Grant Final Report

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Improving Patient Access and Patient-Clinician Continuity through Panel Redesign

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Abstract

Purpose: This R03 proposal investigated optimization models for management and redesign of patient panels in primary care. Specific goals were to model the impact of timely access and continuity as a function of a physician's panel size and case-mix. A panel refers to the patients for whose long term care a physician is responsible.

Scope: None provided.

Methods: We used retrospective patient and panel data from two primary care databases: 1) Primary Care Internal Medicine (PCIM), Mayo Clinic, Rochester, Minnesota and 2) Residency primary care clinics of Massachusetts General Hospital (MGH), Boston. Case-mix was modeled in a variety of ways: 1) age and gender; 2) number of simultaneous chronic conditions; and 3) diversity of major disease groups (relevant for resident training purposes). Probability models were used to determine current access and continuity levels of a group practice and determine the least disruptive way of redesigning panels.

Results: The application of these quantitative models to the two databases revealed that: 1) Adequately redesigning panels allows a practice to empanel 10-15% more patients with the current capacity; 2) Redesign can be achieved by changing less than 8% of total patient-physician relationships; 3) For residency clinics redesign improves diversity of clinical conditions represented in resident panels. Conclusion: In a time where more and more practices are implementing the patient centered medical home, this research provides a framework for dynamic management of physician panels in a primary care group practice to improve access and continuity. The methodology followed can be implemented in a spreadsheet format by practices.

Key Words: None provided.

Final Report

Purpose

Primary care practices in the United States must balance the timeliness of care delivery with its continuity, i.e., balance the lead time for appointments with the goal of having patients see their own primary physician whenever possible. Timeliness and continuity are intrinsically tied to the makeup of the patient population—the "physician-patient panel"—that a physician oversees. Teaching hospitals must also take into account the learning requirements of its medical residents. In order to prepare residents for future practice, residents should be exposed to the widest possible range of clinical experiences.

Using patient appointment data, physician-patient panel sizes, and physician case mix, we investigated how group practices can dynamically manage physician and resident-patient panels to improve timeliness of access and continuity. They will develop a quantitative decision support system to help clinicians, practice managers, and health systems answer the following questions:

Aim 1. How should physician-patient panel composition be altered over time to best match patient demand with physician supply?

Aim 2. How many additional new patients can be empanelled without adversely affecting the goals of timely access and continuity?

Aim 3. How should practices best match patient and physician preferences, while simultaneously considering the influence of panel size and case mix on patient access?

We constructed a general modeling framework for managing physician and resident-patient panels in a group practice and utilized systems engineering algorithms and methods (probability/stochastic models and optimization). We used retrospective patient and panel data from two primary care databases: 1) Primary Care Internal Medicine (PCIM), Mayo Clinic, Rochester, Minnesota and 2) Residency primary care clinics of Massachusetts General Hospital (MGH), Boston.

Aim 1 and Aim 2 were addressed using PCIM data. We developed a modeling framework for a group practice that considers case-mix, panel size, physician daily capacity. We linked these parameters into a single measure, the *probability of overflow*, which is a proxy for both timely access and continuity of care. If overflow in a practice is high, both timely access and continuity of care are adversely affected. An important advantage of the modeling framework is that it can be implemented in an Excel Spreadsheet and can be used by practice managers and administrators to plan long term panel management and redesign decisions. This can be done on a dynamic basis—every week, or month, or on a quarterly basis. It could also be to decide which panel a new patient should be assigned to, whether patient preference for a particular physician can be balanced with the probability of overflow. An example of this for a 4-physician test practice is provided in the results section. We feel this tool could provide a more rigorous way of quantifying the access and continuity in designing patient centered medical homes (PCMH).

For Aim 3 we chose the residency primary care continuity clinics of MGH, Boston. Here physician preferences translate to adequate educational and training of medical residents. This means that resident primary care panels should contain sufficient diversity of clinical diagnoses and representation of disease groups. We demonstrate the impact of a number of simple algorithms on resident panel diversity and patient access. In addition we also demonstrate how the impact of redesign varies by practice size.

Implementation. While implementation in practice was not a part of the proposed tasks, we note that these algorithms are currently in the process of being translated at the Internal Medicine Associates (IMA) clinics of MGH, Boston, in June-July 2012.

Scope

Despite the health insurance reform passed by the Obama administration in 2010, the US healthcare system continues to face serious challenges. Healthcare costs in the US are more than 15% of the GDP - the largest among industrialized countries - and health outcomes are not correspondingly better. While a solution to the crisis in healthcare has to be necessarily multipronged, involving efforts from all stakeholders, policy-makers agree that one of the key areas that needs reform is primary care delivery.

As the first point of contact, primary care is the backbone of any health system. Despite its crucial role, primary care in the United States is experiencing serious challenges due to a nationwide shortage of physicians. Demand, meanwhile, is growing as the population ages and as the number of people with chronic conditions increases. Millions of people currently without insurance are slated to receive coverage in the new few years. This will put an enormous burden on the primary care system. Meanwhile, practices are struggling to provide two metrics vital to primary care: 1) Timely Access, and 2) Patient-physician Continuity. Timeliness refers to the ability to obtain a physician appointment as soon as possible. Patient-physician continuity, on the other hand, is one of the hallmarks of primary care and refers to the ability of practices to provide the patient an appointment with his/her own physician as much as possible.

The benefits of continuity for both patients and physicians have been well documented in the clinical literature. Gill and Mainous (2010) point to several studies which show that patients who regularly see their own providers are 1) more satisfied with their care; 2) more likely to take medications correctly; 3) more likely to have problems correctly identified by their physician; and 4) less likely to be hospitalized. Continuity and coordination are especially important for vulnerable patients with a complex medical history and mix of medications [Nutting et al, 2003]. In practice continuity translates to maximizing patient-PCP matches when appointments are scheduled. But the ability of a PCP to provide continuity and timely access depends on 1) panel size, or the number of patients in her panel; and 2) case-mix, or the type of patients in the panel. For example a panel consisting of mostly healthy patients will have a very different appointment burden compared to a panel consisting mostly of patients with chronic conditions.

