The Hilltop Institute
UMBC

Maryland Primary Care Program (MDPCP) Pre-AH Risk Score Specifications and Codebook

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Version	Date	Description of Primary Change(s)
1	October 3, 2019	Initial Release.
2	January 11, 2020	▪ Added clarification of time lag of estimates; consistency of risk scores over time; reasons for risk; and model performance in production. ▪ Updated model coefficients and appendix table. ▪ Added List of Tables and Figures.
3	June 29, 2020	▪ Added section on nonlinear modeling tests ▪ Updated weighting methodology for environmental risk factors ▪ Added section on new risk factors as of June 2020 ▪ Updated Appendix 1 to reflect additional risk factors

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Pre-AH Risk Score Specifications and Codebook

Table of Contents

List of Tables and Figures

Maryland Primary Care Program (MDPCP)
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1. Overview

The Maryland Primary Care Program (MDPCP) is a key element of the Total Cost of Care (TCOC) All-Payer Model, an agreement between the Centers for Medicare & Medicaid Services (CMS) and the state of Maryland. The MDPCP is a voluntary program that provides funding and support for the delivery of advanced primary care throughout the state. It allows primary care providers to play an increased role in the prevention and management of chronic disease, as well as in the prevention of unnecessary hospital utilization.

As an important part of supporting providers in their care management efforts, the MDPCP will provide to participating practices risk scores of their attributed beneficiaries according to each patient's risk of incurring a potentially avoidable hospitalization or emergency department (ED) visit. Accordingly, The Hilltop Institute, in conjunction with the Maryland Department of Health, has developed the Hilltop Pre-AH (Predicting Avoidable Hospitalizations) Model™ in order to operationalize these risk scores. These patient-level risk scores are provided to participating medical practices on a monthly basis via the MDPCP portal on the Chesapeake Regional Information System for our Patients (CRISP) unified landing page.

This document is intended to explain the intended use, technical implementation, and model performance of the Hilltop Pre-AH Model™ as of June 2020. It will be updated as future versions of the model become operational.

2. Intended Use

The Hilltop Pre-AH Model™ risk scores are intended to add value to the MDPCP primary care transformation process by facilitating improved efficiency in the allocation of scarce care coordination resources. Theoretically, if such resources are limited and the patients in a given practice panel differ in the benefit they would obtain through care coordination, then patient outcomes are optimized by focusing those care coordination resources on the patients for whom these resources will generate the most benefit.[1] Hilltop's model will be used to rank attributed beneficiaries in each practice's panel based on their risk of experiencing an avoidable hospital event in order to assist in the identification and care coordination efforts for those high-risk individuals.

Hilltop conceptualizes benefit, in this context, as the avoidance of a patient-specific adverse event. Many distinct adverse events are possible (ranging from disease onset to institutionalization to death), but given the emphasis of the MDPCP on the reduction of

[1] There is some evidence to suggest that different patients receive different benefits from care coordination services. Researchers have found that proactive care coordination interventions for patients with a high risk of hospitalization have so far led to reductions in avoidable hospitalizations, ED utilization, and readmissions for the Medicaid population but not the Medicare population (Berkowitz et al., 2018).

unneeded utilization, the risk model focuses on *potentially avoidable* hospitalization or ED visits.[2] While this is a composite measure of eleven distinct underlying disease states,[3] each of which entails distinct patient-specific costs, Hilltop treats these events as homogeneous and therefore focuses on patients' *probabilities* of incurring avoidable hospital events. This forms the theoretical foundation for the Hilltop Pre-AH Model™: those individuals with the highest *probability* of incurring an avoidable hospitalization or ED visit are likely to benefit the most from advanced primary care services with respect to that outcome. Through the dissemination of the Hilltop Pre-AH Model™ risk scores, Hilltop aims to facilitate the identification of these individuals within each practice so that practices can allocate their care management resources accordingly.

It is crucial that the risk scores are as accurate as possible: ideally, the riskiest individuals as identified by the model have the highest actual likelihood of incurring an avoidable hospitalization, and the individuals identified by the model as lowest risk have the lowest actual likelihood of incurring an avoidable hospitalization. Due to the nature of the modeling problem—estimating the distribution of risk, rather than binary classification—it is not appropriate to use the traditional Receiver Operator Characteristic curve as a measure of model fit.[4] Instead, the utility of the model is assessed using *concentration curves,* which estimate the share of all avoidable hospital events occurring within the riskiest patients. Concentration curves can indicate, for example, that 50 percent of all patients who experience an avoidable hospital event are in the top 10 percent riskiest patients as estimated by the Hilltop Pre-AH Model™. Concentration curves and month-by-month summary scores for the model are presented in Section 4.3, below.

2.1 Differentiation from CMS HCC Risk Scores

It is important to note that the Hilltop Pre-AH Model™ risk scores are conceptually distinct from the CMS Hierarchical Condition Category (HCC) risk scores that are currently presented in CRISP. The Hilltop Pre-AH Model™ risk scores use risk factors based on diagnoses, procedures, medications, utilization, demographics, and geographic factors in order to produce a practice-specific ranking of patient risk of avoidable hospital events in the near future. The CMS HCC risk scores are based on a model that uses diagnosis codes and a limited set of demographic information from a base year in order to predict *expenditures* over the following year. There is likely to be some overlap among individuals who incur an avoidable hospitalization and individuals who experience high medical spending, but the overlap is unlikely to be complete.[5]

[2] Potentially avoidable hospitalizations/ED visits are those incurred for medical conditions or diagnoses "for which timely and effective outpatient care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition, controlling an acute episodic illness or condition, or managing a chronic disease or condition" (Billings et al., 1993). This measure is discussed in greater detail in Section 3.2.1.

[3] See Section 3.3.1 for further information.

[4] For additional detail on this point, see Section 4.3.

[5] Internal testing shows a limited degree of substitutability between the two sets of risk scores. Specifically, we find that the Hilltop Pre-AH Model™ outperforms the CMS HCC risk score in predicting avoidable hospitalization in the following month: of the top 10 percent riskiest individuals ranked by each risk score, the Hilltop Pre-AH Model™ correctly identifies 45-50 percent of all avoidable hospital events, while the CMS HCC risk score identifies approximately 30 percent. Both concentration curves are presented in Section 4.3, below.

High medical expenditure can reflect a number of factors ranging from moderate utilization of high-cost procedures, high utilization of moderate-cost procedures, underlying morbidity, or geographic differences in treatment or referral practices.

Moreover, the theoretical interpretation of each risk score differs substantially. The CMS HCC risk score was developed as a capitated payment risk adjustment methodology for Medicare Advantage participants in order to "address [the] issue of risk selection and to compensate Medicare Advantage health plans for accepting the risk of enrolling beneficiaries of varying health statuses" (CMS, 2018, pp. 9-10). Additionally, "the underlying risk assessment is designed to accurately explain the variation at the group level, not at the individual level, because risk adjustment is applied to large groups" (CMS, 2018, pp. 9-10). Note that "risk" for the CMS HCC risk model refers to *actuarial* risk: this model seeks to predict average expenditures over large groups of individuals. In contrast, the Hilltop Pre-AH Model™ risk score is designed to estimate, as closely as possible, event risk: that is, an *individual's* risk of an avoidable hospital event in the following months.

There are also differences in the time horizons of each risk score. CMS HCC "final risk scores are generally available 16-18 months after the close of the base year. For example, 2017 risk scores (based on 2016 diagnoses) will be available in the spring of 2018" (Center for Medicare & Medicaid Innovation, 2017, p. 26). The Hilltop Pre-AH Model™ risk scores, however, are updated monthly and use patient-level risk factor information current to the most recently available month of Medicare claims in order to generate risk scores. This is a strength of the Hilltop Pre-AH Model™: these risk scores reflect the underlying patient condition with a lag of only, at most, three months.[6] Finally, by definition, avoidable hospital events are preventable through timely primary care and so, in principle, the identification and management of individuals at high risk of incurring an avoidable hospitalization may result in the avoidance of that particular hospitalization event. High medical expenditures, however, may reflect underlying morbidities that would necessitate utilization *regardless* of primary care intervention.

2.2 *Clinical Vignette*

In order to illustrate the intended use of the Hilltop Pre-AH Model™ risk scores, we have created a hypothetical clinical vignette for an MDPCP Track 1 practice. For the sake of exposition, the patient panel consists of thirteen patients, each of which represents ten similar patients. Table 1

[6] This lag is related to the unavoidable delay in obtaining and processing Medicare CCLF claims data: for example, claims data delivered to Hilltop in late October 2019 reflect utilization through mid-September 2019. Hilltop uses these data to identify individual-level risk factors using all available healthcare claims and applies the model scoring coefficients in order to estimate the risk of an avoidable hospital event for each patient in October 2019. These risk scores are then provided by CRISP to participating practices in mid-November 2019, to be used until the next scores are provided in mid-December 2019. This raises two potential issues: first, that the risk scores do not reflect the most recent utilization for patients, and second, that the risk scores are "outdated" by the time they are received by practices. Internal testing has demonstrated that the risk ranking persists across multiple months and the predictive value of the tool remains strong. We discuss this point further in the "Limitations" section (4.4).

displays the patient panel, along with each patient's (hypothetical) Hilltop Pre-AH Model™ risk score and CMS Risk Tier.

Table 1. Hypothetical Patient Panel

Patient Name	Pre-AH Risk Score (%)	CMS Risk Tier
Patient 1	75%	Complex[7]
Patient 2	15%	Complex
Patient 3	5%	Tier 4
Patient 4	4%	Complex
Patient 5	2%	Tier 3
Patient 6	1%	Tier 3
Patient 7	Less than 1%	Tier 2
Patient 8	Less than 1%	Tier 2
Patient 9	Less than 1%	Tier 1
Patient 10	Less than 1%	Tier 2
Patient 11	Less than 1%	Tier 1
Patient 12	Less than 1%	Tier 1
Patient 13	Less than 1%	Tier 1

Patients in this practice are listed in descending order of risk. Based on the most recently available month of risk factors spanning diagnoses, procedures, medications, utilization, demographics, and geographic information, in conjunction with risk coefficients derived from training data, Patient 1 (or, equivalently, the ten patients represented by Patient 1) has a 75 percent chance of incurring an avoidable hospital event in the near future.[8] Patient 2 is the next riskiest, and has a 15 percent chance of incurring an avoidable hospital event. Patient 3 is the next riskiest, with a 5 percent chance. The distribution of risk is highly skewed: the majority of the practice's panel has less than 1 percent chance of incurring an avoidable hospital event, and all but two of the patients have under a 6 percent event risk.[9]

[7] It is important to note that while the CMS risk tier is correlated with Hilltop Pre-AH Model™ risk scores, the correlation is not perfect for two reasons: first, CMS risk tiers are based on underlying HCC score, which is conceptually distinct from the Pre-AH risk score. Second, certain groups of patients are automatically assigned to certain CMS risk tiers, which further reduces the correlation between the two measures. In particular, beneficiaries without sufficiently long clinical histories are assigned to CMS risk tier 2, while beneficiaries with "a diagnosis of dementia, substance use disorder, or severe and persistent mental illness" are assigned to the Complex tier, regardless of their HCC score (CMMI 2019). These individuals may, in turn, have relatively low (or high) risk of avoidable hospitalizations, meaning that an individual in, for example, the Complex CMS risk tier may have a low Pre-AH risk score. We highlight this point in Table 1 by presenting a non-monotonic relationship between Pre-AH risk score and CMS risk tier.

[8] See Section 3.2 for a more detailed discussion of the training and scoring process.

