to represent a process where increases in efficiency are achieved through improvements in outputs rather than decreases in self-care behavior [24].

1.2 Data

Patient data were obtained from a previous study using survey responses and medical records of a defined random sample of adults diagnosed with Type 2 diabetes mellitus who were continuously enrolled in an HMO for 12 months [36]. Data collection for the study was conducted at a Minnesota HMO with 240,000 members enrolled in a staff-model HMO in 1994. The survey results we report are based on a 61 item questionnaire sent to a randomized sample of 1000 patients who were over 18 years of age in 1994, had defined diagnosis of diabetes mellitus in 1994, and were continuously enrolled in the HMO from December 31, 1994 to January 1, 1996. Six hundred and nine of 828 returned patient surveys had complete data for purposes of our analysis.

Survey items were subjected to factor analysis using a principal component extraction method to identify groups of items used to measure patient compliance with treatment, patient compliance with monitoring, patient confidence in knowledge of their disease process, and patient satisfaction with the care they received. The Kaiser-Guttman rule was used to identify factors that explained more of the total variance than a single variable in the standardized sample (i.e. eigenvalues greater than one). To facilitate interpretation, each solution was rotated using a Varimax method with Kaiser normalization. Cronbach’s Alpha ($\alpha$) was calculated for each scale as a measure of internal reliability: for compliance with treatment (3 items), $\alpha = 0.39$; for compliance with monitoring (4 items), $\alpha = 0.34$; for confidence in knowledge (7 items), $\alpha = 0.93$; and for satisfaction (5 items), $\alpha = 0.61$. The Cronbach’s alphas in the factors measuring compliance with treatment and monitoring are not uncommon among scales using so few items [37].
Survey items correspond in language and composition to their respective construct domains implicating face validity for each scale [38].

Measures of glycosylated hemoglobin (HbA1c) in all study subjects were done in a single accredited clinical chemistry laboratory using a standard liquid chromatographic assay with a coefficient of variation of 0.57% at a HbA1c level of 8.8% normal range 4.5-6.1% [39]. There were no changes in the HbA1c assay procedures during the study period.

Because DEA does not process inputs with negative values, each patient’s HbA1c change score was calculated as:

$$
\Delta\text{HbA1c} = (-1) \cdot \left( \frac{(\text{Final HbA1c}) - (\text{Initial HbA1c})}{(\text{Initial HbA1c})} \cdot 100 \right) + 72
$$

The percent change in HbA1c (ΔHbA1c) was calculated such that decreases in HbA1c were scored as positive and increases in HbA1c were scored as negative. Adding 72 to each patient’s change value does not effect the interpretation of the results. “No change”, in HbA1c is represented as a ΔHbA1c score of 72; scores greater than 72 represent a decrease in HbA1c; scores less than 72 represent an increase in HbA1c.

Diagnosis of diabetes was based on either two ICD-9 250 diagnostic codes in 1994, or a filled prescription by a diabetes-specific drug such as insulin or a sulfonyuria in 1994. The estimated sensitivity of this method is 0.91 and its positive predictive value is 0.94 as previously reported [40].

Results: Transforming Self Care Behaviors into Health Outcomes

We develop a model of outcome variation based on data from a population of patients with Type 2 diabetes. In this section we report patterns and relationships found in these data. Though we use statistical tests to gauge a number of these relationships, the results we report are not presented as formal tests of hypotheses.
The analysis that follows is presented in three parts: (1) We first describe results that characterize the transformation process that converts self-care behavior (inputs) into health outcomes (outputs); (2) we then examine individuals on the best practice frontier in each severity group in Table 1 to determine the variation in outputs among those patients who are most successfully adapted to the conditions of Type 2 diabetes; and (3), we characterize off-frontier patients in terms of their self-care behaviors and determine invariant features of these patients’ response to the environment of illness and care they experience.

1.3 Severity Group Correlation Structure

As background for our analysis, Table 2 presents the correlations between the self-care behaviors and health outcomes in each severity group shown in Table 1. Although some investigators have found a significant relationship between patient satisfaction and indicators of physical health [41], in the present study patient satisfaction and percent change in HbA1c were not significantly correlated (at an \( \alpha \)-level of 0.1) in any of the nine groups. Significant correlations exist, however, among self-care behaviors and between self-care behaviors and output variables in several severity groups.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Group</th>
<th>Treatment</th>
<th>Monitoring</th>
<th>Confidence</th>
<th>Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitoring</td>
<td>A</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.16</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>0.25 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>0.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>0.27 **</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>0.24</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>0.31 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>0.49 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Confidence</td>
<td>A</td>
<td>0.21 *</td>
<td>0.22 *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>0.15</td>
<td>-0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>0.22 *</td>
<td>0.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>0.13</td>
<td>0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>-0.01</td>
<td>0.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>0.10</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>0.24</td>
<td>0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>-0.06</td>
<td>0.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>0.26 *</td>
<td>0.39 **</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
As shown in Table 2, confidence in knowledge is positively correlated with satisfaction (at a significance level of 0.1) in all groups except groups B, D, and E; confidence in knowledge is positively correlated with $\Delta HbA1c$ only in group A. Adherence with monitoring is negatively correlated with satisfaction in groups A and D, and negatively correlated with $\Delta HbA1c$ in group C; it is positively correlated with $\Delta HbA1c$ in groups F and G. Adherence with treatment is not correlated with other self-care behaviors, or with outputs, in any severity group. This latter result is at odds with the typical expectation regarding the relative effectiveness of treatment adherence, namely that compliance with treatment is a primary factor in controlling HbA$_1$c levels [18].