We characterize the interrelationship between panel size, case-mix and the individual capacities of physicians working in a group practice. We do this by measuring the *overflow frequency* of the physicians in relation to each other. The overflow frequency is the probability that the demand from a physician panel (i.e. patient requests for appointments in a day) will

exceed the physician's capacity (i.e. the number of appointment slots a physician has available in a day). A high overflow frequency for a physician implies that patients in the panel will be unable to access their physician in a timely manner and are as a result more likely to visit an unfamiliar physician or emergency room. Thus a high overflow frequency implies that both timely access and continuity of care are compromised.

Our consideration of panel size and case-mix is particularly relevant given the acute shortage of PCPs in the United States. The demand for primary care continues to grow as the population ages and the prevalence of chronic conditions increases. Our approach allows practices to quantify their current supply and demand imbalances and use available capacity in the most efficient manner possible. Case-mix is an important consideration given that patient demographics and care needs vary from community to community and from one geographic region to another.

Our analysis is at the aggregate planning level, where a practice has to decide how many and what type of patients are appropriate in each panel to ensure patients have adequate levels of access and continuity. In the long term, if imbalances in workload exist among the physicians, a practice may be interested in *redesigning* panels - that is in changing the size and case-mix of individual physician panels so that each physician's capacity is in balance with her demand. While this involves changing existing panel configurations, opportunities for redesign arise constantly in primary care. For example, new patients may join the practice, existing patients may move from the area, and patient preferences about who their PCP should be may change over time. On the capacity side, a physician may leave the practice or retire, with the result that patients in that physician's panel now need to be reassigned.

In residency practices found in academic medical centers, the turnover of residents every year provides constant opportunities for piloting panel redesign. However, there are additional considerations in teaching clinics. They need to give to provide timely access to patients while giving trainees a consistent teaching experience, a broad range of clinical experiences to learn from, timely access to preceptors, and maximize continuity. This report also includes a detailed study of panel management at residency clinics of MGH, Boston.

Organization of Report

Because there are relatively two self-contained studies that resulted from this proposal, based on Mayo and MGH datasets respectively, we divide the methods and results part of this report into two distinct sections. We first describe the modeling framework and results that came from study of Mayo Clinic, PCIM data, and then describe the MGH residency clinics study. While both involve panel management in a group practice and redesign, the outcomes and interpretations are different.

Part 1: Panel Redesign for a Group Practice—A Stochastic Modeling Framework

Data Sources

We use data from the Primary Care Internal Medicine (PCIM) practice at the Mayo Clinic in Rochester, MN. This practice empanels around 20,000 patients and employs 39 physicians. Many of these physicians worked part time. Panel data enabled us to identify which patient belonged to which physician. Patient level data included the number and type of chronic conditions afflicting each patient as well as the number of visits for each patient for 3 years (2004, 2005 and 2006). The list of chronic conditions included commonly occurring diseases such as hypertension, depression, diabetes, osteoporosis, urinary tract infections, hyperlipidemia, coronary artery disease and otitis. We use this data to infer case-mix and visit dates, which we discuss next.

Methods

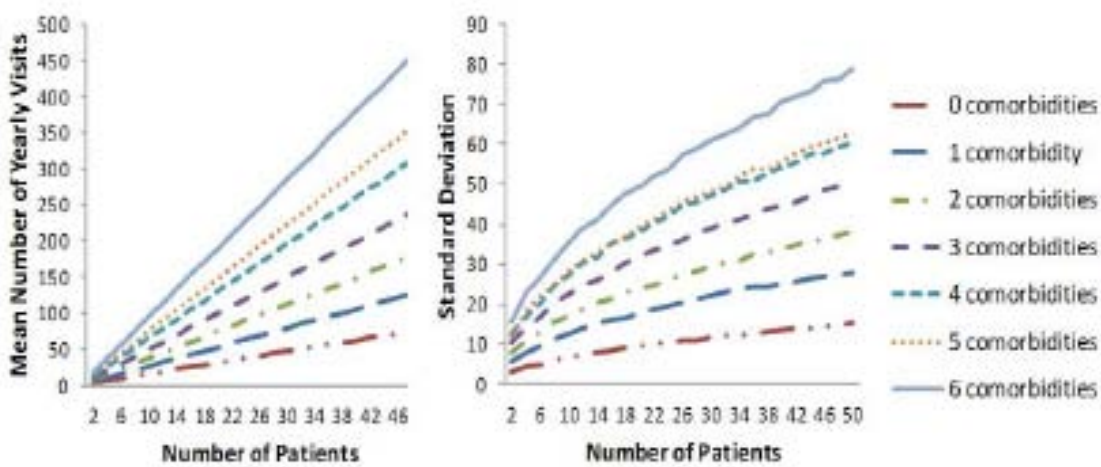
Modeling Case-mix. Patients can be characterized by various attributes, such as age, gender and the chronic conditions afflicting the patient. Our interest is in attributes that play an important role in determining the distribution of visits. For example, a panel where the majority of patients are young and healthy will have a different appointment profile compared to a panel consisting mostly of elderly patients with chronic conditions. In addition to operational and capacity planning reasons, patient classification can be useful for clinics because they enhance a practice's understanding of its population and disease trends, and allow it to design its care models effectively. Barbara Starfield's seminal work about ACGs (Ambulatory Care Groups) (Starfield et al, 1991) argued that understanding the role of patient clinical complexity in care utilization forms the cornerstone for effective resource planning and determining payment methods in healthcare.

What classifications are the most effective in predicting appointment request rates? Age and gender is the simplest patient classification in absence of other data, yet is generally effective (Murray et al 2007; and Balasubramanian et al. 2010). In this project, we use the number of simultaneous chronic conditions a patient has as a predictor of the number of visits. In clinical parlance, these conditions are *comorbidities*. Our choice is based on the following reasons. First, comorbidity counts have clinical relevance and are widely accepted by the primary care practices we have interacted with. Focusing on all comorbidities of a patient is more holistic than focusing in isolation on specific chronic conditions, and primary care was conceived to be a holistic approach rather than a disease specific approach. Secondly, our categorization has been used both in literature and practice. Naessens et al (2011) show that the number of simultaneous chronic conditions is a strong predictor of the number of office visits. Comorbidity counts have also been used in a new payment scheme for primary care proposed by the Minnesota Department of Health (2011). Finally, statistical analysis of our patient level data from Mayo Clinic (using classification and regression trees, CART) revealed the count of comorbidities as the strongest predictor of appointment request rates.