[9] While the data for this clinical vignette are hypothetical, the Hilltop Pre-AH Model™ risk scores are, in actuality, even more skewed: the average probability of incurring a future hospitalization is roughly 0.6 percent, while the maximum probability in the MDPCP cohort is greater than 99 percent.

Based on the MDPCP Care Management Fee (CMF) structure, this practice would receive approximately $2,600 each month.[10] Distributing the CMF revenue equally in care support of all 130 underlying patients would result in each patient receiving $20.00 of advanced primary care services each month. This distribution is unlikely to have a significant impact on patient outcomes: the low-risk individuals would be low-risk even without the advanced primary care intervention, and the high-risk individuals may require more resource-intensive interventions in order to experience improvement in outcomes.[11] The Pre-AH Model™ risk scores, used in conjunction with provider clinical guidance, can assist practices with a more efficient and impactful allocation of their care management efforts.

2.3 Care Interventions

Hilltop remains agnostic as to the particular types of interventions that are best-suited for the high-risk MDPCP population. Many interventions are possible, ranging from medication reconciliation to patient education to scheduling assistance, and patients are likely to respond best to different interventions based on their clinical and social needs. Interested readers should see published best practices in care coordination and care management.[12] Whatever the intervention strategy, Hilltop recommends that care managers and other users of the Hilltop Pre-AH Model™ risk score allocate their effort first to individuals with the highest risk of incurring an avoidable hospital event in the following month. This risk score is not, however, meant to override the clinical and subject matter expertise of the practice or their care transformation organization (CTO) partners and should be used in conjunction with the practice's current care coordination protocols. For details on the user interface of the Hilltop Pre-AH Model™ risk scores, readers should see the CRISP user manual.[13]

2.4 Reason for Risk

As of January 11, 2020, the Hilltop Pre-AH model™ has displayed to practices the top actionable risk factors underlying each patient's risk of incurring a future avoidable hospital event. The intention of this update is to augment the information provided to practices in order to further facilitate patient-specific advanced primary care. For example, in addition to a risk score of 3.2 percent for a particular patient, care managers will also be able to see on the CRISP dashboard

[10] $50 for each of the 30 patients in the Complex tier; $30 for each of the 10 patients in Tier 4; $16 for each of the 20 patients in Tier 3; $8 for each of the 30 patients in Tier 2; and $6 for each of the 40 patients in Tier 1. For the purposes of this clinical vignette, we do not account for the Performance-Based Incentive Payment (PBIP), although this would potentially add $325 per month to this practice's MDPCP revenues.

[11] Liaw et al. (2015) conclude that, based on a review of four CMS-funded demonstrations involving care management fees, "to generate savings, resource allocation cannot be homogeneous. Instead, practices must focus more intensely on those at highest risk of utilization" (p. 557). Indeed, this may (partly) explain the varying effectiveness of care management, care coordination, and intensive primary care interventions as documented in the academic literature; many patients have low underlying risk of adverse outcomes, thus obviating the need for intervention, and the few high-risk patients may require significant intervention resources. For summaries of the literature on this subject, see Edwards et al. (2017) and Baker et al. (2018).

[12] See examples at Hong et al. (2014); McCarthy et al. (2015); and Anderson et al. (2015).

[13] https://crisphealth.org/resources/training-materials/

that the patient (for example) meets the clinical criteria for diabetes and heart failure and incurred a claim for insulin within the past year (in descending order of contribution to risk). While that patient may also have had other salient risk factors—for example, meeting the clinical criteria for depression—Hilltop only displays the most predictive, intervene-able risk factors in order to allow care mangers to focus their attention on the most pressing patient needs.[14]

These reasons for risk are based on the underlying risk factor coefficients, which are derived from the training phase of the model (see Section 3.3.2 of this documentation for additional details). It is important to note that these coefficients do not necessarily have a *causal* interpretation: they only capture the strength of *association* between a given risk factor and the risk of incurring a future avoidable hospital event. For example, if the risk factor coefficient for diabetes is positive, then that could mean that having diabetes *causes* an increased risk of avoidable hospital events; however, it could also mean that having diabetes is only *correlated* with some unobserved factor that causes an increased risk of avoidable hospital events. While these risk factors do not have a strictly causal interpretation, they are intended to provide care managers with a useful starting point from which to address specific patient needs.

In order to operationalize the identification of reasons for risk, the Hilltop team first re-coded all applicable risk factors in the model so that a higher level of a given risk factor is theoretically associated with greater risk of incurring an avoidable hospital event. Consider the example of flu vaccinations: there is evidence that influenza and/or pneumococcal vaccinations reduce the risk of hospitalization for various PQI in various populations (Nichol et al., 2003; Hedlund et al., 2003; Furomoto et al., 2008). This implies that receipt of a flu vaccination should be *negatively* associated with the risk of incurring an avoidable hospital event.[15] This risk factor, then, was re-coded to be 1 if the individual has **not** received a flu vaccination, and 0 if the individual **has** received a flu vaccination. Appendix A has been updated to reflect this re-coding.

The Hilltop research team used two criteria for determining which risk factors to recode. First, we reviewed the existing evidence for the sign and magnitude of risk factors based on the foundational Pre-AH Model™ literature review (Pelser et al., 2019). If there was strong *a priori* empirical evidence that certain risk factors—again, like having had a flu vaccination—have a negative association with the risk of incurring an avoidable hospitalization, then the variable was re-coded accordingly. Second, if the literature review indicated that the impact of a given risk factor on the risk of incurring an avoidable hospital event was ambiguous, then the Andersen Behavioral Model of health services utilization was applied to guide the re-coding logic. The Andersen model posits that health services utilization is a function of predisposing, enabling, and

[14] Hilltop collected stakeholder feedback from clinical partners in order to ensure that we only displayed those risk factors over which patients, providers, and care managers can exert some control. We did not, for example, include most environmental risk factors, since providers cannot directly assist patients with the management of this factor.
[15] The initial release of the Pre-AH Model™ confirms this: receipt of a flu or pneumonia vaccination in the past year was associated with a 12.8 percent reduction in the probability of incurring an avoidable hospital event in the coming months.

need factors (Andersen, 1995). Consensus was required among members of the Hilltop research team before recoding using this criterion.

While the baseline model contains approximately 190 risk factors, only a subset of these are included in the pool of potential reasons for risk for reasons of statistical interpretation and clinical utility. Most non-binary and non-count risk factors are excluded because these cannot easily be translated into reason for risk contributions for lack of a meaningful reference group. Additionally, based on the feedback from stakeholders, Hilltop excludes risk factors that are not potentially modifiable; that is, for which the effects cannot be meaningfully modified by clinical intervention (like, for example, area income). Finally, risk factors that are not positive and statistically significant are also excluded.

Consider the following illustrative example. Suppose that the model contains only three risk factors: a flag for diabetes, the number of recent avoidable hospitalizations, and a flag for heart failure. In this example, the coefficients for these three risk factors are 0.1, 0.08, and 0.07, respectively. The coefficient for diabetes represents the increase in risk of avoidable hospitalizations associated with having diabetes (relative to not having diabetes), holding all other factors constant.[16] The coefficient for the number of avoidable hospitalizations reflects the added risk associated with one additional previous avoidable hospitalization, and the coefficient for heart failure reflects the added risk associated with having heart failure (relative to not having heart failure), again holding all other factors constant.

It is important to note that these risk coefficients are marginal effects; that is, the *additional* risk due to, for example, a patient having one additional previous avoidable hospitalization. In order to translate these marginal effects to reason for risk contributions, Hilltop multiplies each marginal estimate by the level of that risk factor for each individual. Thus, if an individual has four previous avoidable hospitalizations, then the risk contribution of avoidable hospitalizations is 4*0.08 = 0.32.[17] Crucially, this risk contribution is still interpreted relative to a reference category: in this case, that of individuals with no history of avoidable hospitalizations. More broadly, the risk contribution should be interpreted relative to individuals without that particular risk factor.[18]

Suppose that, in this example, there are four patients in the MDPCP program. Patient 1 has diabetes, no history of avoidable hospitalization, and heart failure. Patient 2 does not have diabetes, has no history of avoidable hospitalization, and has heart failure. Patient 3 has diabetes, four prior avoidable hospitalizations, and does not have heart failure. Finally, patient 4

[16] Since our baseline model is a multivariate logistic regression, the coefficient is technically the marginal impact on log odds of incurring an avoidable hospital event. For the sake of exposition, we label this as "risk."
[17] This assumes that marginal effect is constant across units: that is, that the effect neither grows, nor shrinks, as the level of the risk factor rises. Since the vast majority of the reason for risk factors are binary variables, for which this assumption does not bind, we believe that this is a reasonable simplification.
[18] This motivates the exclusion of continuous (that is, non-binary and non-count) risk factors from the reason for risk pool: there is no natural reference group for these risk factors. For example, there is no meaningful group of people that do not have the "age" risk factor.

does not have diabetes, has one previous avoidable hospitalization, and has heart failure. This information is presented in Table 2, below.

Table 2. Hypothetical Reason for Risk Example

Patient ID	Diabetes	Diabetes * Coefficient	# AH	# AH * Coefficient	Heart Failure	Heart Failure * Coefficient
1	1	0.1	0	0.0	1	0.07
2	0	0.0	0	0.0	1	0.07
3	1	0.1	4	0.32	0	0.0
4	0	0.0	1	0.08	1	0.07

In this example, the top reason for risk for Patient 1 is diabetes: this risk factor yields the largest positive contribution (risk factor level * coefficient) among all the risk factors for that individual. For Patient 2, the top reason for risk is heart failure; for patient 3, the top reason for risk is the history of avoidable hospitalizations; and for patient 4, the top reason for risk is the history of avoidable hospitalizations. The second reason for risk is calculated analogously: it is the second highest contribution of (risk factor level * coefficient) for each individual. All other reasons for risk are estimated in a similar fashion.

In the CRISP dashboard, users can also see the contribution of each risk factor category (Condition, Demographic, Pharmacy, Utilization, and Environmental) in percentage terms. These are intended to provide a high-level description of the contribution of various types of risk factors that are positive and significant for an individual. The contribution for a given category is calculated as the sum of (risk factor level * coefficient) for all reasons for risk in that category, divided by the sum of (risk factor level * coefficient) for all positive, statistically significant reasons for risk. This is an important point: an individual's *overall* risk is a function of **all** risk factors, including those that are not included as potential reasons for risk. The category contributions, however, are only interpretable relative to the reason for risk factor pool, which is restricted to the operationalizable, modifiable risk factors.[19]

3. Technical Implementation

This section presents details on data sources, risk factors, and methodology.

[19] If an individual has 3.2 percent overall risk and the Condition category contribution is 50 percent, it is not appropriate to conclude that 50 percent of that individual's risk is due to Condition risk factors. Instead, it is appropriate to conclude that, of the positive, statistically significant, operationalizable, modifiable risk factors for that individual, conditions represent 50 percent of the total (risk factor level * coefficient).

3.1 Data Sources

The Hilltop Pre-AH Model™ relies largely on data from Claim and Claim Line Feed (CCLF) Medicare claims files, supplemented with various publicly available environmental data sets used to generate the environmental risk factors. These data sources are detailed below.

3.1.1 CCLF Data

The majority of the risk factors in the Hilltop Pre-AH Model™ are derived from CCLF Medicare Parts A, B, and D claims files. Each month, Hilltop receives Part A claims, Part A revenue centers, Part A procedure codes, Part A diagnosis codes, Part B claim lines, Part B durable medical equipment claims, Part D claims, and patient demographic information (which also includes eligibility information) from CMS.[20] Additionally, Hilltop receives beneficiary attribution files and practice rosters each quarter.