The lack of association of satisfaction and $\Delta HbA1c$ deserves comment. In theory, satisfaction influences glycemic control and other dimensions of chronic disease care through a positive impact on adherence [42]. However physician expression of uncertainty is often a part of chronic disease care, and is related to lower patient satisfaction [43]. Further, there is little direct evidence to relate antecedent higher satisfaction to subsequent better outcomes in patients with chronic diseases [44, 45]. In diabetes care,

<table>
<thead>
<tr>
<th>Satisfaction</th>
<th>A</th>
<th>-0.18*</th>
<th>0.24 **</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>0.24</td>
<td>-0.17</td>
<td>0.12</td>
</tr>
<tr>
<td>C</td>
<td>0.15</td>
<td>-0.01</td>
<td>0.22 *</td>
</tr>
<tr>
<td>D</td>
<td>-0.04</td>
<td>-0.24 *</td>
<td>0.17</td>
</tr>
<tr>
<td>E</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>F</td>
<td>0.08</td>
<td>0.07</td>
<td>0.25 **</td>
</tr>
<tr>
<td>G</td>
<td>0.15</td>
<td>0.13</td>
<td>0.4 **</td>
</tr>
<tr>
<td>H</td>
<td>0.07</td>
<td>0.17</td>
<td>0.53 **</td>
</tr>
<tr>
<td>I</td>
<td>-0.15</td>
<td>-0.02</td>
<td>0.29 *</td>
</tr>
</tbody>
</table>

| Change in HbA1c | A  | -0.03 | 0.18 * | 0.14 |
|-----------------|----|---------|---------|
| B               | 0.12 | 0.01 | 0.11 | 0.01 |
| C               | -0.14 | -0.25 * | 0.11 | -0.08 |
| D               | 0.02 | 0.15 | 0.16 | 0.11 |
| E               | 0.19 | 0.03 | 0.10 | 0.03 |
| F               | 0.70 | 0.17 * | 0.03 | -0.03 |
| G               | 0.20 | 0.31 * | -0.02 | 0.17 |
| H               | 0.20 | 0.12 | 0.25 | -0.01 |
| I               | 0.08 | -0.03 | 0.07 | -0.14 |

* p-value < 0.1  ** p-value < 0.01  ***p-value < 0.001
providers make lifestyle, treatment, or monitoring recommendations that many patients resist, resent, or feel threatened by [46]. Under such circumstances it may not be surprising that physician recommendations designed to improve glycemic control do not uniformly lead to higher levels of patient satisfaction.

1.4 Variation in Frontier (Best Practice) Patients

The distribution of both frontier and off-frontier patients in each severity group with respect to percent change in HbA1c ($\Delta$HbA1c) and efficiency (fitness) is given in Figure 1. Most frontier patients in each group (individuals with efficiency scores equal to 1) have either improved or unchanged $\Delta$HbA1c. Some frontier individuals also have worse $\Delta$HbA1c than comparable non-frontier patients. The distribution of patient satisfaction shows similar variation.
1.1 EFFICIENCY SCORE

Figure 1. Change in HbA1c vs. Efficiency--For Patients in Each Severity Group (Cells A-I)
We examine the parameters of the transformation process for frontier patients using the concept of returns to scale [47], which describes how a production function responds to scale changes in inputs [48]. There are three types of returns to scale: constant, increasing, and decreasing. Constant returns to scale exists when a scale change in input produces the same proportionate change in output. When a less than proportionate change is produced, there are decreasing returns to scale. When a greater than proportionate change is produced, there are increasing returns to scale. Adaptations on the frontier in regions of constant returns to scale are located such that all other adaptations are on or below the line connecting the adaptation and the origin: Banker [49] identifies these points as most productive scale size (MPSS).

Patients in the MPSS region of the frontier balance their self-care behaviors with respect to outputs, relative to the remaining patients on the frontier. Frontier patients who are not part of this set are in regions of either increasing or decreasing returns to scale. Frontier patients in regions of increasing returns to scale do not take full advantage of their self-care behaviors in producing the outputs of Satisfaction and change in HbA1c. These individuals could achieve a proportionately greater increase in outcomes for a marginal increase in input. Frontier patients in regions of decreasing returns to scale achieve proportionately smaller increases in outputs for a marginal increase in self-care behaviors.

Figure 2 shows the proportion of frontier patients in each returns to scale category for each severity group in Table 1. The proportion of frontier patients in the region of MPSS increases with disease duration for those severity groups with low HbA1c (i.e. severity groups A, B, and C). For severity groups with high HbA1c levels (groups G, H, and I), the proportion of patients in the region of MPSS decreases with duration of disease. Frontier patients with good HbA1c levels appear to value compliance behaviors less over time; they also fail to adopt compliance behaviors in regions with decreasing returns to scale. Frontier patients with poor HbA1c levels appear to value self-care behaviors more as their disease progresses, leading them to adopt behaviors in regions of decreasing returns to scale (i.e. regions of greater compliance).
In each severity group, variation in self-care behaviors and knowledge of their disease is greater for patients in the region of MPSS than for patients in the corresponding region of decreasing returns to scale. MPSS patients appear to have greater variation in the process that generates health outcomes than patients in the region of decreasing returns to scale. Such variation often implies resilience in the face of a changing environment [50], suggesting that frontier patients in the region of MPSS may be less likely to move from this adaptation.