We note, however, that the models proposed in this paper can be applied to any patient classification. While patient classification is important, the central theme of this paper is not to find the ``best'' classification. Rather, it is to show the impact of patient classes on access measures. To illustrate the impact of comorbidity counts, we analyzed the patient population (around 20,000 patients) empanelled at the Primary Care Internal Medicine Practice (PCIM) at the Mayo Clinic in Rochester, Minnesota. Examples of commonly observed chronic conditions in patients included hypertension, depression, diabetes, osteoporosis, urinary tract infections, hyperlipidemia, coronary artery disease and otitis. We divided patients based on the number of comorbidities they had. In all there were 8 patient categories as patients with more than 7 comorbidities was extremely rare.

Figure 1 shows mean and standard deviation of visit rates as a function of the number of patients under various counts of comorbidities, resulting from our simulation. The data was simulated using empirical distributions based on historical visits of 20,000 patients empanelled in PCIM. Clearly, not only does the mean number of visits increase with the number of comorbidities, the variance does as well. For instance if a physician has 50 6-comorbidity patients then he will have 450 appointment requests on average each year. If he has same number of 0-comorbidity patients he will have only 75 yearly visits on average. The same trend is true for the standard deviation as well.

Figure 1. (Top) Number of yearly visits and standard deviation as a function of the number of comorbidity counts. (Bottom) Binomial probability p_i that a patient with *i* comorbidities will request an appointment on any given day)



p_0	p_1	p_2	p_3	p_4	p_5	p_6	p_7
0.006242	0.010571	0.014907	0.019914	0.025987	0.029823	0.03799	0.041167

For our modeling framework, we also calculate the probability p_i that a patient with *i* comorbidities will request for an appointment on any given day. This probability is calculated using total office visits from all patients with *i* comorbidities in a 3 year period, divided by total number patients with *i* comorbidities times the total number of workdays in the 3 year period. This method is adapted from Green, Savin and Murray (2007).

Stochastic Modeling Framework. Our work on redesign of physician panels, published in the *Journal of General Internal Medicine* [Balasubramanian et al, 2010; AHRQ funding acknowledged], explored the possibility of shifting patients between panels as a way to improve timely access and continuity of care. By moving high demand, high variability patients (characterized by age and gender) from an overburdened physician to a physician with available capacity, it was possible to improve both timely access and number of redirections to unfamiliar physicians by 40%. We argued in the discussion that while changing physician panels between panels is not easy, a practice can move towards better panel compositions over time, by identifying as yet uncommitted patients and as new patients join the practice.

The simplest version of the panel redesign optimization problem can be formally described as follows. Suppose all patients empanelled in a practice have been categorized into i=1…m patient classes, and that there are N_i total patients in patient class i. A physician j's panel currently consists of n_{ij} patients from each category i (clearly $n_{ij} <= N_i$). The physician's current panel size is therefore $\sum_{i=1}^{m} n_{ij}$. Each physician has a capacity C_j, which is the total number of appointment slots the physician has available in a day (it is also possible to use week or year, depending on the level of aggregate analysis desired). A patient of category i has a probability p_i of requesting an appointment on a given day. If we assume that the patients within a class in a physician panel are identical and request independently of each other then the number of patient requests from that class follows a binomial distribution. Based on the current panel allocation, the mean number of patients from class i requesting for an appointment for physician panel j on any given day is $n_{ij}\ p_i$ and the variance is $n_{ij}\ p_i\ (1-p_i)$.

The current panel design is given by the n_{ij} values. If the practice decides to redesign panels, then the decision variable x_{ij} expresses the number of patients that should be allocated from patient category i to physician panel j. The objective is to optimize the x_{ij} variables (the allocations) to minimize the maximum overflow over all the physicians in the practice. Overflow happens when the demand for the day exceeds the physician's total available slots for the day. Patients that are not seen either visit an unfamiliar physician or an ER, or may choose to wait to see the physician on another day. Thus, if overflow is high, both timely access and continuity are adversely affected.

More precisely, the overflow, O_j, for physician j, is the probability that the demand from the panel will exceed the capacity. The demand for physician j is a function of x_{ij} variables corresponding to the physician. The mean demand (μ_j) and standard deviation of demand (σ_j) can be expressed as:

$$\mu_j = \sum_{i}^{M} x_{ij} * p_i \text{ , } \forall \text{ j} \qquad (1)$$

$$\sigma_j = \sqrt{\sum_{i}^{M} x_{ij} * p_i * (1 - p_i)} \text{ , } \forall \text{ j} \qquad (2)$$

If we assume that the sum of m binomial random variables gives us a normal random variable, then O_j is related to the percentile of the standard normal distribution, given by Φ, in the following way:

$$O_j = 1 - \Phi\left(\frac{C_j - \mu_j}{\sigma_j}\right)$$

The optimization attempts to level the load over all physicians in the practice to minimize the maximum overflow:

$$\text{Min } (Max_j(O_j)) \ \forall \text{ j}$$

s.t.

$$\mu_j = \sum_i^M x_{ij} * p_i \text{ , } \forall \text{ j} \qquad (1)$$

$$\sigma_j = \sqrt{\sum_i^M x_{ij} * p_i * (1 - p_i)} \text{ , } \forall \text{ j} \qquad (2)$$

$$\sum_j^N x_{ij} = N_i \qquad \forall \text{ i} \quad (3)$$

$x_{ij} \geq 0$ and integer

Results

We now give an example of how the stochastic modeling framework is applied to Mayo Clinic PCIM data. Case-mix is represented by comorbidity counts. We consider an example of a 4 physician practice (Physicians 39,8,19 and 34 in PCIM). Each physician has around 1060 patients and a capacity of 17 slots per day. The number of patients in each of the comorbidity count categories is also shown. We then list the panel demand mean (μ_j), panel demand variance (σ_j^2), the overflow, O_j (calculated as described in the previous section) and the utilization (μ_j divided by C_j). All these calculations can be carried out in Excel. Indeed, the table below can considered the prototype of an Excel based decision tool that practices can use.