Upon receipt of the monthly claims files, Hilltop first performs automated data validity checks in order to assess the integrity of the CCLF data files, followed by a data reduction step that subsets the claims files against the beneficiary attribution file. The resulting files retain the raw claims data that are inputs to the risk factor feature engineering process, but discard the claims for individuals that are not in the MDPCP population. The resulting data comprises approximately 350,000 individuals across over 475 practices. These individuals incurred approximately 3.1 million part A claims, 55.9 million part B claim lines, and 19.7 million part D claims in the three-year period of May 2017 to April 2020.

Using SAS 9.4, Hilltop creates the model using risk factors identified in the literature review.[21] The risk factors are described in Section 3.2 and in greater detail in Appendix 1.

3.1.2 Social Determinants of Health Data Set

In order to control for environmental factors that may affect patients' probabilities of incurring avoidable hospitalizations, the risk model includes a rich set of area-level covariates derived from publicly available sources. Based on the "beneficiary ZIP code as per Medicare enrollment" (BENE_ZIP_CD), each attributed beneficiary is linked to environmental characteristics in his or her residential area.

3.1.2.1 Data Imputation and Sources

It is important to note that ZIP codes, which are generated by the United States Postal Service, do not represent polygonal shapes; instead, they represent collections of mailing addresses. The

[20] For detailed documentation of these files, please see "Maryland Primary Care Program (MDPCP) CRISP Extract" (June 2019).

[21] Certain risk factors identified in the literature review were not ultimately operationalizable in Phase 1 of the Hilltop Pre-AH Model™. We will incorporate additional risk factors in future iterations of the model.

U.S. Census Bureau uses an analogous concept—the ZIP Code Tabulation Area (ZCTA)—in order to publish data tables at a ZIP code-like level of granularity.

ZCTAs are approximate area representations of U.S. Postal Service 5-digit ZIP code service areas that the Census Bureau creates using census blocks to present statistical data from censuses and surveys.[22] The Census Bureau defines ZCTAs by allocating each block that contains addresses to a ZCTA, usually to the ZCTA that reflects the most frequently occurring ZIP Code for the addresses within that block. Blocks that do not contain addresses but that are completely surrounded by a single ZIP code tabulation area (enclaves) are assigned to the surrounding ZCTA; those surrounded by multiple ZCTA will be added to a single ZCTA based on the longest shared border. ZIP Codes that cover primarily nonresidential or P.O. box addresses may not have a corresponding ZCTA because the delineation process uses primarily residential addresses. The Census Bureau (2018a; 2018b) notes that "in most instances the ZCTA code is the same as the ZIP code for an area."

Of the 33,120 ZCTAs in the United States, approximately 24.6 percent are missing data for at least one variable of the Hilltop Pre-AH Model™ ZIP code-level data set.[23, 24] This issue is ameliorated, although still present, in the estimation sample of Medicare beneficiaries attributed to MDPCP-participating practices: of the approximately 350,000 individuals in the baseline beneficiary demographic file with a valid ZIP code, at least one variable in the ZIP code-level data set is missing information for under 2 percent of individuals.[25]

In order to address this issue, Hilltop leverages the informational content of ZIP codes to impute the missing values of these ZIP code-level variables. Within each five-digit ZIP code, the first three digits represent the "Sectional Center Facility," a centralized mail distribution hub that sorts and distributes mail to local post offices according to the fourth and fifth digits in the ZIP code. (Congressional Research Services, 2006; U.S. Postal Service Office of Inspector General, 2013). For example, consider ZIP code 21250, which is located in Catonsville, MD. The first three digits indicate that this is served by Sectional Center Facility 212. All other ZIP codes beginning with 212, then, are *also* served by that particular Sectional Center Facility, implying that they are relatively spatially proximal to ZIP Code 21250. These spatially proximal ZIP codes are the basis for the imputation procedure. Specifically, Hilltop imputes missing data for a given variable in a given ZIP code as the population-weighted average value of that variable for all non-missing ZIP codes within a given Sectional Center Facility.

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[22] Note: USPS ZIP codes are not areal features but a collection of mail delivery routes.

[23] It is important to note that two variables—"Social Workers per 1,000 population" and "Percent Physician Diversity"—are only available for a subset of counties due to geographical identification in underlying American Community Survey data. In the data creation process, we impute the missing values for these variables as using the geographically *unidentified* value for each variable within a given state. This is discussed in greater detail below.

[24] While ZIP codes and ZCTAs capture different underlying geographic concepts, they are used interchangeably for the purposes of this discussion.

[25] Additionally, several hundred individuals do not have a ZIP code that merges on to the ZCTA-level data set (usually due to beneficiaries using P.O. boxes as their address of record, which are not attributed to ZCTAs). The ZCTA is imputed for these individuals as described in Section 3.3.2.

To fix ideas, consider three ZIP codes within a given Sectional Center Facility code: 55501, 55502, and 55503. Suppose that the value of the variable "Percent of Population Aged 65+" is missing for ZIP code 55503 but is 20 percent for 55501 and 10 percent for 55502. Additionally, suppose that ZIP code 55501 contains 10,000 individuals, and ZIP code 55502 contains 1,000 individuals. The imputed value for ZIP code 55503 is (10,000/11,000)*20 percent + (1,000/11,000)*10 percent = 19.1 percent. This imputed value is almost certain to contain noise: the weighted average will not exactly equal the unobserved value of this variable for ZIP code 55503. However, to the extent that spatially proximal ZIP codes (that is, within a given Sectional Center Facility catchment area) are *similar* in terms of observable characteristics, this imputation method balances computational feasibility with accuracy.[26]

Twenty-three ZIP codes are located in Sectional Center Facility catchment areas (202, 204, 205, 753, and 772) with zero total population.[27] These ZIP codes appear to be attributed to specific buildings in urban areas (for example, the Federal Bureau of Investigation building, in 20535). The imputation procedure fails for these ZIP codes because it is impossible to calculate population-weighted averages for the ZIP codes within those areas. Consequently, all missing values for these particular ZIP codes are imputed as 0.

Appendix 1 lists the general data sources for each of the risk factors. See below for details of the data sources for these environmental risk factors.

- ACS data are from the American Community Survey. ZCTA data were obtained through Census Bureau's American FactFinder (https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml). Data are at granularity of ZCTA.
- IRS SOI data are from the Internal Revenue Service Statistics of Income. ZCTA data were obtained through https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-2016-ZIP-code-data-soi. Data are at granularity of ZIP Code.
- USDA rural-urban commuting data are Version 3.10 of the ZIP code Rural-Urban Commuting Areas (RUCA) taxonomy. These data are comprised of 10 codes that "delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows." Census tract level data and documentation are here: https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/. Researchers at the University of North Dakota have published a ZIP code-level data set here: https://ruralhealth.und.edu/ruca. The ZIP code-level data are used in the Hilltop Pre-AH Model™.
- Neighborhood Atlas data are from the University of Wisconsin School of Medicine. 2015 Area Deprivation Index (ADI) data were obtained at the Census Block Group level from https://www.neighborhoodatlas.medicine.wisc.edu/download. The ADI is a national

[26] In future phases of MDPCP, Hilltop will seek to improve the accuracy of imputation through the use of geographic software and more sophisticated spatial imputation techniques.

[27] The ZIP Codes are: 20202, 20204, 20228, 20230, 20240, 20245, 20260, 20405, 20418, 20427, 20506, 20510, 20520, 20535, 20540, 20551, 20553, 20560, 20565, 20566, 20593, 75390, and 77201.

ranking (from 1 to 100) of census block groups by socioeconomic disadvantage. Lower scores indicate less disadvantage, and higher scores indicate more disadvantage.

- CMS provider locations are from the December 2018 Public Use Provider of Services file (https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Provider-of-Services/). The ZIP codes for active providers were extracted and merged on to the Census ZCTA template. Hilltop used active short-term/critical access/transplant hospitals for its hospital-based risk factors.
- Veterans Affairs provider locations are from the VA directory (https://www.va.gov/directory/guide/rpt_fac_list.cfm). Locations are retained if the name of the facility contains the term "Clinic" or "Medical Center." ZIP Code was extracted from the address field.
- AMA data are "Census tract layer attributes for American Medical Association Primary Care Physician Data, 2011," published by the Health Resources and Service Administration (HRSA) data warehouse. Specific source: https://data.hrsa.gov/DataDownload/PCSA/2010/t_ama2011_060614.dbf. Data are at the granularity of Census tract.
- Land area is from the 2018 Census Gazetteer (https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html). Area is in square miles.
- Pharmacy data are from the Maryland Pharmacy Board (MBP). Hilltop filed a roster request with the MBP on March 30, 2020, to obtain the ZIP code for all licensed pharmacies in Maryland (https://health.maryland.gov/pharmacy/Pages/roster-request.aspx). This ZIP code was merged into the Census ZCTA template in order to calculate the number of pharmacies per 1000 population in each ZCTA.
- National Walkability Index data are from the Environmental Protection Agency (https://www.epa.gov/smartgrowth/smart-location-mapping#walkability). This index, published by the Environmental Protection Agency, ranks areas according to "characteristics of its built environment that influence the likelihood of walking being used as a mode of travel."[28] Data are originally at the Census Block Group level.
- Air pollution data are from the Environmental Protection Agency (https://healthdata.gov/dataset/daily-census-tract-level-pm25-concentrations-2011-2014). Data are originally at the Census Tract level.
- Area Health Resources File (https://data.hrsa.gov/data/download) contains county-level data on a variety of health-related topics.
- ACS individual-level data are from IPUMS (https://usa.ipums.org/usa/index.shtml). Individual-level microdata are filtered to retain only certain occupations and then aggregated to the county level.

[28] For additional information, see https://catalog.data.gov/dataset/walkability-index

The variables derived from this data set—"Social Workers per 1,000 population" and "Percent Physician Diversity"—are populated only for a subset of counties covering approximately 1/3 of ZCTAs nationally. This is due to county identification in the underlying source data: the American Community Survey microdata does not publically identify counties for respondents. Instead, IPUMS—an organization based at the University of Minnesota that cleans, documents, and integrates data across publicly available data sets—identifies counties, where possible, from other low-level geographic identifiers and all remaining unidentified counties within a state are aggregated together (Ruggles et al., 2019).[29] For example, of the 24 counties in Maryland (including Baltimore City), only 12 counties have county-specific values for "Percent Physician Diversity." The value for the remaining 12 counties is 10.22 percent.

Hilltop imputes the missing county-level values for these two variables using the geographically *unidentified* value for each variable within a given state. To continue the example above, each of the 12 counties in Maryland missing the value of "Percent Physician Diversity," then, would be imputed at 10.22 percent.[30]

3.1.2.2 Weighting Methodology

Several of the underlying data sources for the environmental risk factors are not originally at the ZCTA level; therefore, these data need to be transformed to the ZCTA level in order to be incorporated into the Hilltop Pre-AH Model™. We perform three types of geographical transformations: Census Tract to ZCTA; Census Block Group to ZCTA; and County to ZCTA.