There are eight frontier patients across all nine severity groups in the region of increasing returns to scale (low compliance). This suggests that parameters of the transformation process for most frontier patients (represented by the values $v$ and costs $w$ in equation (3)) produce an equilibrium of adaptation in regions with lower returns to scale (higher compliance and patient knowledge).

Based on the analysis of data for frontier (best practice) patients we posit four propositions: (1) the transformation of self-care behaviors into health outcomes generates variation in health outcomes among frontier patients; (2) variation in $\Delta HbA_1c$ decreases with duration of disease for frontier patients with both good and poor initial $HbA_1c$; (3) the value patients associate with compliance decreases with duration of disease if $HbA_1c$ is good, and increases with duration if $HbA_1c$ is poor; (4) and in general, frontier
patients in the MPSS region are more resilient to changes in their disease environment than similar patients in regions of decreasing returns to scale.

1.5 Variation in Off-Frontier Patients

We assume a process that transforms patient behaviors into health outcomes. The level of output for a given level of input varies according to the efficiency (fitness) of this process. We describe variation in outputs in terms of input values, severity group (i.e. the environment \( e \)), and the estimate of the fitness \( \epsilon \) as follows:

\[
\text{Outcomes} = \epsilon F_e(\text{Inputs})
\] (7)

Different parameterizations generate variability in how this process transforms inputs into outputs. For a given process \( F_e \) and input level, outputs vary according to the efficiency (fitness) with which the transformation is effected.

In terms of DEA methodology, \( F_e \) represents a frontier defined by a piecewise linear function. For example, the frontier shown in Figure 3 is described by the function

\[
F(\text{Input}) = \begin{cases} 
F_{AB} (\text{Input}) & \text{if } A < \text{Input} \leq B \\
F_{BC} (\text{Input}) & \text{if } B < \text{Input} \leq C \\
F_{CD} (\text{Input}) & \text{if } C < \text{Input} \leq D \\
F_{DE} (\text{Input}) & \text{if } D < \text{Input} \leq E 
\end{cases}
\] (8)
Figure 3. Example Frontier with Regions of Adaptation (A1, A2, and A3) for 1 Input and 1 Output
Each facet of the frontier has a unique outcome gradient (set of vectors $dy^T/dx$) represented in Figure 3 by the slope of the facet. Each non-frontier patient is located as a fraction, $\varepsilon$, of the frontier value for the corresponding facet. For example, the patient indicated as the point “a” in Figure 3 is located as:

$$\text{Output}_a = \varepsilon_a \cdot F(\text{Input}_a)$$  (9)

The term $\varepsilon_a$ represents DEA efficiency: the fitness of a given patient’s adaptation relative to a frontier point with similar inputs. This function preserves two influences on outputs in our analysis: changes in self-care behavior (inputs) and changes in efficiency. An increase in inputs without a change in efficiency will increase the output level according to the patient’s outcome gradient. An increase in efficiency without a change in input level will increase outputs regardless of the patient’s outcome gradient. As shown in Figure 3 points “a” and “b” are different both because they have different inputs and efficiencies, and also because they are associated with different frontier outcome gradients (different slopes on the frontier).

For all patients, variation in health outcomes increases with increased efficiency (the Goldfeld-Quandt F-test of increasing heteroskedasticity [51] is significant at the 0.1 level in all severity groups for $\Delta HbA_1c$ and in groups C through I for Satisfaction). For off-frontier patients the distribution of $\Delta HbA_1c$ is sensitive to changes in environment: both the mean and variance of $\Delta HbA_1c$ vary significantly across severity group (the F-test for equal means based on an ANOVA and Bartlett’s test for equal variance both have p-values = 0.000). At the same time, the distributions of patient satisfaction do not vary significantly across severity group (the F-test has a p-value = 0.29 and Bartlett’s test has a p-value = 0.12).

Results using linear regression indicate that compliance with treatment, compliance with monitoring, and patient knowledge are not significantly associated with $\Delta HbA_1c$ (F-test p-values = 0.677, 0.19, 0.33 respectively); however, both compliance with treatment and patient knowledge are significantly associated with patient satisfaction (F-test p-values = 0.03 and 0.001 respectively; p-value for compliance with monitoring is 0.52). Each association is positive for each severity group, except for the effect of treatment in severity group I. Outcome gradients appear to be associated with satisfaction but not $\Delta HbA_1c$ for off-frontier patients.
To further examine the relations between self-care behaviors and health outcomes we partition the input/output space into regions of adaptation based on patient compliance. We set the boundary between high and low values for each compliance behavior in each severity group (compliance with treatment and compliance with monitoring) based on the mean of each response scale: “High” corresponds with responses greater than or equal to the mean response, “Low” corresponds with responses less than the mean response. We label the four compliance regions of adaptation as HH, HL, LH, and LL, where the first letter in each pair represents high (H) or low (L) compliance with treatment, and the second letter represents high (H) or low (L) compliance with monitoring.