From Table 1, we see that the current practice (or baseline) has uneven overflows for the four physicians. Physicians 39 and 19 have lower utilizations and lower overflows while Physicians 8 and 34 have higher overflows. The latter two physicians will have to work longer hours to provide access and continuity to their patients. The table also shows three other panel designs: Capacity Based; Heuristic 1 and Heuristic 2. Capacity Based simply divides patients from each comorbidity count category *equally*. While this minimizes the maximum overflow, we note that to achieve such a redesign, the practice will have to change 193 existing patient-physician relationships. Compared to the total population of patients empanelled with the 4 physicians, these switches amount to less than 5%. However, a number of patients from the high comorbidity count categories are also shifted.

Table 1. Example of panel redesign for a 4-physician group practice (data from PCIM, Mayo Clinic)

		Co-morb. 0	Co-morb. 1	Co-morb. 2	Co-morb. 3	Co-morb. 4	Co-morb. 5	Co-morb. 6	Co-morb. 7	Panel Size	μ_j	σ_j^2	C_j	O_j	Utili-zation
Current	Phy 39	290	296	218	145	84	27	12	5	1077	14.73	14.47	17	0.28	0.87
Current	Phy 8	260	249	226	161	108	42	14	3	1063	15.54	15.26	17	0.35	0.91
Current	Phy 19	299	293	212	147	77	26	6	1	1062	14.10	13.86	17	0.22	0.83
Current	Phy 34	214	253	223	177	115	44	21	5	1053	16.16	15.85	17	0.42	0.95
Current	# Switched	0	0	0	0	0	0	0	0	0					
Capacity Based	Phy 39	266	272	220	157	96	34	14	3	1062	15.11	14.83	17	0.31	0.89
Capacity Based	Phy 8	266	272	220	157	96	34	14	3	1062	15.11	14.83	17	0.31	0.89
Capacity Based	Phy 19	265	273	219	158	96	35	13	4	1063	15.15	14.87	17	0.32	0.89
Capacity Based	Phy 34	266	274	220	158	96	36	12	4	1066	15.17	14.90	17	0.32	0.89
Capacity Based	# Switched	58	44	9	23	31	16	9	3	193					
Heuristic 1	Phy 39	357	296	218	145	84	27	12	5	1144	15.14	14.89	17	0.32	0.89
Heuristic 1	Phy 8	194	249	226	161	108	42	14	3	997	15.13	14.85	17	0.31	0.89
Heuristic 1	Phy 19	461	293	212	147	77	26	6	1	1223	15.11	14.87	17	0.31	0.89
Heuristic 1	Phy 34	51	253	223	177	115	44	21	5	889	15.15	14.84	17	0.32	0.89
Heuristic 1	# Switched	229	0	0	0	0	0	0	0	229					
Heuristic 2	Phy 39	292	298	220	147	86	30	14	7	1094	15.13	14.86	17	0.31	0.89
Heuristic 2	Phy 8	258	247	224	159	106	39	12	1	1046	15.14	14.87	17	0.31	0.89
Heuristic 2	Phy 19	305	299	218	153	83	31	11	6	1106	15.11	14.84	17	0.31	0.89
Heuristic 2	Phy 34	208	247	217	171	109	39	16	0	1007	15.15	14.87	17	0.32	0.89
Heuristic 2	# Switched	8	8	8	8	8	8	7	7	62					

(*Current* indicates the panels currently used at PCIM. *Capacity-based, Heuristic 1 and Heuristic 2* refer to three different ways of redesigning panels. Each involves changing current panels. The *# Switched* shows how many patients from each comorbidity count category had to be changed to achieve improved design. Other test cases, in the same format, are available in Ozen and Balasubramanian 2012)

Note that Heuristic 1 and Heuristic 2 also produce optimal overflows. However, Heuristic 1 shifts 229 of the 0-comorbidity (apparently healthy) patients, and does not switch patients from any of the other categories. These patients are likely to be more willing to change their PCPs. Heuristic 2 shifts the fewest patients (62), but this does involve patients with higher comorbidity counts.

The advantage of this framework is that a practice can use such a decision tool to make new empanelment decisions on a regular basis, test the impact of adding new patients on overflow measures, decide which providers should receive additional nurse practitioner or physician assistant support, and how provider teams could be formed to alleviate the detrimental effects of supply-demand imbalances.

Full details of other test cases, practical implications, and theoretical derivations can be found in Ozen and Balasubramanian [2012] (currently under review in *Health Care Management Science*; AHRQ funding acknowledged).

Part 2: Panel Management in Residency Clinics—Balancing Residents Educational Needs with Access to Care

Data Sources

We collected encounter data from primary care residency clinics (appendix) at Mass General Hospitals over a twenty-one month period (July 1, 2008 to April 30, 2010). The practice consisted of 258 residents and approximately 17,000 patients who visited over that time. For an initial analysis we grouped patients by gender and age, which was further subdivided into ten-year increments. These classifications were chosen as preliminary parameters to determine frequency demographics and the dependency patient visits may have with regards to age and gender.

Measures of Panel Case-Mix and Complexity

To characterize case-mix and complexity within each resident's panel, we first determined the mix of diagnoses in each resident's panel. This was done using the diagnoses codes associated with patient visits. To make interpretations of panel case mix easier, diagnosis codes were grouped by major disease category, both acute and chronic. Examples of major disease categories include are Neuro Acute, Neuro Chronic; Cardio Acute, Cardio Chronic, Psych Acute, Psych Chronic etc. In all there are 44 disease categories. We were thus able to identify diagnoses represented in each resident panel and under each major disease category.