It is important to note that, unlike many Census geographies, ZCTAs are not nested: they can (and do) cross County and Census Tract boundaries.[31] Therefore, in order to geographically translate the data sources to the ZCTA level, it is necessary to account for the *intersections* formed by the different levels of geography and ZCTAs. We use the 2010 Census relationship files which contain, for various levels of geography, all intersections between each jurisdiction and each ZCTA, as well as the fraction of the population (of both the ZCTA and the other level of geography) accounted for by that intersection.[32]

The weighting methodology depends on the nature of the underlying variable. Suppose we need to translate the number of physicians per Census Tract to the number of physicians per ZCTA. Count variables—like the number of physicians—are assumed to have the same distribution as population within each Tract. We estimate the number of physicians in a Tract-ZCTA intersection as the number of physicians in the corresponding Tract multiplied by the fraction of the Tract's

[29] For additional documentation, see https://usa.ipums.org/usa-action/variables/COUNTYFIP#description_section.
[30] Data are missing for counties in Puerto Rico, so these values are imputed at the national average.
[31] In contrast, Census Blocks are nested within Block Groups, which are nested within Tracts, which are nested within Counties, which are nested within States (https://www2.census.gov/geo/pdfs/reference/geodiagram.pdf?#)
[32] The Census relationship files can be located here: https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html

2010 population represented by that intersection. We then sum the estimated totals for each intersection to the ZCTA level.

This method is inappropriate, however, for Tract-level averages (for example, the average pollution level within a Tract). We no longer need to estimate the value for each Tract-ZCTA intersection; instead, we assume that each intersection inherits the average pollution level from the corresponding Tract, and then aggregate these intersection values in proportion to the intersection's contribution to the ZCTA's 2010 population. For ZCTAs that lie completely in another jurisdiction, this value will simply take the value of the containing jurisdiction.

We use the above methods for translating from both the Census Tract and County levels to the ZCTA level. For risk factors at the Census Block Group level, we first aggregate to the Census Tract level, and then translate as above.

3.2 Risk Factors

Based on the literature review, Hilltop identified and operationalized approximately 190 risk factors to be included in the risk model. While some of these risk factors are eliminated in the variable selection step, this process is data-driven, and all risk factors are included in the pool of *potential* risk factors to be used in the model. A high-level description of risk factors is provided in the Sections below. For a description of each risk factor, along with data source and sample statistics, see Appendix 1.

3.2.1 Literature Review

As a first step in the development process for the Hilltop Pre-AH Model™, Hilltop conducted a comprehensive literature review. The goal of the review was to find peer-reviewed academic journal articles that identified risk factors for potentially avoidable hospital events, thus providing a basis for risk factor extraction and feature creation. Identified risk factors were coded using CCLF and other publicly available data sources and included in the final risk model as potential predictors of avoidable hospitalization or ED use. The literature review provided the foundation for the risk model and was a crucial step in the modeling process. Using inclusion and exclusion criteria designed to reflect the MDPCP patient population, the Hilltop team screened over 3,300 articles in both a primary and secondary literature search, ultimately selecting 211 articles for risk factor extraction. For additional detail, see Pelser et al. (2019).

3.2.2 Part A Risk Factors

Risk factors based on Part A claims cover information on admissions over the past 12 months; nursing home stays over the past 12 months; and certain procedures. Additionally, the Part A claims are used in order to construct the avoidable hospital event outcome, as well as the diagnostic condition flags. These condition flags rely on diagnostic information from Part A and Part B claims in conjunction with Chronic Conditions Data Warehouse (CCW) coding

specifications in order to generate beneficiary-level risk factors that represent underlying disease states.[33]

3.2.3. Part B Risk Factors

Risk factors based on Part B claims cover utilization of certain services (such as vaccinations, lab tests, or J-code procedures), place of service (for example, urgent care or rural health clinic), and provider specialty (for example, endocrinology or oncology). Hilltop also created risk factors to capture a beneficiary's primary care utilization and continuity of care. Finally, as above, the Part B claims are used in order to construct the avoidable hospital event outcome, as well as the diagnostic condition flags.

3.2.4 Part D Risk Factors

Using Medicare Part D claims, Hilltop flags utilization of drugs identified in its literature review as potential risk factors for potentially avoidable hospital events. In order to capture compound drugs, which are drugs that contain multiple active ingredients, Hilltop relies largely on text-based, "contains"-type searches of the FDA's "National Drug Code Directory."[34] See Table 3 below for Hilltop's primary search strategy, as well as for a list of the substances flagged.

Table 3. Primary Search Strategy for MDPCP Pharmacy Risk Factors

Risk Factor	Primary Search Method in NDC	Substances Flagged
Rivaroxaban use	Nonproprietary name contains "RIVAROXABAN"	RIVAROXABAN
Losartan use	Substance name contains "LOSARTAN"	LOSARTAN POTASSIUM; LOSARTAN POTASSIUM and HYDROCHLOROTHIAZIDE
Warfarin use	Substance name contains "WARFARIN"	WARFARIN SODIUM
Cilostazol use	Substance name contains "CILOSTAZOL"	CILOSTAZOL
Insulin use	Substance name or nonproprietary name contains "INSULIN" and marketing category name does not contain "UNAPPROVED"	INSULIN ASPART; INSULIN DEGLUDEC; INSULIN DEGLUDEC and LIRAGLUTIDE; INSULIN DETEMIR; INSULIN GLARGINE; INSULIN GLARGINE and LIXISENATIDE; INSULIN GLULISINE; INSULIN HUMAN; INSULIN LISPRO
Statin use	Drug Class contains "HMG-CoA Reductase Inhibitor" or substance name contains "ROSUVASTATIN CALCIUM"	SIMVASTATIN; LOVASTATIN; PITAVASTATIN; ROSUVASTATIN CALCIUM; PRAVASTATIN SODIUM; FLUVASTATIN SODIUM; PITAVASTATIN CALCIUM; ATORVASTATIN CALCIUM; ATORVASTATIN CALCIUM TRIHYDRATE; ATORVASTATIN CALCIUM PROPYLENE GLYCOL SOLVATE; EZETIMIBE and SIMVASTATIN; NIACIN and LOVASTATIN; SIMVASTATIN and NIACIN;

[33] Additional detail on the CCW condition flag specifications can be found here: https://www.ccwdata.org/documents/10280/19139421/ccw-chronic-condition-algorithms.pdf, https://www.ccwdata.org/documents/10280/19139421/ccw-chronic-condition-algorithms-reference-list.pdf

[34] For example, "Simcor" contains two active substances: Simvastatin and Niacin. This is flagged as a statin because one of its active ingredients is a statin. Source for the FDA NDC directory: https://www.fda.gov/drugs/drug-approvals-and-databases/national-drug-code-directory

Risk Factor	Primary Search Method in NDC	Substances Flagged
		AMLODIPINE BESYLATE and ATORVASTATIN CALCIUM; AMLODIPINE BESYLATE and ATORVASTATIN CALCIUM TRIHYDRATE
Leukotriene Receptor Modifier use	Drug class contains "Leukotriene Receptor Antagonist"	MONTELUKAST; MONTELUKAST SODIUM; ZAFIRLUKAST
Beta Blocker use	Substance Name contains "METOPROLOL" or "CARVEDILOL"[35]	CARVEDILOL; CARVEDILOL PHOSPHATE; METOPROLOL SUCCINATE; METOPROLOL TARTRATE; METOPROLOL TARTRATE and HYDROCHLOROTHIAZIDE; METOPROLOL SUCCINATE and HYDROCHLOROTHIAZIDE
Oral Corticosteroid use	Drug class contains "Corticosteroid" and route is "ORAL" and dosage form contains either "CAPSULE" or "TABLET" and marketing category does not contain "UNAPPROVED"	BUDESONIDE; CORTISONE ACETATE; DEFLAZACORT; DEXAMETHASONE; HYDROCORTISONE; METHYLPREDNISOLONE; PREDNISOLONE; PREDNISOLONE SODIUM PHOSPHATE
Antidiabetes Medication	Substance name contains "FLOZIN", "GLIPTIN", "THIAZOLIDINEDIONE", "ROSIGLITAZONE", or "PIOGLITAZONE"	ALOGLIPTIN BENZOATE; ALOGLIPTIN BENZOATE and METFORMIN HYDROCHLORIDE; ALOGLIPTIN BENZOATE and PIOGLITAZONE HYDROCHLORIDE; CANAGLIFLOZIN; CANAGLIFLOZIN and METFORMIN HYDROCHLORIDE; DAPAGLIFLOZIN; DAPAGLIFLOZIN PROPANEDIOL; DAPAGLIFLOZIN PROPANEDIOL and METFORMIN HYDROCHLORIDE; DAPAGLIFLOZIN and SAXAGLIPTIN HYDROCHLORIDE; EMPAGLIFLOZIN; EMPAGLIFLOZIN and LINAGLIPTIN; EMPAGLIFLOZIN and METFORMIN HYDROCHLORIDE; ERTUGLIFLOZIN PIDOLATE; ERTUGLIFLOZIN PIDOLATE and METFORMIN HYDROCHLORIDE; ERTUGLIFLOZIN PIDOLATE and SITAGLIPTIN PHOSPHATE; LINAGLIPTIN; LINAGLIPTIN and METFORMIN HYDROCHLORIDE; METFORMIN HYDROCHLORIDE and PIOGLITAZONE HYDROCHLORIDE; PIOGLITAZONE; PIOGLITAZONE HYDROCHLORIDE; PIOGLITAZONE HYDROCHLORIDE and GLIMEPIRIDE; PIOGLITAZONE HYDROCHLORIDE and METFORMIN HYDROCHLORIDE; ROSIGLITAZONE MALEATE; SAXAGLIPTIN HYDROCHLORIDE; SAXAGLIPTIN HYDROCHLORIDE and METFORMIN HYDROCHLORIDE; SITAGLIPTIN PHOSPHATE; SITAGLIPTIN PHOSPHATE and METFORMIN HYDROCHLORIDE
Oral Antibiotics	Substance name contains prescription names in NCQA "Antibiotics of Concern" and "All other Antibiotics" and route is "ORAL"– See Appendix 2.	See Appendix 2.

[35] Based on Table 1 from Brophy et al., 2001.

3.2.5 Environmental Risk Factors

Several of the risk factors Hilltop identified during the literature review were individual-level demographic and socioeconomic factors that are unavailable in the CCLF data (for example, marital status). Consequently, corresponding area-level risk factors (for example, the percentage of the population aged 15+ that is currently married) are included in the risk model in order to proxy for the unobserved individual-level variables. Other environmental risk factors (for example, the area poverty rate) are intended to capture the social determinants of health: the neighborhood conditions in which people live and age that may affect health outcomes. Hilltop plans to refine these measures to incorporate greater geographic granularity in future versions of the risk model and will update the documentation accordingly.

3.2.6 Risk Factor Update (June 2020)

As part of the ongoing development process, Hilltop added eight new risk factors to the model in June 2020. These risk factors are: an indicator for frailty, an indicator for original Medicare eligibility due to a non-age related reason, an indicator for DME use within the past year, the number of ED visits in the past 6 months, an indicator for sickle cell anemia, ZIP code pollution level, ZIP code walkability, and ZIP code pharmacy density. Additional information about these risk factors can be found in Appendix A.

3.3 Modeling

Methodologically, Hilltop relies on a discrete time survival model that uses current values of procedural, diagnostic, utilization-based, pharmacy, demographic, and environmental risk factors to predict the likelihood that an individual incurs an avoidable hospitalization or ED visit in the *following* month. The parameter estimates generated in the model training are subsequently used to generate individual risk predictions in the scoring step. Each of these points are discussed below.

3.3.1 Avoidable Hospitalizations and Emergency Department Visits

The outcome measure in the Hilltop Pre-AH Model™ is a 0/1 indicator variable denoting whether an individual incurred an avoidable hospitalization or ED visit in a given month. In order to construct this measure, Hilltop relies on 2018 technical definitions provided by the Agency for Healthcare Research and Quality (AHRQ) as part of its prevention quality indicator (PQI) measures.[36] Diagnosis codes from Part A inpatient and ED claims are used to flag the following conditions, which are the basis for the composite PAH flag:[37]

[36] For more information, see https://www.qualityindicators.ahrq.gov/modules/pqi_resources.aspx.