The high compliance region (HH) in a two dimensional DEA model (i.e. one-input and one-output) is associated with a relatively flat (less steep) frontier outcome gradient compared to the low compliance region (LL). In two dimensions, HH corresponds to a region similar to A3 shown in Figure 3; LL corresponds to a region similar to A1. The region A3 has higher inputs than A1 but a flatter frontier and a correspondingly lower outcome gradient than region A1.

Table 3 gives the frequency of patients in each compliance region by severity group for patients off the best practice frontier. For comparison purposes, Table 3 also presents data for corresponding frontier patients. Across severity groups (except groups A and E), HH contains more off-frontier patients while LL contains more frontier patients than other regions.
The distribution of both off-frontier and frontier patients across compliance regions is independent of severity group (the Chi-square tests of independence have p-values 0.114 and 0.597 for off-frontier and frontier respectively). For off-frontier patients, the distribution of compliance regions is dependent on

### Table 3: Frequency of Patients On and Off the Frontier in Each Severity Group and Compliance Category.\(^1\)

<table>
<thead>
<tr>
<th>Frontier Category and Severity Group</th>
<th>Compliance Category</th>
<th>Total(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HH</td>
<td>HL</td>
</tr>
<tr>
<td>Off-Frontier</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>30</td>
<td>31</td>
</tr>
<tr>
<td>B</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>C</td>
<td>28</td>
<td>13</td>
</tr>
<tr>
<td>D</td>
<td>19</td>
<td>11</td>
</tr>
<tr>
<td>E</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>F</td>
<td>35</td>
<td>14</td>
</tr>
<tr>
<td>G</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>H</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>I</td>
<td>12</td>
<td>7</td>
</tr>
<tr>
<td>On-Frontier</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>B</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>D</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>E</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>G</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>H</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>I</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>192</td>
<td>138</td>
</tr>
</tbody>
</table>

\(^1\)In each compliance category the first letter represents compliance with respect to treatment (e.g., H is greater than or equal to the mean response; L is less than the mean response); the second letter represents compliance with respect to monitoring.

\(^2\)Row totals for off and on frontier give the number of patients in each severity group in Table 1 (e.g., 108+18=126 for group A).

The distribution of both off-frontier and frontier patients across compliance regions is independent of severity group (the Chi-square tests of independence have p-values 0.114 and 0.597 for off-frontier and frontier respectively). For off-frontier patients, the distribution of compliance regions is dependent on
disease duration (the Chi-square test has a p-value of 0.009). As disease duration increases, compliance decreases. For frontier patients, distribution of compliance regions is dependent on HbA1c levels (the Chi-square tests based on the columns and rows in Table 1 have p-values of 0.405 and 0.098 respectively). As HbA1c levels increase, compliance increases.

1.6 Archetypical Adaptations
We next partition patient adaptation by level of satisfaction in order to investigate the transformation process of specific patient groups. In particular, we focus on those patients with low compliance (i.e. the LL pattern) and high satisfaction. This partition represents a classification of patient adaptation that often draws particular attention from healthcare providers [46]. Low compliance would appear to be at odds with the goals of the healthcare system. To have low compliance and yet be correspondingly satisfied provides a provocative combination—particularly for those patients with poor HbA1c levels. This region of adaptation captures patients that are non-compliant with their treatment regimes, yet are satisfied with their health care.

Such a region reflects what we shall term an archetypical (characteristic) adaptation to the conditions of chronic disease [52]. Following O’Connor, et al. [46] we term the region of low compliance and high satisfaction as a “Don’t Worry Be Happy” (DWBH) archetype of adaptation. A contrasting region of adaptation is that associated with high compliance and high satisfaction. Patients in this region are satisfied and in conformance with the healthcare system’s efforts. In the spirit of O’Connor et al., we term individuals with these adaptations as instances of a “Happily Compliant” (HC) patient archetype.

From Table 4 we find that off frontier patients in both archetypes have worse ΔHbA1c scores when initial HbA1c is relatively good (< 8 percent - groups A, B & C). By contrast off frontier patients in both archetypes have either improved or no change in their ΔHbA1c scores when initial HbA1c is ≥ 8 percent (the other six severity groups). All frontier patients in both archetype groups have either no change or improved ΔHbA1c change scores. The healthcare system appears to be equally successful (or unsuccessful, depending on severity group) in managing the health outcomes of DWBH and HC patients.
Table 4: Mean Percent Change in HbA1c by Archetype, Severity Group, and Frontier Category

<table>
<thead>
<tr>
<th>Frontier Category and Severity Group</th>
<th>Archetypes</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>DWBH</td>
<td>HC</td>
</tr>
<tr>
<td>Off-Frontier</td>
<td>A</td>
<td>65.67</td>
<td>70.88</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>69.10</td>
<td>70.30</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>70.38</td>
<td>68.01</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>74.88</td>
<td>81.49</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>72.00</td>
<td>71.83</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>74.01</td>
<td>74.52</td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>72.00</td>
<td>85.05</td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>86.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>77.85</td>
<td>78.53</td>
</tr>
<tr>
<td>On-Frontier</td>
<td>A</td>
<td>73.72</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>72.65</td>
<td>72.00</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>74.10</td>
<td>72.00</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>89.25</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>80.65</td>
<td>95.30</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>82.89</td>
<td>72.00</td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>81.90</td>
<td>100.75</td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>80.85</td>
<td>101.95</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>84.40</td>
<td></td>
</tr>
</tbody>
</table>

1 Changes greater than 72 reflect improved HgA1c; changes less than 72 reflect worse HgA1c; values of 72 reflect no change in HgA1c.