We note here that a patient may contribute more than one diagnosis and that a single patient's diagnoses may fall in *different* disease categories. For example, one patient may have 5 diagnoses but all be cardiovascular acute diagnoses; another patient may also have 5 diagnoses, but 2 may fall under Pysch, 2 under cardiovascular chronic, and 1 neurological acute. The former patient spans only 1 major disease category, while the latter patient spans 3 major disease categories.

Therefore, another way of capturing the case-mix of a particular resident panel is to count the number of patients whose diagnoses fall in k disease categories, where k can take on any value from 1 to 44 (the total number of disease categories), although it is rare for patients to span more than 12 major disease categories.

Measure of Imbalance

We quantify the imbalance across residents by using a standard deviation (SD) measure for each disease category. For example, if there are four residents, R1, R2, R3 and R4, and the total diagnoses (across all disease categories) in their panels is 127, 244, 145 and 169 respectively, then the imbalance is simply the standard deviation of these four numbers, 51.46. The higher the

standard deviation, the more unequal the exposure rate. Since the standard deviation is for diagnoses, we call it SD_DIAG.

In the same way, we calculate the standard deviation with regard to number of total number of patients (SD_PAT) annual visits (SD_VIS). The standard deviation in diagnoses of a particular disease category is SD_ followed by the name or abbreviation of the disease category. SD_PSYCHA for example, stands for standard deviation in acute Psych diagnoses between the residents.

Table 2 shows the case-mix of 3 preceptors for a sample the most commonly represented major disease categories (some acute, some chronic) as well as the mean and standard deviations for the diagnoses count within these categories. The table also provides SD_DIAG, SD_PAT and SD_VIS.

Table 2. Example of resident panel case-mixes and standard deviation in diagnoses counts

Pre-ceptor	ResID	Acute: CVS	Acute: GI	Acute: ID	Acute: Neuro	Acute: Pulm	Chronic: CVS	Chronic: GI	Chronic: Neuro	Chronic: Psych	Tot Dia	Tot Vis	Tot Pat
3009	11214	16	13	33	11	5	75	21	6	9	296	444	79
3009	12325	17	29	30	14	11	48	25	14	26	325	468	67
3009	15876	5	22	35	12	10	24	18	5	4	235	321	56
3009	17081	2	3	14	8	3	12	9	2	5	124	179	35
3009	19746	9	18	24	14	8	28	7	5	10	203	361	49
4171	13354	19	28	28	13	17	36	12	10	4	259	423	57
4171	16701	7	14	24	23	12	50	11	2	7	279	469	71
4171	17907	7	10	18	10	6	26	4	7	13	160	249	42
4171	18610	0	0	8	6	6	7	2	1	0	62	90	10
4171	19850	7	13	24	20	6	22	5	3	2	199	284	52
6826	12865	12	24	19	36	14	25	10	4	5	228	335	71
6826	16114	6	12	14	15	11	24	7	1	5	162	268	49
6826	17607	10	22	19	31	13	15	13	0	3	235	309	54
6826	18184	6	20	20	22	13	33	14	1	5	215	336	68
	Mean	8.8	16.3	22.1	16.8	9.6	30.4	11.3	4.4	7.0	212.4	324.0	54.3
	STD	5.5	8.6	7.7	8.7	4.0	17.7	6.6	3.9	6.4	69.3	108.8	17.7

For this practice SD_DIAG, SD_VIS and SD_PAT are 69.3, 108.8 and 17.7 respectively. STD_CVSA (standard deviation across the residents for the CVS acute major disease category) for this practice is 5.5 while STD_PSYCHC (standard deviation across the residents for the Psych chronic major disease category) is 6.4. Clearly, there is a high variation and imbalance in all of the following: the diagnoses counts, number of visits, number of patients and diagnoses counts in the major disease categories.

Table 3 shows case-mix as function of the number of patients that span *k* major disease categories. Here too, using a standard deviation measure (STD_CAT), we see that residents differ with regard to the number of low and high complexity patients that each resident has. Resident 12358 who works with preceptor 1308 has15 patients whose diagnoses span 3 major disease categories, while Resident 10884, who also works with the same preceptor, has only 5.

Table 3. Standard deviations across residents of number of patients spanning *k* categories

ProvID	RevID	1	2	3	4	5	6	7	8	9
1308	10884	12	8	5	11	0	2	1	0	0
1308	12358	10	18	15	14	6	3	2	1	0
3009	12325	14	16	8	5	3	1	0	1	0
3009	15876	14	12	12	12	3	2	0	0	0
3009	19746	10	12	5	9	8	3	2	0	1
4171	13354	9	17	10	8	5	1	0	1	0
4171	16701	14	7	12	5	8	0	2	1	1
4171	19850	12	12	4	5	8	2	2	1	0
	Std. Dev	2.03	4.03	4.02	3.50	2.95	1.04	0.99	0.52	0.46

Patient Reassignment Algorithms

We next describe simple patient reassignment algorithms to minimize the standard deviation measures described above across residents. Our algorithms can be broadly classified into two types. The first type (Diag) uses the diagnosis count of a patient to characterize complexity, while the second (Cat) uses the number of major disease categories spanned by a patient.

We now describe the algorithm based on patient diagnosis count. The algorithm is executed in two parts. First, the patients are sorted in decreasing order of the number of diagnoses associated with each patient. At this point of the algorithm, the resident panels are empty; their diagnoses counts are zero. In the second part of the algorithm, patients are assigned one at a time, to the resident who has the smallest count of diagnoses (a running count of diagnoses per resident is maintained as each patient gets assigned). In other words, the next most complex patient on the list is assigned to the resident who has the smallest count of number of diagnoses. In case of a tie,

Assigning based on diagnosis counts does explicitly account for the fact that individual disease categories will be balanced. However, since a large number of patients are being reassigned and moreover since patient diagnoses cut across disease categories, we expect that imbalances will be smoothed out for the most part.

The algorithm based on number of major disease categories spanned works in exactly the same way, except that patients are first sorted in decreasing order of the number of categories spanned. The next patient on the list is assigned to the resident who has the smallest count of number of categories spanned.