[37] Specifically, Hilltop defines these claims as those with a claim type of either 60 or 61 (indicating an inpatient claim) or a claim type of 40 (indicating an outpatient claim) and revenue center codes of 0450-0459 and 0981. Source: https://www.resdac.org/articles/how-identify-hospital-claims-emergency-room-visits-medicare-claims-data. To the extent that claims for observation stays are coded in this manner in the CCLF Medicare claims, then observation stays are included in this outcome. Additionally, Hilltop did not include PQI #2 (Perforated Appendix) or PQI #9 (Low

- PQI #1: Diabetes Short-Term Complications
- PQI #3: Diabetes Long-Term Complications
- PQI #5: COPD or Asthma in Older Adults
- PQI #7: Hypertension
- PQI #8: Heart Failure
- PQI #10: Dehydration
- PQI #11: Bacterial Pneumonia
- PQI #12: Urinary Tract Infection
- PQI #14: Uncontrolled diabetes
- PQI #15: Asthma in Younger Adults
- PQI #16: Lower-Extremity Amputation among Patients with Diabetes

This is implemented in the model as an indicator variable at the person-month level. If an individual incurs at least one avoidable hospitalization or ED visit in a given month, then that person receives a value of 1 for this variable—and 0 otherwise.

3.3.2 Statistical Model

Avoidable hospitalization/ED visits are recurrent events with time-dependent covariates. Accordingly, the Hilltop Pre-AH Model™ is operationalized as a discrete-time survival model that uses the *current* month of risk factors in order to predict avoidable hospitalization/ED visits in the *following* month. The model uses month as a time unit—instead of, for example, weeks or years—in order to balance the increased model accuracy obtained by a more granular time unit with the increased prediction error due to rare events.

The raw CCLF data span three years, or 36 person-months for individuals with full coverage. Since the model estimates the risk of incurring an avoidable hospitalization in the *next* month, however, it is not possible to use the most recently available month of risk data in the training model (since the next month's avoidable hospitalizations have not been realized at this point).[38] Therefore, the training data are based on underlying data covering 35 person-months per attributed patient with full coverage. While, in general, a reduction in sample size can adversely impact the statistical precision of the risk factor estimates, lagged predictors are used for three reasons.[39]

Birth Weight) in the composite outcome because these events were deemed to be not sufficiently modifiable by primary care providers and not relevant to the MDPCP cohort, respectively.

[38] It is important to note that while the model estimates the probability of an individual incurring an avoidable hospital event in the next month, these scores have high month-over-month persistence and therefore can be used to approximate risk over a longer time horizon.

[39] We address the reasons for using a one-month lag, as opposed to a two-month lag, in Section 4.4.1.

First, several of the risk factors—such as the count of hospitalizations in the previous 12 months, or the condition flag for diabetes—overlap with the definition of an avoidable hospital event. Consequently, including these risk factors as *contemporaneous* predictors could artificially increase the predictive power of the model. Second, Hilltop believes that using lagged predictors aids in the interpretability of the model. The goal of the Hilltop Pre-AH Model™ is to predict future avoidable hospitalizations, and using contemporaneous predictors to generate future risk scores requires the assumption that individuals' risk factors do not change in the future. Finally, the use of lagged predictors implies a natural "person-now" data set: the most recent month of risk factors, which is not included in the training data set.

The statistical model is trained on an 80 percent sample of our analytical person-month data set. The functional form of the statistical model is:

$$\log\left(\frac{p_i(t)}{1-p_i(t)}\right) = \varphi(t) + \beta X_i(t-1) + \Omega V_i$$

- $\varphi(t)$ is a cubic function of time, accounting for the time effect
- β and Ω are the vectors of model parameters to be determined by training data
- $X_i(t-1)$ is a vector of patient $i's$ time-dependent features in the previous month
- V_i is a vector of patient *i*'s time-independent features
- $p_i(t)$ is the probability of avoidable hospitalization or ED visit of patient i at time t (i.e., the month following the realization of the risk factors)
- t is duration of time in months
    - counting start from the first month of available data if the patient is in coverage longer than three years, or
    - counting from the coverage start month if the patient's coverage start is within three years

The statistical model uses six types of risk factors: diagnostic, pharmacy, procedural, utilization-based, geographic, and demographic. It is important to note that not all risk factors are available for every person-month. Hilltop uses a twelve-month lookback period for most of the time-varying risk factors, implying that an individual with, for example, five months of claims history will have incomplete information in her risk factors: if this individual truly has glaucoma, then it is possible that she will not amass the claims history by month five that meets the qualifications required for a glaucoma flag in our model. Furthermore, while most individuals in the data have valid ZIP codes that link to the environmental risk factor data set, several hundred beneficiaries have ZIP codes for which there is no equivalent ZCTA, and therefore receive no environmental risk factors.[40] Table 4 presents the risk factor availability, depending on claims history and the availability of ZIP code data.

[40] These individuals appear to use P.O. boxes as their mailing address, which, being point representations, do not have ZCTA areal equivalents.

Table 4. Availability of Risk Factors for Scoring

		At Least 12 Months of Claims History	
		Yes	**No**
Availability of ZIP Code Risk Factors	Yes	Dx/Rx/Proc/Util/Geo/Demo	Geo/Demo
	No	Dx/Rx/Proc/Util/Demo	Demo

Risk factor availability is an issue for the "scoring" step, in which risk scores are assigned to every individual based on the parameter estimates derived in the training step. For example, suppose that the vector of estimated coefficients from the logistic regression is as follows in Table 5.

Table 5. Example Risk Model Coefficients

Risk Factor	Value for individual i
Asthma Flag	.1
…	
ZIP Code Income	-.00001
…	
Age	.02

These hypothetical risk factor coefficients indicate that, as expected, if an individual meets the clinical criteria for asthma, the risk of avoidable hospitalization is higher; if he or she lives in a ZIP code with higher income, the risk is lower; and if he or she is older, the risk is higher. The scoring step will apply this vector of coefficients to the "person-now;" that is, the current month for each individual. Individual *i*'s predicted probability of incurring an avoidable hospitalization in the next month, then, will be scored as follows:

$$Risk_i = \frac{e^{.1*Asthma_i + \cdots - .00001*ZIP\ Code\ Income_i + \cdots + .02*Age_i}}{1 + e^{.1*Asthma_i + \cdots - .00001*ZIP\ Code\ Income_i + \cdots + .02*Age_i}}$$

Suppose that these variables (Asthma Flag, ZIP Code Income, and Age) are the only three risk factors in the model. Furthermore, suppose that individual *i* has the following characteristics:

Table 6. Example Risk Factors

Risk Factor	Value for individual i
Asthma Flag	1
ZIP Code Income	$55,000
Age	66

This hypothetical individual has asthma, lives in a ZIP Code in which the median income is $55,000, and is 72 years old. Then, that individual's risk of an avoidable hospital event in the following month is $\frac{e^{(.1*1 - .00001*55{,}000 + .02*66)}}{1 + e^{(.1*1 - .00001*55{,}000 + .02*66)}}$ = 70.47 percent.

Suppose, however, that this individual is newly eligible for Medicare and does not have sufficient claims history to meet the criteria for an asthma flag (anything under 12 months). In this

instance, the individual might truly have asthma as an underlying disease state, but this is not observable. The individual's risk factors, then, are:

Table 7. Example Risk Factors with Missing Information

Risk Factor	Value for individual i
Asthma Flag	NOT OBSERVED
ZIP Code Income	$55,000
Age	66

If the model's coefficients are applied only to the risk factors that are *observed*, then this individual's estimated risk is 68.35 percent. By failing to account for the risk factors that are not present in the model, the risk of incurring an avoidable hospital event is underestimated for individual *i*.

Hilltop's solution to this issue is to estimate four different models based on the risk factors that are available for each group. This allows the risk factors that are present to "compensate," to a certain extent, for the risk factors that are missing due to data availability. For example, suppose that an individual lacks sufficient claims history to generate diagnostic risk factors but does have the following demographic risk factors: age, gender, and race. If gender is correlated with the unobserved diagnostic risk factors (if, for example, female beneficiaries are more likely to experience chronic conditions than male beneficiaries), then the coefficient for the "gender" risk factor will capture this correlation, and thus represent the marginal impact of being female *and* the portion of unobserved diagnostic risk factors that is correlated with gender. Consequently, if female beneficiaries are more likely to experience chronic conditions than male beneficiaries, then the risk factor coefficient for "gender" will be larger in the models without diagnostic risk factors than in the models with diagnostic risk factors.[41] By allowing observed risk factors to capture some of the predictive power of unobserved risk factors, the loss in predictive power due to missing data is minimized. Note that this method is analogous to that used in the CMS HCC Risk Adjustment Model (CMS, 2019, p. 80).

The four models are trained on the subset of person-months for which all risk factors are complete (that is, person-months with at least 12 months of claims history and a valid ZIP code), and include the following sets of risk factors (analogous to the four partitions of the person-month sample):

- Model 1: use Rx/Dx/Util/Proc/Geo/Dem risk factors
- Model 2: use Geo/Dem risk factors
- Model 3: use Rx/Dx/Util/Proc/Dem risk factors
- Model 4: use Dem risk factors

[41] This is, indeed, the case: in the initial version of the full model, males were 7.4 percent less likely to experience an avoidable hospitalization than females. In the model with only demographic risk factors, however, males were 13.1 percent less likely to experience an avoidable hospitalization.

Variable selection can improve the performance of predictive models by reducing prediction variance and increasing generalizability (Bagherzadeh-Khiabani et al., 2016; Walter & Tiemeier, 2009). Hilltop performed this in two steps: first, the team selected initial risk factors based on an extensive literature review, which screened over 3,300 articles and ultimately selected 211 published, peer-reviewed papers from which to extract risk factors (see Section 3.2.1 for additional detail). This generated a pool of roughly 190 risk factors. Additionally, Hilltop used stepwise selection in the multivariable logistic model in order to remove insignificant predictors from the model before adding significant predictors.

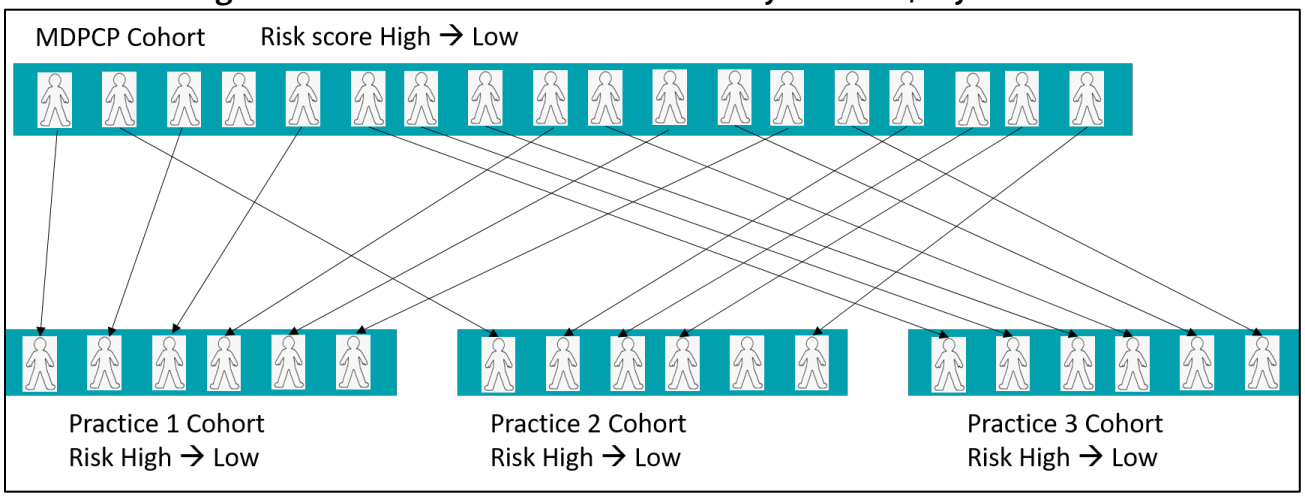
In the current version of the Hilltop Pre-AH Model™, the risk factors enter the model additively: that is, if an individual has both diabetes and heart failure diagnostic flags, then his or her risk score will reflect the risk coefficient for the diabetes flag, plus that of the heart failure flag. It is possible, however, that there is additional risk due to the fact of the beneficiary having *both* conditions, over and above the sum of the risks of having each condition. Future versions of the model will identify and include these interaction variables.