The percent of DWBH patients on the frontier varies between 30 and 100 percent across severity groups. The percent of HC patients who are on the frontier varies between 0 and 33 percent. Sixty-eight percent
of the frontier DWBH individuals and 30 percent of the frontier HC individuals are in the region of MPSS. The adaptation of satisfied but non-compliant patients (DWBH) is efficient and apparently situated to take advantage of lower self-care behaviors. The adaptation of satisfied compliant patients (HC) is less efficient and situated to take advantage of relatively higher self-care behaviors.

The DWBH and HC regions of adaptation do not exhaust archetypical patient groups. We have described them in some detail because they are indicative of adaptations that represent significant sources of variation in patient and practitioner views of the chronic disease process [53]. In the O’Connor et al. analysis individuals in the DWBH region persist over time and move to other regions of adaptation based largely on personal experiences and life events. To the extent these and other psychological variables that motivate behavioral change can be identified [54], the management of patient adaptations to the condition of their disease may be substantially improved [55].

Based on analysis of data presented in this section we posit four propositions: (1) adaptations with greater fitness have greater variation in health outcomes; (2) while compliance behavior of off-frontier patients is associated with disease duration, compliance behavior of frontier patients is related to HbA1c level; (3) in general, the adaptation of off-frontier patients appears to be based on compliance; and (4), patients who are satisfied but not compliant (DWBH) are more likely to be on the frontier and in regions of MPSS than patients who are satisfied and compliant (HC).

Explanatory Model
We now turn to the task describing variation in health outcomes based on the proposition that such variation is associated with patients’ adaptation to the conditions of chronic disease. In what follows we first develop constructs from the literature on behavioral change and adaptation. We then combine these constructs with the theoretical proposition from section 2 into a model that accounts for the differences we have described.

1.7 Behavioral Change
We begin by conceptualizing changes in self-care behaviors as state transitions motivated by (1) differences in the utility of alternative states, and (2) the effort associated with moving from one state to another [56]. Relative to a reference (or current) state, those patient states with greater utility correspond to a likelihood of transitioning, whereas patient states with lower utility correspond to a likelihood of
staying in the current state (what is associated in the literature with an individual’s readiness to change behavior—e.g., [56]). The more effort it takes to transition to a given state, the lower the readiness to make that change.

We represent transitions based on readiness to change from one state, $s_j$, to another state, $s_i$, as a function $G$ of the difference in utility $\Delta U_{ij}$ between the two states, and $E_{ij}$ the effort required to make the change in states ($E_{ij}$ incorporates the parameter $w$—the marginal cost of the inputs). The function $G$ relates these factors to readiness to change such that increased changes in utility lead to increased readiness to change, and increased effort leads to decreased readiness to change. The following model of readiness to change, based on Helbing [56], where $RTC(s_i|s_j)$ is the readiness to change to state $s_i$ from state $s_j$, captures this proposition:

$$RTC(s_i|s_j) = G(\Delta U_{ij}, E_{ij})$$

(10)

Changes in utility due to small changes in behavior (inputs) can be partitioned into two effects: (1) an effect generated through changes in health outcomes and (2) an effect generated through changes in other conditions of the patient’s environment ($Z$). The first effect can be expressed as a product of the change in utility due to a change in outcomes ($U_{\theta}$, based on the parameter $v$—the marginal value of the output) and the outcome gradient (which is approximately $\varepsilon \cdot R$, fitness times the outcome gradient of the frontier) multiplied by the change in behavior ($\Delta s$). The second effect ($\Delta U_z$) is the change in utility due to other factors multiplied by the change in behavior.

Substituting into the readiness to change equation and suppressing the state subscripts on the right hand side for notational convenience yields the relationship:

$$RTC(s_i|s_j) = G(\varepsilon \cdot R \cdot U_{\theta} \cdot \Delta s + \Delta U_z, E)$$

(11)

We expect that patients with a lower outcome gradient are less ready to change than patients with higher outcome gradient; more efficient patients (those with higher outcome gradient) have a greater level of readiness to change.
If such an effect is not exhibited, the model provides three explanations. First, the patients in a given region of adaptation emphasize other factors ($\Delta U_z$) that counter the effects of health outcomes on utility; second, the effort ($E$) in changing states for patients in a given region is sufficiently high to counter the effects of increased outcomes; or third, a combination of these two effects is present.

Changes in behavior typically require more than a high level of readiness to change. Bandura [57, 58] has proposed individuals’ judgements of their abilities to successfully execute a change in behavior influences the level of effort they will expend in attempting that change. The evaluation of one’s abilities to execute a change in behavior is a parameter in the structure of adaptation termed self-efficacy.