The two reassignment algorithms, which we refer to as Diag and Cat, are applied to four different settings:

1) Reassignment Within Preceptor (RWP): Here, the patient reassignment algorithms are applied only to residents of a preceptor. No patients are reassigned across preceptors

2) Reassignment Within Group (RWG): Patients are reassigned for all residents who are within a group of preceptors. To begin with, we set group size equal to 4. Later we examine how group size affects our measures of imbalance. The motivation behind RWG can be described as follows. A group of preceptors choose to pool all their patients and distribute them among their residents to minimize the measures of imbalance. Since there is now a larger pool of patients, we expect the measures of imbalance to higher than RWP. But RWG comes the cost of preceptor-patient continuity.

3) Reassignment Across Clinic (RAC): This represents the case where a clinic chooses a complete redesign to minimize the measures of imbalance. Therefore all patients in the practice are reassigned among all the residents in the practice. We expect RAC to produce the best measures of imbalance. RAC allows the residency practice greater opportunity to correct imbalances since a larger pool of patients is likely to have greater diversity of diagnoses. But this comes at the cost of complete redesign and a loss of patient-preceptor continuity.

The three settings above in combination with the two reassignment algorithms give us 6 different combinations. We test the algorithms on 25 residents with 1300 panel patients belonging to 12 preceptors at an MGH outpatient clinic. Our method, however, is applicable to any number of residents and for any number of patients.

Results

Figure 2 shows the mean number of visits by age and gender for the 21 month period in which the data was collected.

Figure 2. Age, gender and visit distribution among the patients at MGH residency clinics

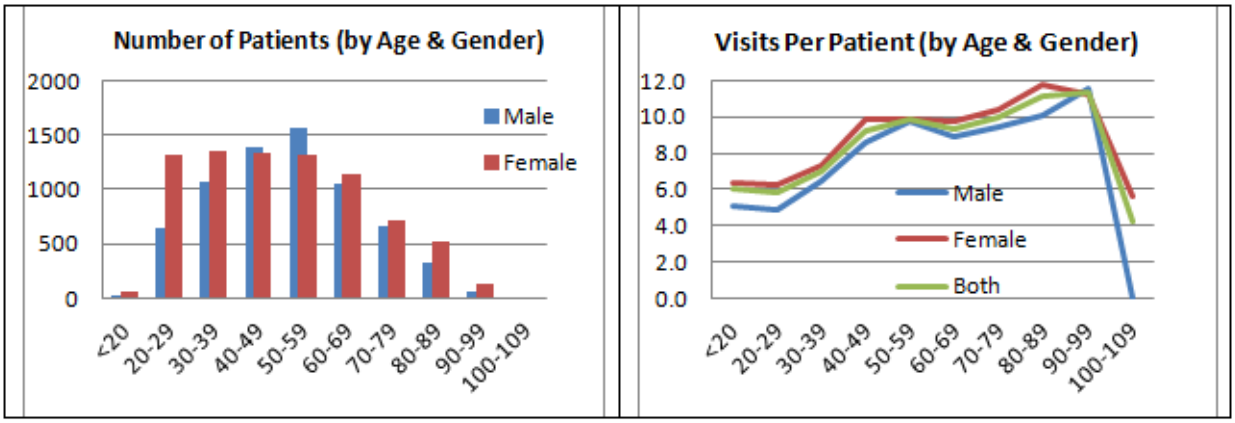
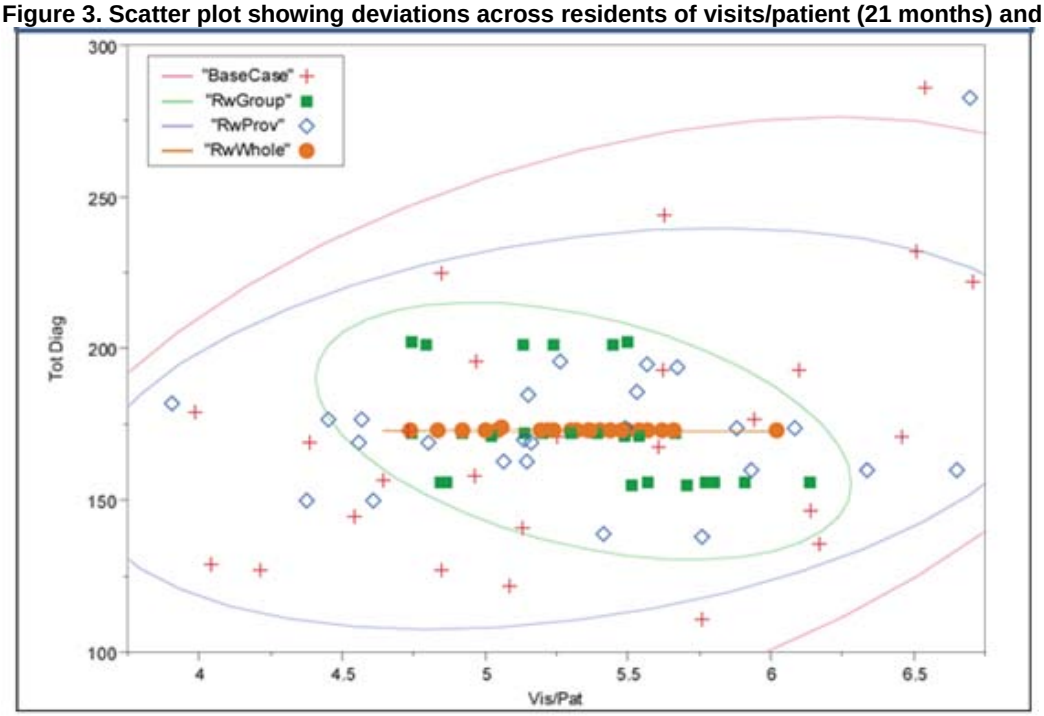