3.3.3 Scoring

The four risk models above are trained on the subset of data with at least twelve months of claims history and full ZIP code-level data in order to estimate the vectors of coefficients for the risk factors in each model. Section 4.1 below presents these coefficients for Model 1 as odds ratios. Then, using the most recently available month of risk factors (that is, the "person-now" data set), individuals are scored using the model coefficients that correspond to the risk factors available in the person-now data set.

The Hilltop Pre-AH Model™ will generate risk scores for the entire MDPCP cohort, but individual practices will receive only practice-specific risk scores. This has the consequence that, if a practice contains disproportionately high-risk patients, and another practice contains disproportionately low-risk patients, then the riskiest patients within each practice will differ in their *absolute* risk. Figure 1 presents a diagram of this point.

Figure 1. Stratification of MDPCP Cohort by Practices/Physicians



3.3.4 Model Training and Scoring Schedule

Hilltop will train the model once per quarter. This entails creating the risk factors from the raw claims data and estimating the four models discussed in Section 3.3.2, above. The resulting risk factor coefficients will then be used to score the MDPCP cohort once per *month*. This entails creating the risk factors from the raw claims data for the most recent month of claims history and then applying the most recent set of model coefficients.

For example, suppose that the four models are trained on January 1, 2019, April 1, 2019, July 1, 2019, and October 1, 2019, and that the previous month of claims data are available on the first day of the following month (so, in this example, claims data for June 2019 are available on July 1, 2019).[42] The model training generates risk factor coefficient estimates—one estimate for each risk factor—and these coefficient estimates are applied to the most recent set of risk factors in order to generate risk *scores*. For example, the coefficients estimated in the July 1, 2019 training will be used with the June 2019 risk factors in order to predict risk of avoidable hospitalization in July 2019 (which, remember, has not yet been observed as of the July 1, 2019 training date). These same risk factor coefficient estimates will be used with the July 2019 risk factors to predict August 2019 avoidable hospitalization and with August 2019 risk factors to predict September 2019 avoidable hospitalizations. Then, since the model is re-trained on October 1, 2019, September 2019 risk factors will be used with the new training model coefficients to predict avoidable hospitalizations in October 2019, and so on.

It is possible that the risk predictions may fall in accuracy as the training data model coefficients "fall behind" the person-now scoring data in time. For example, it is possible that, for the July 1, 2019 model training, the predictions are most accurate for July 2019 avoidable hospital events and then become less accurate for August 2019, and even less accurate for September 2019, since the training model coefficients become more removed from the current underlying data generating process. Hilltop does not believe that this represents a significant threat to the model's predictive accuracy. Any systematic bias would have to be the result of underlying structural changes in the relationship of certain risk factors to the risk of incurring an avoidable hospital event, which seems unlikely to occur in a three-month window. However, Hilltop will monitor this and increase the training schedule as needed.

It is also possible that the latest month of claims for a given training data set will not be complete: for example, suppose that CCLF data received by Hilltop in July 2019 contains claims only through mid-June 2019. In this instance, Hilltop will still use these June 2019 risk factors in order to score the MDPCP cohort in July 2019, for two reasons. First, since all of the time-variant risk factors include at least 12 months of lookback, there is relatively low month-to-month variation; consequently, there is a relatively low chance of failing to include salient risk factors as a result of the missing data from the second half of June 2019. Second, it is imperative for the

[42] This example is only for the purposes of exposition; in reality, there is a lag of approximately 1 month in the CCLF claims.

utility of the risk scores that the Hilltop Pre-AH Model™ uses the most recently available risk factors.

However, incomplete data for the final month of claims may introduce bias into the training model risk coefficients. To continue the example above, the training data will include beneficiaries' risk factors from May 2019, which are used to predict avoidable hospital events in June 2019. Since, in this example, claims information from late June 2019 will be missing, it will *appear* in the analytic data set as if most individuals did not incur an avoidable hospitalization in this month. Thus, in the extreme, May 2019 risk factors will be used to model all zeros for June 2019 outcomes, which would bias the risk factor coefficients toward zero. Given that 24 months of data are used in order to train the model, this is unlikely to meaningfully affect the training coefficients. Hilltop will monitor this and, if needed, will train the model only on the months of data for which we have full information for the outcome variable. To finish this example, May 2019 risk factors (and June 2019 outcomes) would not be included in the training model.

3.3.5 Nonlinear Model Testing

As part of the ongoing development process for the Hilltop Pre-AH Model™, the research team conducted internal testing on the utility of nonlinear modeling to predict avoidable hospital events in the MDPCP cohort. The goal of the testing was to assess whether nonlinear modeling would improve model performance sufficiently to justify the development costs and reduced interpretive intuition that would result from deploying the nonlinear model into production.

The question of how much improvement in model fit is "enough" is inherently subjective. We used a decision-theoretic framework to guide this decision: given that development time is costly and the coefficients of non-linear models can be difficult to interpret, how best to allocate development effort in order to improve the Pre-AH Model™ performance? In general, it is possible to improve a model's predictive performance in two ways: either by adding new information to the model in the form of new risk factors, or by using existing information in different ways (for example, by adopting a different modeling methodology). In the June 2020 re-training, we added eight new risk factors to the Hilltop Pre-AH Model™: an indicator for frailty, an indicator for original Medicare eligibility due to a non-age related reason, an indicator for DME use within the past year, the number of ED visits in the past 6 months, an indicator for sickle cell anemia, ZIP code pollution, walkability, and pharmacy density. This led to an increase in the Model 1 holdout sample C-statistic of 0.0051, and an increase in the holdout sample Gini score of 0.0107.[43] We used these improvements in model performance as a baseline for gauging the added value of developing a nonlinear prediction model: in order to further pursue nonlinear modeling, the internal testing would need to demonstrate an increase in either the C-statistic or Gini score by at least 0.0051 or 0.0107, respectively.

We evaluated two separate nonlinear modeling methods: neural network modeling and the inclusion of interaction terms into the baseline model. We describe both strategies below. Neither method demonstrated improvement in predictive power in excess of what was gained

[43] Estimated on the holdout samples from the two most recent years of data, excluding the most recent month.

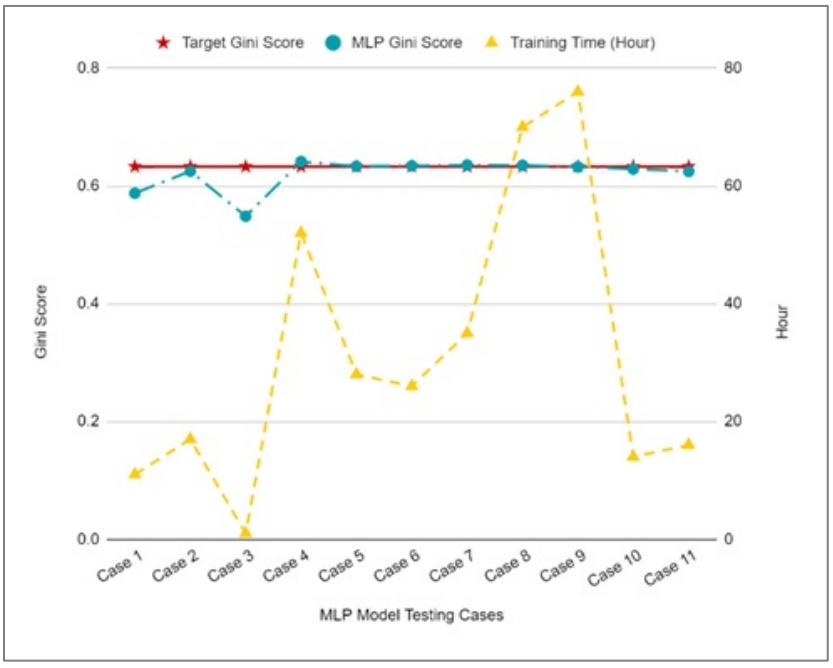
by adding new risk factors to the model; thus, neither model augmentation was deemed to justify the development costs of inclusion into the production model.

3.3.5.1 Neural Network Modeling

Neural networks are machine learning models that can, in principle, approximate any underlying function (Hornik et al., 1989). These models estimate highly nonlinear and complex relationships between risk factors and the target variable to be predicted (in our case, avoidable hospital events), and then use these relationships in order to generate predictions. Researchers have documented that neural networks improve predictive models relative to logistic regression in certain contexts, but at the cost of considerable computational time and a loss of modeling transparency (Tu, 1996).

We tested eleven different neural networks with varying combinations of hyperparameters (that is, technical aspects of neural network models). We used the Multi-Layer Perceptron (MLP) model, which is a standard neural network model that is available in SAS. Results of this testing is summarized in Figure 2, below.

Figure 2. Results of Neural Network Testing



We found that none of these eleven tests resulted in a substantially improved model performance, and most entailed significant computational costs. The best model performance was obtained in Case 4, which resulted in a 0.0085 increase in Gini score relative to baseline. However, this did not meet our internal standard for further development.

3.3.5.2 Interaction Terms

As a second strategy, we assessed the improved model fit that would result from including interaction terms in the model. Interaction terms capture *accumulative effects*: for example, in addition to avoidable hospital event risk due to Heart Failure and risk due to COPD, it is possible that there is additional risk that accrues to individuals with both Heart Failure and COPD. For this test, we included various sets of interaction terms into our baseline model risk factors and assessed the resulting increase in C-statistic.

Given that the baseline model contains approximately 200 risk factors, it was computationally prohibitive to include all possible combinations of interaction terms; therefore, we estimated a machine learning decision tree model in order to determine the most "important" variables in our baseline model and then used these variables to create interaction terms. We determined these variables to be the number of avoidable hospital events in the previous year, the number of ED visits in the previous six months, the total number of medications, an indicator for having heart failure, an indicator for having COPD, and an indicator for having diabetes with complications.

We created all fifteen possible two-way interactions from these six covariates, and including various combinations of these two-way interactions in our baseline model. We ran approximately 275 regressions and recorded the resulting C-statistic from each regression model. We found that, at most, the C-statistic rose by 0.0017. As above, this did not meet our internal standard for further development.

4. Model Performance

This section presents the details of the Hilltop Pre-AH Model™ performance using data from the period of May 2017 to April 2020.

4.1 Coefficients

Table 8 presents risk factor coefficient estimates for Model 1 for the training performed in June 2020. This model includes all six types of risk factors: diagnostic, pharmacy, procedural, utilization-based, geographic, and demographic. The risk factors in Table 8 are those that were included in the final model. All other risk factors were eliminated in the variable selection step due to insufficient predictive power. Note that the risk factor coefficients are presented as odds ratios, which can be interpreted in terms of a multiplicative impact: for example, an odds ratio of 1.05 indicates that if that risk factor were to increase by one unit, then the risk of incurring an avoidable hospitalization would increase by 5 percent.