Health behaviors related to self-efficacy include exercise, nutrition, weight control, dental health behavior, sexual risk-taking behavior and addictive behaviors (see [59], for a summary of the literature regarding self-efficacy and health behavior). Following the Theory of Planned Behavior [60], we assume self-efficacy functions as a multiplier such that behavior change will not occur if self-efficacy is zero. For example, Madden, Ellen, and Ajzen [61] have shown that including self-efficacy in this capacity substantially improves theory predictions of targeted behaviors including, among others, exercise, sleep habits, avoiding caffeine and taking vitamin supplements.

If an individual’s expenditure of effort falls short of that required to sustain a specific change, the individual’s level of self-efficacy will decrease, which diminishes the effort expended on subsequent attempts. This reinforcing (positive) feedback loop can either entrench an individual in a current state or spiral them out of a current situation depending on whether they are engaged in a failure/decreased self-efficacy mode or a success/increased self-efficacy mode.

The effort patients expend often outweighs the effect of a change in utility for small but not large changes. If the increment of behavior change is small, readiness to change may decrease. The threshold for decreasing the magnitude of change is associated with patient adaptation through the outcome gradient: higher outcome gradients allow smaller increments of change because the increase in utility is larger. Under these circumstances small changes may be more likely to succeed for adaptations with high outcome gradient and high levels of fitness.
1.8 Fitness Change

We assume patients improve their health outcomes through the modification of psychosocial and physical attributes that parameterize the transformation of self-care behavior into outcomes. Attributes that generate better outcomes are better fit. Improved fitness is indicative of changes in patient attributes. We model fitness change by specifying a set of attribute structures \( A = \{ \alpha_1, \alpha_2, \alpha_3, \ldots \} \) that undergo modification during the adaptation process. Initially, we adopt four types of attributes that compose the adaptive structures for patients with chronic disease (i.e. \( \alpha_i = \{ a_{i,1}, a_{i,2}, a_{i,3}, a_{i,4} \} \)): a set of physiological attributes and three sets of psychosocial attributes.

Physiological attributes reflect the patient’s response to changes in the environment and internal states. Psychosocial attributes include: (1) the value a patient associates with health outcomes; (2) the psychosocial cost associated with changes in behavior; and (3) the extent to which patient perceptions include being capable of making specific changes in behavior (i.e. patient self-efficacy).

Changes in fitness result from the modification of a patient’s current attribute structure (i.e. changing at least one of the four attributes). For example, a physician may effect change in fitness by prescribing drugs that facilitate a better physiological response to the patient’s disease process. Members of the patient’s social environment may effect fitness changes by influencing the patient’s relative valuing of health outcomes. Patient fitness may also change through singular events (e.g. heart attack, blindness). More generally, improvements in fitness have a two-part effect on health outcomes: (1) a direct effect that produces an immediate gain in outcomes without a change in behavior, and (2) an indirect effect based on improvements in outcome gradients associated with higher fitness.

As we have seen, the direct effect of improvements in fitness on outcomes is greatest for regions of high compliance; in Figure 3, this is where the frontier is flattest. Regions of high compliance correspond to regions with higher possible outcomes, where the range of outcome values is larger, (i.e. the change in outcome per change in fitness is greater). This is shown in Figure 3 by comparing the change in output associated with a 25% increase in fitness between points \( e_0 \) and \( c_1 \) and between points \( d_0 \) and \( d_1 \): the set of points in the region of low outcome gradient (\( d_0 \) and \( d_1 \)) have a greater increase in output.

The indirect effect of improvements in fitness on outcomes is typically greatest in regions where the outcome gradient is steep, typically regions of low compliance. Here, an increase in fitness corresponds
to a greater potential gain in output for a given change in behavior (Figure 3). For example, the indirect effect of changing fitness by moving from point $c_1$ to $c_2$ in Figure 3 leads to an increase in compliance, until the slope of the gradient corresponding to 75% is equal to the slope of the gradient corresponding to the previous 50% (associated with point $c_0$). The indirect effect approaches zero as the slope of the frontier approaches zero because in this region an increase in fitness does not change the corresponding outcome gradient.

Changes in patient self-care behaviors in regions where the outcome gradients is relatively flat move the patient along the line of equal fitness generating only small increases in health outcomes. In these regions, increasing fitness will be more productive than changing self-care behaviors. Where the outcome gradient is relatively steep, changes in patient self-care behaviors will produce better outcomes than where the outcome gradient is shallow.

1.9 Accounting for Variation in Chronic Disease Outcomes

The model we construct is based on the proposition that variation in the attribute structures of patient adaptation ($\alpha \in \mathcal{A}$) explains variation in health outcome ($y \in \mathcal{Y}$). More formally, we assume a function that maps patient attribute structures onto a subset of health outcomes. Describing this function with a first order Taylor series, we express the relationship between changes in the attribute structure and changes in outcomes as:

$$\Delta_y = \frac{dy}{d\alpha_e} \cdot \Delta \alpha$$ \hspace{1cm} (12)

Where the subscript $e$ denotes dependence on a given environment (e.g. severity groups in this analysis). From equation (2), health outcomes can be expressed as a function of fitness $\varepsilon$ and self-care behavior $x$.