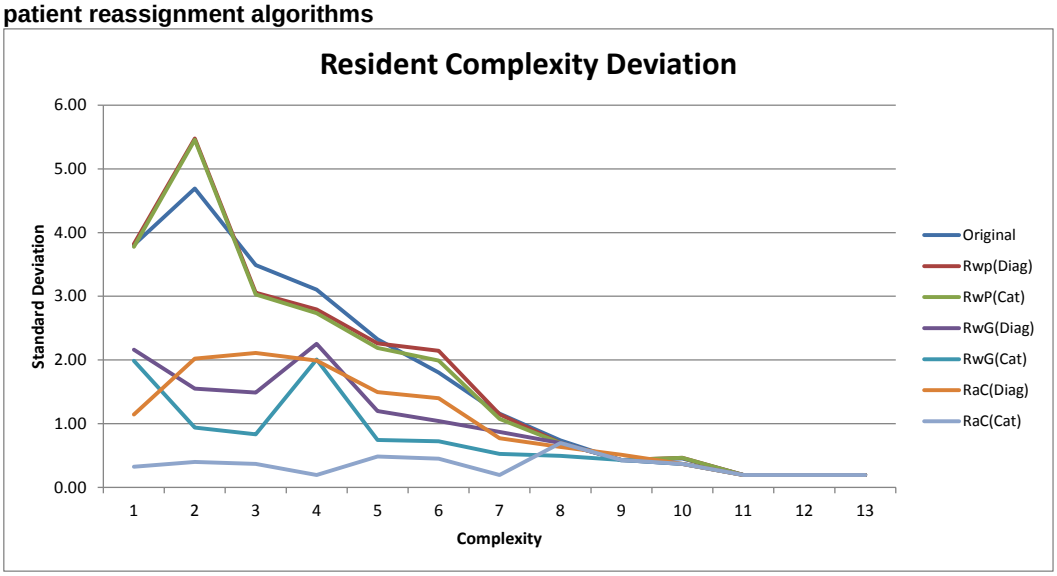
Figure 3 shows the results of the patient reassignment algorithms in the form of a scatter plot, with Visits/Patient on one axis and Diagnosis Count on the other. The greater the scatter the greater the standard deviation. Reassignment within preceptor (RwP) did not produce significant reductions in the standard deviation of either number of disease categories or diagnoses across residents. Reassignment in preceptor groupings of 4 preceptors or larger resulted in a significant reduction in category and diagnostic variance relative to base case (original case-mix). Reassignment across all preceptors reduced variance the most but comes at the cost of reduced patient-preceptor continuity.

Figure 3. Scatter plot showing deviations across residents of visits/patient (21 months) and diagnoses



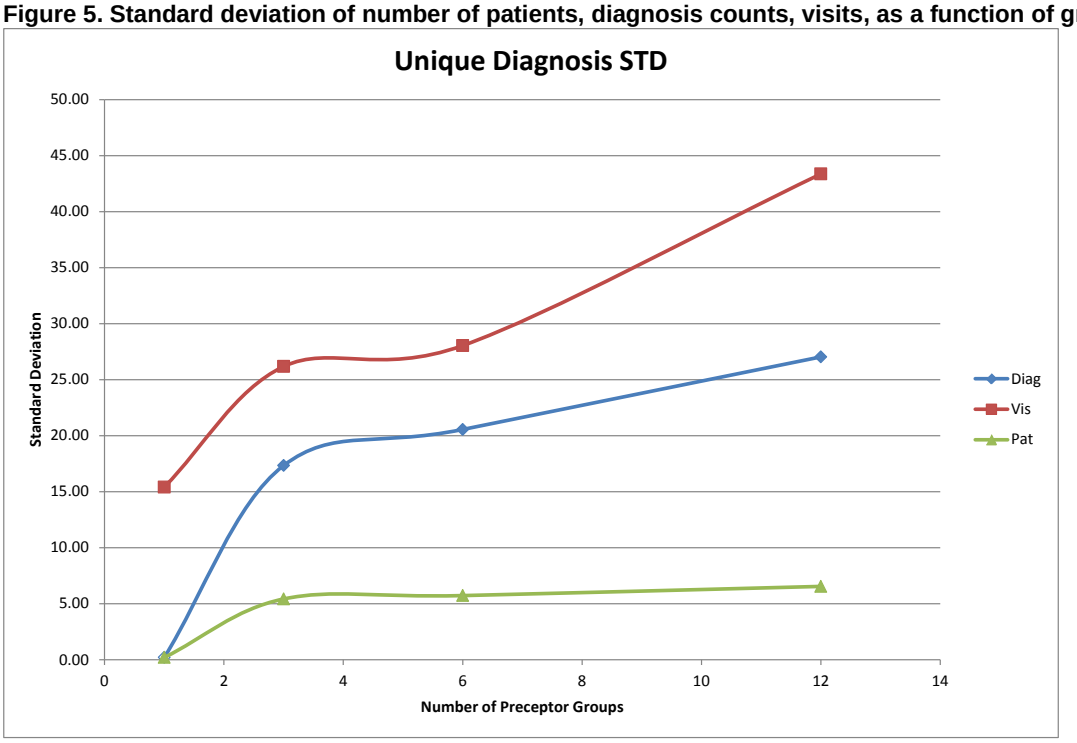
In Figure 4, we see that the STD_CAT for k =1…12 as function of the 6 algorithms proposed in Section 2.3. We see that Cat algorithms are somewhat more successful in minimizing STD_CAT. We also notice that both RAC (Cat) produces a significant improvement in STD_CAT for k = 1…6 compared to the original case-mix as well as RWP (Diag) and RWP (Cat). The RWP algorithms do not produce a significant reduction of STD_CAT compared to the original case-mix.

Figure 4. Standard deviation of patient complexity (the number of disease categories spanned) under the patient reassignment algorithms



In Figure 5, we see STD_DIAG, STD_VIS and STD_PAT as a function of the number of groups in the practice. In other words, if reassignment were to be carried out among preceptor only, and there are 12 preceptors in the clinic (which is the case for our test data), then there would be 12 groups in the practice (with each preceptor working independently). If 3 preceptors formed a group, then there would be 4 groups. If all preceptors decided to work together, then there would only be 1 group. We see from Figure 5, that the standard deviation measures decrease with the number of groups. Not surprisingly, lowest standard deviation is with a group size of 1. However, it's also clear that the greatest gain is from a group size of 12 to 6—two preceptors forming a group, which is realistic team care model in practice. Going from 6 to 3 does not produce much improvement, compared to 12 to 6. A practice can use such output to make appropriate choices about provider teams.