Table 8. Risk Model Odds Ratios for Model 1

Risk Factor	Odds Ratio
Prior hospitalization discharge status - other (relative to no prior admission)	2.246
CCW indicator for chronic obstructive pulmonary disease (COPD) and bronchiectasis	1.618
Indicator for retinopathy	1.540
Indicator for hospice enrollment	1.448
Prior hospitalization admission type - emergency (relative to no prior admission)	1.422
Indicator for original Medicare eligibility for a non-age related cause	1.415
CCW indicator for heart failure	1.409
Number of avoidable hospitalizations	1.382
Beneficiary race - Black	1.357
Indicator for urinary tract infection	1.338
Prior hospitalization admission type - urgent (relative to no prior admission)	1.296
Indicator for dual eligibility with Medicaid	1.268
Indicator for insulin use	1.267
CCW indicator for hypertension	1.247
CCW indicator for tobacco use	1.244
Indicator for durable medical equipment (DME) use	1.220
Indicator for arrhythmia	1.210
CCW indicator for chronic kidney disease	1.208
Indicator for fluid and electrolyte imbalance	1.205
CCW indicator for intellectual disabilities and related conditions	1.199
Indicator for problems with care provider dependency	1.193
Discontinuity of primary care - Proportion	1.191
CCW indicator for asthma	1.180
Indicator for metastatic cancer	1.167
Indicator for no statin use	1.154
CCW indicator for lung cancer	1.153
CCW indicator for ischemic heart disease	1.152
CCW indicator for pressure and chronic ulcers	1.144
CCW indicator for diabetes	1.135
Indicator for oral antibiotic use	1.128
CCW indicator for anxiety disorders	1.121
Indicator for frailty	1.120
Indicator for respiratory infection	1.119
Indicator for albuminuria	1.119
CCW indicator for atrial fibrillation	1.113
Indicator for no vaccination (flu or pneumonia)	1.108

Risk Factor	Odds Ratio
Indicator for diabetes with complications	1.107
CCW indicator for peripheral vascular disease	1.093
Number of emergency department visits within the past 6 months	1.093
Indicator for pneumonia	1.089
CCW indicator for depression and depressive disorders	1.088
Indicator for no anti-diabetes medication use	1.083
CCW indicator for Alzheimer's disease and related disorders or senile dementia	1.082
Indicator for provider administered drug	1.081
Located in whole county mental health care shortage area	1.075
Indicator for oral corticosteroid use	1.071
Beneficiary gender - female (relative to male)	1.068
Number of urgent care visits	1.044
Age	1.022
Percent with less than high school education, ages 65+	1.004
Number of medications	1.003
Percent married	0.995
Number of prior admissions	0.955
Indicator for no beta blocker use	0.952
CCW indicator for rheumatoid arthritis/osteoarthritis	0.943
CCW indicator for glaucoma	0.929
Indicator for prior surgery	0.905
CCW indicator for cataracts	0.905
CCW indicator for hyperlipidemia	0.895
Air pollution level	0.880
CCW indicator for viral hepatitis	0.875
CCW indicator for personality disorders	0.871
Indicator for prior nursing home stay	0.808
Beneficiary race - Unknown	0.772

It is important to note that risk factor coefficient estimates will change as the model is re-trained. Risk factor coefficients for other models are available upon request.

4.2 Predicted Probabilities

The outcome of the Pre-AH Model™ is a set of probabilities that estimate the patient-specific risk of incurring an avoidable hospital event in the following months. In general, these events are rare: the MDPCP patient population numbers approximately 350,000 and there are typically 2,100 to 2,500 patients that experience at least one avoidable hospital event in a given month. As a consequence, the predicted probabilities are low. For patients with scores released in February 2020, the average probability of incurring an avoidable hospital event in the following month was 0.0066. Only 0.61 percent of the patient population had risk scores above 5 percent,

and only forty-eight patients had risk scores above 50 percent. Hilltop does not interpret this as a limitation of the risk scores; rather, this reflects the relative rarity of avoidable hospital events. Moreover, the *relative* risk is the key metric that should be used to allocate care resources: no matter the absolute risk of the patient panel, the efficient allocation of care resources requires the identification (and treatment) of the riskiest patients.

Patient-level risk tends to persist across time: that is, high-risk patients tend to remain high-risk from one month to the next, and low-risk patients tend to remain low-risk. For example, risk scores from May 2020 to June 2020 display a correlation of .98; from April 2020 to May 2020, the correlation is .97. This is likely due to two factors. First, in order to prevent coding idiosyncrasies from introducing noise into the predictions, all risk factors are coded with at least one year of lookback. This has the consequence of making the Pre-AH Model™ risk factors relatively stable over time, and thus, smoothing out variation in the risk scores. Second, it is likely that true, underlying patient risk is also persistent: if some patients tend to have high (or low) risk for structural reasons, then the risk scores should also be relatively stable across time.

However, large month-to-month changes can occur in risk scores for two reasons. First, using a given set of risk factors coefficients, any changes in underlying risk factors will lead to changes in patients' predicted risk. For example, if an attributed beneficiary meets the conditions for heart failure beginning in July 2019, then her risk score will risk significantly from June 2019 to July 2019 because of that underlying change. Second, Hilltop will estimate new risk factor coefficients every quarter (in the model re-training step). As a result, not only can the underlying risk factors for a given patient change from one month to the next, the *relationship* between that risk factor and the risk of avoidable hospital events can also change upon retraining. To continue the previous example, suppose that the model is retrained in July 2019, and that the risk factor coefficient for heart failure rises. As a consequence, that individual's risk score will now rise for two reasons: not only does she now have a heart failure risk factor, the heart failure risk factor has risen in predictive importance.[44]

4.3 Predictive Power

It is imperative that the accuracy of predictive models be assessed during both model development using validation data, and in a production environment. Below, we present the results of both.

4.3.1 Concentration Curves

Traditionally, the discriminatory power of predictive models has been summarized using the c-statistic, which is a measure of the area under the Receiver Operating Characteristic (ROC) curve (Steyerberg et al., 2016). The ROC curve plots the true positive rate against the false positive rate for binary classifiers using successive cutoff thresholds and "measures the probability that a randomly selected diseased subject has a higher predicted risk than a randomly selected non-

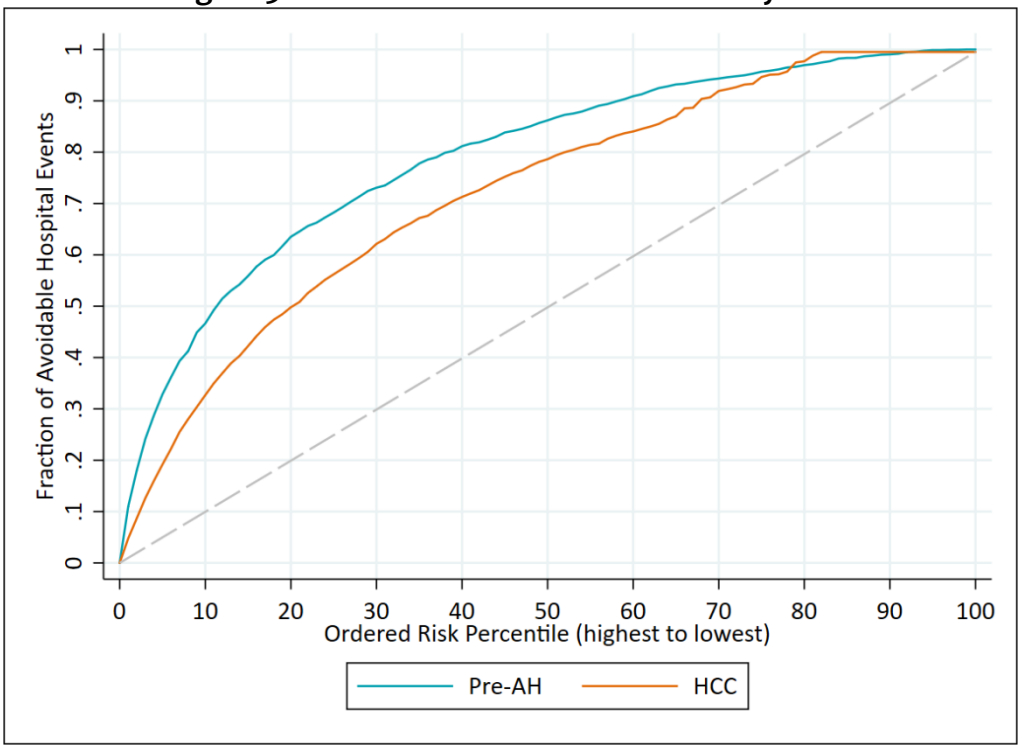
[44] In practice, large month-over-month changes are rare. Of the 342,375 individuals with risk scores in both May and June 2020, only 205 experienced a change of larger than 5 percentage points.

diseased subject" (Maugen & Begg, 2016). However, this measure is uninformative regarding model calibration, which is the degree to which estimated risk scores match underlying true risk: it is possible to have a model with good discrimination and poor calibration (Alba et al., 2017). Moreover, the objective of the Hilltop Pre-AH Model™ is not binary classification, but instead the estimation of individual-level risks of incurring an avoidable hospital event so that care managers can, by focusing on the riskiest individuals, potentially intervene to prevent the most likely avoidable hospitalizations. To that end, the performance of the Hilltop Pre-AH Model™ is assessed using the *concentration curve*.[45]

This measure of model accuracy estimates the cumulative share of all avoidable hospital events incurred by the riskiest patients, where the reader can determine the share of all avoidable hospital events occurring for individuals above different risk thresholds. In order to estimate the concentration curve, the patient cohort is ordered from most to least risky (in terms of predicted risk) on the X axis, and the fraction of total avoidable hospital events captured by the riskiest patients on the Y axis. In Figure 3, below, we use the Pre-AH Model™ scores released on January 10, 2020, to estimate the concentration curve for these scores on actual avoidable hospital events for the period January 10, 2020 – February 13, 2020. We find that the top 10 percent riskiest patients accounts for approximately 47 percent of all avoidable hospital events in the following month, and the top 20 percent riskiest patients account for almost two-thirds of all avoidable hospitalizations.

[45] This is very similar to the Lorenz curve, which "is especially useful in the context of disease prevention because it maps out what public health policy investigators need to know. That is, it tells us how much disease burden will occur in any given proportion of the population with risks above a chosen threshold" (Maugen & Begg, 2016).