Expanding $\frac{dy}{d\alpha_e}$ in terms of $\varepsilon$ and $x$, and substituting into equation (12) gives

$$\Delta_y = \left( \frac{\partial y}{\partial \varepsilon} \cdot \frac{\partial \varepsilon}{\partial \alpha_e} + \frac{\partial y}{\partial x} \cdot \frac{\partial x}{\partial \alpha_e} \right) \cdot \Delta \alpha$$ \hspace{1cm} (13)
Equation (13) is the final form of the model we propose to describe the relationship between patient adaptation and variation in health outcomes. Each term in parenthesis represents a component of the analysis we have described in the preceding sections. The first term, \( \frac{\partial y}{\partial x} = \epsilon \frac{\partial F}{\partial x} \), is the outcome gradient of the patient’s adaptation (i.e. \( r \) in equation 4). The second term, \( \frac{\partial x}{\partial \alpha} \), represents a change in behavior as described is section 1.7. The third term, \( \frac{\partial y}{\partial e} \), represents the correspondence between fitness and health outcome (which, from equation (2), is the outcome \( F_e(x) \) of the adaptation with fitness = 1). The fourth term, \( \frac{\partial e}{\partial \alpha} \), is the change in fitness described in section 1.8.

Equation (13) proposes that changes in the patient adaptation affect outcomes through changes in self-care behavior and fitness. The effect through self-care behavior depends on the rate of change in outcomes relative to behavior. The effect through fitness depends on the maximum attainable outcome for a given self-care behavior. The rate of change in outcomes and the maximum attainable outcome can be at odds: as fitness increases, greater attainable outcomes may correspond to lower outcome gradients, and lower attainable outcomes may correspond to higher outcome gradients (see Figure 3).

The propositions at the end of sections 1.4 and 1.6 regarding variation in health outcomes are explained by equation 13 either as effects of within environment variation (i.e. variation in patient adaptation (\( \alpha \)) propagated via its two pathways) or as effects of across environment variation (for example, differences in health outcomes across severity group). In section 1.4 we observe that within environment variation exists among fully adapted patients. This is explained as variation due to the first term in the parentheses of equation 13. Differences in variation among frontier patients across duration levels are explained by variation in the environment. In section 1.6 we observe variation in health outcomes among off-frontier patients due to each mode of variability in equation 13: variation in fitness (\( e \)), variation in self-care behavior \( \frac{\partial x}{\partial \alpha} \), and variation in environment (\( e \)).
The result of our analysis, together with the model expressed as equation 13, suggests that strategies for improving health outcomes may be tailored to regions of patient adaptation. Thus, for example, patients in regions of low compliance may improve in health outcomes, without changing compliance levels, if more effective medications are used. The consequent increase in the outcome gradient associated with the new fitness level may motivate patients to improve their compliance behavior, further increasing health outcomes. Patients in regions of high compliance, having relatively flat outcome gradients, benefit little from improved compliance; however, more effective medications can improve fitness and consequently improve health outcomes without requiring behavior change.

Organizations influence adaptation by adopting policies (e.g. drug formularies and clinical guidelines) that affect the patient’s environment and the transformation process. In our analysis, different formularies may define different frontiers if the effectiveness of available drugs interacts with patient compliance (i.e. define a different set of possible health outcomes, given self-care behaviors). Policies that generate greater health outcomes in one region of the input space may not dominate all regions (i.e. some drugs may be more effective at low compliance, while others are more effective at high compliance). A policy that generates greater outcomes in one severity group may not be as effective in other severity groups.

Drivers of Fitness
The model presented in section 1.9 stipulates that adaptation generates variation in health outcomes due to differences in fitness. In this section we investigate two drivers of fitness (i.e. variables that explain variation in fitness [24]): patient comorbidities and health care charges. We consider Comorbidity based on its role as feedback regarding the state of patient health. Unlike lab results, comorbidity directly affects lifestyle and its affect on patient adaptation depends on whether patients attribute comorbidities to their disease. Health care charges are used as a proxy for the resources invested in patient care by the health care system. We consider resources to be a driver of fitness based on the proposition that chronic illness is managed by the health care system and efforts to improve patient fitness require resources.

We investigate drivers of fitness using a Tobit regression of DEA efficiency on comorbidities and charges, each interacted with severity group as well as compliance with treatment and monitoring [62]. We include patient self-care behaviors as covariates. The regression model considers efficiency as censored at the upper limit of 1. Due to the interaction with treatment and monitoring, the overall effect of each driver can be a function of compliance behavior.
We use the Charlson comorbidity scale [63, 64] to represent severity weighted cumulative patient comorbidities. The Charlson score for each patient is defined such that higher scores indicate more severe comorbidites. One year mortality rates in elderly patients (65 years old or older) have been estimated as 8% among patients with Charlson scores of 1 or greater, 14% among patients with Charlson scores of 2 or greater, and 33% among patients with Charlson scores of 3 or greater [65]. The charge data presented here include all inpatient, outpatient, and pharmacy charges for each patient and are reported as average dollars per day over the eighteen-month study period.