Figure 5. Standard deviation of number of patients, diagnosis counts, visits, as a function of group size



Summary of Findings

Mayo Clinic Study. In summary, we have found that a simple stochastic modeling framework, implementable in an Excel spreadsheet is capable of factoring panel size, case-mix and physician capacity to quantify levels of access. We also demonstrated that a practice can be redesigned in multiple different ways and the number of existing patient-PCP relationships changed due to redesign, in all cases, can be less than 8% of the total patients empanelled in the practice. This Excel tool can be used on a on-going basis by a practice, to assist in new patient empanelment and planning additional capacity.

MGH Study. We found that simple patient reassignment algorithms can significantly improve the distribution of patient complexity in primary care residency clinics. The measures of imbalance decrease as a function of practice size. Both diagnoses counts as well as category span counts work as good measures of complexity.

Discussion, Significance and Implications

Since the principal contribution of this proposal revolved around redesigning panels, it is important to discuss how feasible or useful such a framework is to practices, individual physicians and patients. Redesigning panels implies changing existing patient-physician relationships, and there appears to be a paradox. To improve timely access and continuity and improve resident education in the long run a practice has to invest in the short term disruption of existing-patient relationships. It is natural therefore to ask: how realistic is redesign in practice?

The feasibility of redesign would be a very valid concern if each patient in the panel was very loyal to the physician and had spent many years visiting the physician. Enforcing a break in that relationship would not be satisfactory to both the patient and the physician. But in practice, a panel is a lot more fluid. While there exist many patients who have spent years with the physician (we do not recommend that these relationships be disrupted), there also exist patients who are newly registered or are as yet uncommitted to their physician even though they have been assigned to a panel. It is these patients who would be amenable to redesign.

For example, in order to improve access to care, continuity and care coordination, Group Health practice of Seattle recently reduced panel sizes from 2300 per physician to 1800 per physician [Reid et al (2009)]. They hired new physicians and reassigned 500 patients per physician to either new physician or physicians who had available capacity. Patients were invited to an open house to meet their new physicians and surveys were used to identify patients who were willing to change their PCP.

In their papers, Reid et al (2010) and Coleman et al (2010) analyze the Group Health clinic after the implementation. They used survey-based measures to quantify patient satisfaction and staff burnout. The results of the implementation were: 1) Staff burnout decreases since they find that emotional exhaustion becomes less frequent for physicians; 2) Patients experience improves in terms of access to care and doctor-patient interactions (and this manifests itself in 29%fewer emergency department (ED) visits and 11% fewer hospitalizations); 3) During the reassignment, when physicians are given the chance to choose patients to keep in their panel, they prefer the elderly and sicker patients, who create a greater density of visits and need more continuity; and 4) Reassigned patients use primary care less, but there is no significant increase in their use of the ED.

While Group Health seems to have successfully achieved its redesign to improve patient centeredness, access and continuity, their reassignment of patients does not seem to have followed a quantitative basis. For example, how did the practice decide that 500 patients per physician (more than 20% of the original panel size of 2300) had to be reassigned? Could fewer patients have been reassigned or could do panel sizes need to be even smaller? Quantitatively capturing the beneficial effects of redesign and the impact on the number of patients affected - which is the focus of this paper - will help individual physicians and the practice as a whole to make the choices that are most appropriate for them.

Indeed our experimental results suggest that panel redesign will affect at most 5-8% of the total patients (250 patients out of 4300 total) in the practice. Furthermore, the number of patients

affected can be as low as 2% (less than 100 out of 4300 total). So the very large majority of patient physician relationships will remain unaffected. Yet, we find that the improvements in overflow frequency due to redesign are significant for the overburdened physicians in the PCIM practice. There is thus a strong incentive for overburdened physicians to consider redesign, since it improves access measures for their patients.

Furthermore, as Balasubramanian et al (2010) argue, redesign does not need to be carried out instantly as in the Group Health case, but can be achieved by most practices in the long term. Every practice has a natural attrition rate as well as a group of new patients wanting to join the practice. Patients' comorbidities can change over time as well. Retiring physicians will need to transition their patients to newly hired physicians. These rates could be used, over time (a period of 1-2 years or perhaps more) to adjust case-mixes so that timely access and continuity are improved. Indeed we view the framework of this paper not as a strict prescription that dictates what practices should do. Rather we see it as an assessment tool, which practices can use to benchmark their current access and continuity levels on a quarterly or yearly basis and use whatever leverage they have to change panels.

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List of Publications and Products

1. H. Balasubramanian, R. Banerjee, B. Denton, J. Naessens, D. Wood, and J. Stahl. Improving clinical access and continuity using physician panel redesign. *Journal of General Internal Medicine*, 25(10):1109-15, 2010. (AHRQ Funding Acknowledged)

2. Ozen, A., and Balasubramanian, H., The impact of case-mix on timely access to appointments in primary care group practices, under review at *Health Care Management Science* (AHRQ Funding Acknowledged)

3. Balasubramanian, H., Muriel, A., Ozen, A., Wang, L., Hippchen, J., and Gao, X., Capacity allocation and flexibility in primary care, Springer Book on Healthcare Operations Management, Editor: Brian Denton, forthcoming: Fall 2012. (AHRQ Funding Acknowledged)

4. Overko, S., Balasubramanian, H., Fosburgh, B., and Stahl, J., Optimizing outpatient residency training: Balancing clinical experience with access to care, working paper to be submitted to the journal *Medical Decision Making*.

5. Overko, S., Balasubramanian, H., Fosburgh, B., and Stahl, J., Optimizing outpatient residency training: Balancing clinical experience with access to care, peer reviewed abstract under review for the Society of Medical Decision Making, Annual Conference, Phoenix, AZ, October 2012.

6. Overko, S., Balasubramanian, H., Fosburgh, B., and Stahl, J., Optimizing outpatient residency training: Balancing clinical experience with access to care, peer reviewed abstract presented at the Harvard Primary Care Innovations Conference, October 2011.