As shown in Table 5, comorbidity has a significant effect on patient fitness at the $\alpha = 0.1$ level. Charges do not. For patients who attribute comorbidities to their disease, we expect comorbidity to have a positive correlation with fitness. For patients that do not attribute comorbidities to their disease, we expect comorbidity to have a negative correlation with fitness. Results of the regression analysis conform to these expectations. Among patients with high compliance, comorbidities correspond to better fitness (i.e. a positive relationship between comorbidities and efficiency); among patients with low compliance, comorbidities correspond to lower fitness (i.e. a negative relationship between comorbidities and efficiency).
We have assumed that health care resources (charges) are required to maintain patients in adaptations with high fitness and high compliance. Thus we may expect resources to be positively related to fitness among patients with high compliance and negatively related to fitness among patients with low compliance, due to increased charges associated with poor health states. Because our data do not provide
an opportunity to attribute health care charges to specific types of encounters with the health care system, the lack of a significant influence of resources on fitness may not be surprising. Future investigations regarding the role of health care resources and patient adaptation will require measures that capture those resource components associated with diabetes and distinguish between inpatient vs. outpatient care.

Overall, the results reported in Table 5 support a relationship between the model presented in equation 13 and expectations regarding influences of external factors on patient adaptation to the conditions of Type 2 diabetes. Further evaluation of this relationship will require longitudinal as well as cross-section studies that incorporate specific characteristics of patient self-care behaviors and the interaction between patients and documented features of their healthcare environment (e.g., providers, clinics). Such research conducted across a variety of chronic diseases and levels of aggregation (e.g., studies of patient, physician and management decision making) will provide more comprehensive understanding of sources of meaningful variation in the outcomes of improved healthcare practice.

Conclusions
We have developed a model of variation in health outcomes based on the proposition that patients with chronic disease progressively modify their behavior in response to changes in their environment. We have characterized the process through which this modification takes place as adaptation. We have further argued that the environment that drives the adaptation of a given chronic disease patient includes the experienced conditions of that disease, the healthcare system (including providers), and various psychosocial features of the patient’s life.

Using the concept of frontier analysis we have proposed that the adaptation of individual patients can be understood relative to the adaptation of the most successful patients with similar characteristics. We have described results of a study in which patient adaptation to the conditions of Type 2 diabetes are represented as a transformation of three self-care behaviors into two health outcomes. Patients who are most successful at this transformation we have termed frontier or best practice patients. These individuals achieve optimal adaptation to the experienced environment of their disease. Patients who are less successful at this transformation we have termed off-frontier or non-best practice patients.

The data we present indicate that variation in health outcomes exists among maximally adapted (frontier) patients. This variation can be partitioned based on the gradient of change associated with the
transformation process for each patient’s self-care behaviors. In the case of off-frontier patients we find that variation in health outcomes has two parts. One source of variation is based on characteristic patterns of self-care behaviors. These patterns reflect regions characterized by the outcome gradient of specific frontier patients. The second source of variation in health outcomes for off-frontier patients is based on their degree of fitness within characteristic (archetypical) regions of adaptation.

The model we propose is extended to clinics and physicians by the assumption that each patient’s adaptation is influenced by the decision premises of other agents. From the perspective of the clinic these premises consist of organizational policies (e.g., clinical care guidelines). From the perspective of the physician these premises take several forms, including: 1) range of practice (the variation in patients seen and the conditions under which patients are referred to other physicians), 2) continuity of care (the extent to which decisions regarding patients are made on the basis of a presumed long-term patient relationship) and 3) patient empowerment (means used to improve patient self-care behaviors) [66].

Although the work we present is based on specific assumptions about the process of patient adaptation, we note that adaptation to an environment can take more than one characteristic form. Using Ashby’s Law of Requisite Variety [67], Beer [68] argues for three cases. In the first case, an agent (individual or group) attempts a one to one match between variation in its behavior and variation in the environment. In medicine we see this form of adaptation in providers who attempt to tailor their policies and behavior to the condition and experience of each individual patient. In the second case described by Beer, adaptation is achieved by treating all variation alike. Some applications of clinical practice guidelines in medicine reflect efforts for this type of control.

The third form of adaptation described by Beer is based on the use of what Ashby calls a variability amplifier. In this case, the adapting agent uses one to many mappings between its behavior and categories of environmental variation. Here, the analogy in health care is the provider who refers to groups of patients using labels such as ‘Don’t Worry Be Happy’. The use of categories (what we have termed patient archetypes) reduces the information-processing load associated with keeping track of patient variation and, depending on the categories, can improve the power and reliability of provider behavior [22, 69, 70].
The adaptations we have described represent variability amplifiers for patients as well as the physicians who care for them. From the perspective of physicians, and other policy-making agents, adaptations provide a means of interpreting variation in patients and their health-related behaviors. From the perspective of patients, adaptations represent learned patterns of response to an uncertain and sometimes difficult environment. Research directed towards improved understanding of patients and the adjustments they make to the conditions of chronic illness provides important insights into the persistent finding of outcome variation in the delivery of healthcare services.
Footnotes

1 All vectors in this paper are written as column vectors. The superscript $^T$ indicates the transpose operation on the preceding vector or matrix.

2 The transformation process we describe is similar to Grossman’s health production model in which health is produced from patient actions (typically an investment of medical care) [71]. Unlike the Grossman model, however, we embed the transformation process within the context of patient adaptation and introduce the concept of fitness as a determinant of variation in outcomes. Whereas Grossman’s model is used to estimate the demand for health care [72, 73, 74], the analysis we present informs the development of specific treatment policies.
References


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