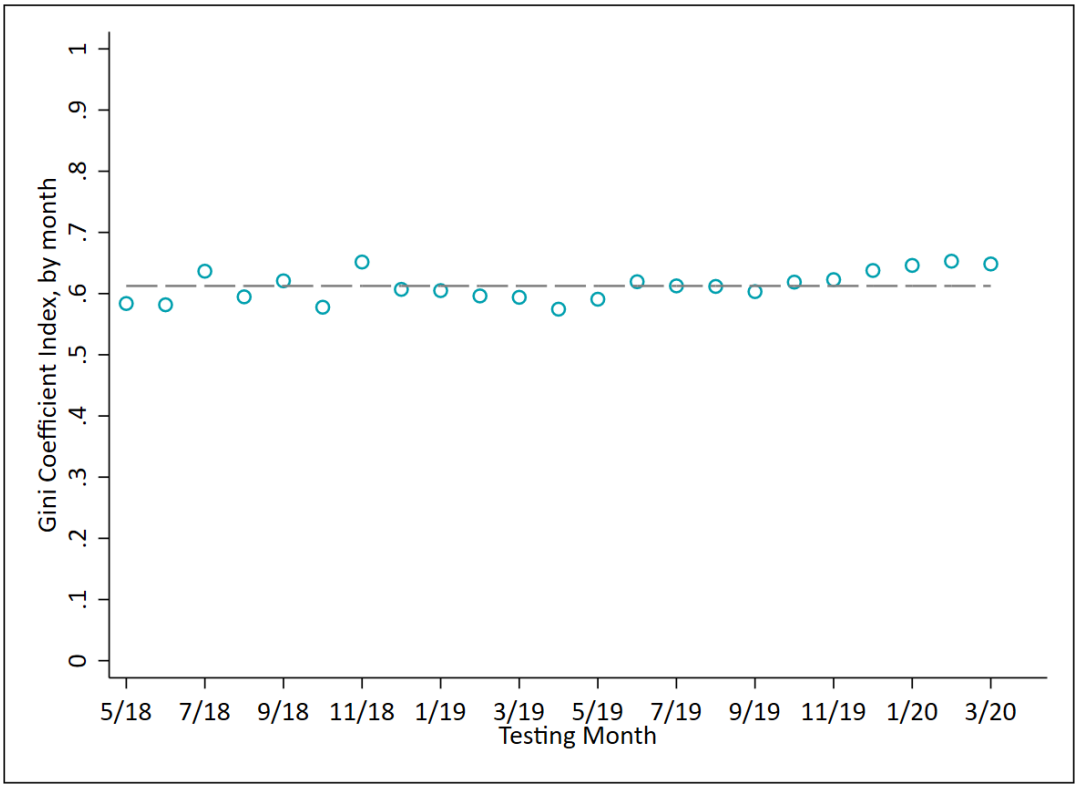
Figure 3. Concentration Curves as of January 2020



We performed the same exercise using the CMS HCC risk score for the January 2020 MDPCP attributed beneficiary cohort instead of the Hilltop Pre-AH Model™ risk score. This is also presented in Figure 3. Note that the top 10 percent riskiest patients account for approximately 33 percent of all avoidable hospitalizations in the following month, and the top 20 percent riskiest patients account for approximately 50 percent of all avoidable hospitalizations. Given a baseline of approximately 2,500 avoidable hospital events per month, this implies that if care managers were to rely solely on the CMS HCC risk score and focus on the riskiest 10 percent of the cohort, then they would fail to identify 350 avoidable hospital events (relative to the number that would be identified using the Hilltop Pre-AH Model™ risk scores).

The Hilltop Pre-AH Model™ fit can also be summarized using the Gini coefficient, which is a measure (from 0 to 1) of the area between the concentration curve and the dotted 45-degree line. A higher Gini coefficient indicates better model fit. In order to assess whether model performance is improving or declining over time, we estimated monthly concentration curves for the 20 percent holdout sample of the training data set. While this is not production data, as above, this holdout data *was not used to train the model*, and therefore represents a test of model performance as if it were in a production environment. Figure 4 plots the Gini coefficients from 23 months of data based on the concentration curves estimated on the 20 percent holdout sample from each month. The final month of holdout data was not used due to incomplete information on avoidable hospital events in that month.

Figure 4. Gini Scores by Month



These scores indicate that model performance is steady over time, with a very slight upward trend. This is consistent with the risk factors becoming more predictive as additional claims history becomes available.

4.3.2 Production Data Testing

Post-deployment model evaluation is a crucial component of the predictive model lifecycle. The first Pre-AH Model™ risk scores were released to participating providers on October 11, 2019, and have been subsequently updated on the second Friday of every month since then. As of June 2020, the CCLF data appear to be reasonably complete through mid-April 2020, thus allowing Hilltop to test the accuracy of the Pre-AH Model™ predictions in a production environment for the first six months of scores.

In Table 9, below, we present these results. For the scores released on October 11, 2019, we find that the top 10 percent riskiest patients accounted for 47.2 percent of all avoidable hospital events over the following month (until the next score release). We find similar results for all other months of scores, with performance ranging from 45.0 – 47.3 percent.

Table 9. Predictive Performance of Pre-AH Model™ Scores by Month

Evaluation Period	Top 10% of Patients, by Risk
10/11/2019 – 11/07/2019	47.2%
11/08/2019 - 12/12/2019	47.3%
12/13/2019 - 01/09/2020	45.0%
01/10/2020 - 02/13/2020	46.6%
02/14/2020 - 03/12/2020	45.0%
03/13/2020 - 04/09/2020	45.9%

We will continue to monitor the field performance of the model as additional data updates are received.

4.4 Limitations

There are three main limitations of the Hilltop Pre-AH Model™ that are important to consider when implementing the model for guiding care coordination services: the timing lag, the lack of clinical risk factors, and the granularity of the environmental risk factors. We discuss each in turn below.

4.4.1 Timing Lag

As noted Section 2.1, Hilltop receives the Medicare CCLF claims with a lag of over one month. Claims that arrive in, for example, late October 2019 cover utilization through mid-September 2019. Hilltop uses these data to calculate risk factors based on utilization in September 2019, and then applies the risk model coefficients in order to estimate the risk of incurring an avoidable hospitalization in October 2019. These scores are then posted to CRISP in mid-November 2019 for use by providers and care managers. This raises two distinct, but related, issues. First, by providing the one-month predictions (in this example, predicting October 2019 events) to care managers over a two-month time horizon (here, in November 2019), the risk predictions may be "outdated" by the time they are used by care managers and providers. Second, the risk predictions do not incorporate the most recent patient experience, which may degrade the quality of the risk scores.

Hilltop does not believe that this issue—the possibility that the risk score quality is impaired due to either being "outdated" or missing relevant recent information—substantively impacts the utility of the Pre-AH Model™ risk scores, for four reasons. First, the time-variant risk factors in the Pre-AH Model™ are all estimated with a look-back period of at least one year. This has the consequence that risk factors tend to change slowly, meaning that the risk scores also change slowly. As a result, there is high consistency of risk scores across months: patients that have high risk scores in October 2019 will also have high risk scores in November 2019. Second, internal testing has verified that applying one-month predictions on a two-month time horizon is substantively equivalent to directly estimating two-month predictions. Third, Hilltop has determined that the Pre-AH model has good discrimination and calibration in the production environment: applying the one-month predictions to a two-month horizon results in the

identification of almost 45 percent of all avoidable hospital events in the riskiest 10 percent of patients. Fourth, to the extent that structural factors determine the risk of incurring an avoidable hospital event, it is likely that high-risk *behavior* persists across time; that is, most individuals will not suddenly "become" high-risk in the interval between the most recent CCLF claims data and receipt of the Pre-AH Model™ risk scores by care managers and providers.

Finally, it is possible that improvements in revenue management systems will reduce the CCLF delivery lag so that, for example, risk scores estimated using September 2019 data can be provided to participating providers in early October 2019. In this case, the prediction time horizon would be one month (as in the current configuration of the Pre-AH Model™). Reconfiguring the model now to generate risk scores at a two-month horizon would entail development costs, and then, should the time lag be reduced, reconfiguring the model again to generate risk scores at a one-month horizon would entail additional costs. Therefore, Hilltop will continue to estimate next month's avoidable hospital events. However, we will continue to monitor this issue, and update the model as needed.

4.4.2 Clinical Data

The Medicare CCLF data do not include information on vital statistics—for example, blood pressure or lab results—meaning that Hilltop is unable to incorporate those clinical risk factors into the Pre-AH Model™. It is likely that development of clinical risk factors would improve the predictive power of the model, although researchers have documented only relatively modest improvements in model performance for claims-and-clinical models relative to claims-only prediction models for heart failure patients (Hammill et al., 2011). Hilltop hopes to include this information in future versions of the model once the level of information exchange between electronic health records allows.

4.4.3 Environmental Risk Factors

In order to control for environmental factors that may affect patients' probabilities of incurring avoidable hospital events, the Pre-AH Model™ includes a rich set of ZIP code-level covariates derived from publicly available sources. These data have two main limitations: first, they are relatively coarse. Maryland has 468 ZIP Code Tabulation Areas, each containing, on average, roughly 13,000 Maryland residents. To the extent that risky individuals tend to live in the same ZIP codes, then ZIP code-level risk factors offer little predictive power.

Second, the data are static: the environmental risk factors for a given attributed beneficiary do not change over time. This is largely due to data availability, as the publically available data sources are only refreshed periodically. Hilltop plans, in the future, to use the address-level information available in the CCLF claims to disaggregate (and refresh) the area-level risk factors as much, and as frequently, as possible. Additionally, if available in the future, individual-level social welfare screening data will be added to provide a more robust individual-level risk prediction.

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Appendix 1. Risk Factor Codebook

Age: For each person-month, this variable records person age as of the end of the month.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Age	72.429	19	108

Number of avoidable hospitalizations: For each person-month, this variable counts the number of avoidable hospitalizations incurred within the prior 12 months (not including the month in which the avoidable hospitalization occurred).

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Number of avoidable hospitalizations	.058	0	49

Indicator for no anti-diabetes medication use: For each person-month, this variable takes the value of 1 if a person did not incur a claim for anti-diabetes medication within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no anti-diabetes medication use	.965	0	1

Indicator for no beta blocker use: For each person-month, this variable takes the value of 1 if a person did not incur a claim for beta blockers within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no beta blocker use	.832	0	1

CCW indicator for acquired hypothyroidism: For each person-month, this variable records whether the person meets the CCW clinical criteria for acquired hypothyroidism. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for acquired hypothyroidism	.135	0	1

CCW indicator for acute myocardial infarction: For each person-month, this variable records whether the person meets the CCW clinical criteria for acute myocardial infarction. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for acute myocardial infarction	.005	0	1

CCW indicator for ADHD, conduct disorders, and hyperkinetic syndrome: For each person-month, this variable records whether the person meets the CCW clinical criteria for ADHD, conduct disorders, and hyperkinetic syndrome. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for ADHD, conduct disorders, and hyperkinetic syndrome	.006	0	1

Indicator for albuminuria: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for albuminuria within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for albuminuria	.015	0	1

CCW indicator for alcohol use disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for alcohol use disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for alcohol use disorders	.002	0	1

CCW indicator for Alzheimer's disease and related disorders or senile dementia: For each person-month, this variable records whether the person meets the CCW clinical criteria for Alzheimer's disease and related disorders or senile dementia. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for Alzheimer's disease and related disorders or senile dementia	.051	0	1

CCW indicator for anemia: For each person-month, this variable records whether the person meets the CCW clinical criteria for anemia. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for anemia	.182	0	1

CCW indicator for anxiety disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for anxiety disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for anxiety disorders	.112	0	1

Indicator for arrhythmia: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for arrhythmia within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for arrhythmia	.16	0	1

CCW indicator for asthma: For each person-month, this variable records whether the person meets the CCW clinical criteria for asthma. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for asthma	.048	0	1

CCW indicator for atrial fibrillation: For each person-month, this variable records whether the person meets the CCW clinical criteria for atrial fibrillation. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for atrial fibrillation	.065	0	1

CCW indicator for autism spectrum disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for autism spectrum disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for autism spectrum disorders	.002	0	1

CCW indicator for benign prostatic hyperplasia: For each person-month, this variable records whether the person meets the CCW clinical criteria for benign prostatic hyperplasia. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for benign prostatic hyperplasia	.066	0	1

CCW indicator for bipolar disorder: For each person-month, this variable records whether the person meets the CCW clinical criteria for bipolar disorder. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for bipolar disorder	.02	0	1

CCW indicator for cataracts: For each person-month, this variable records whether the person meets the CCW clinical criteria for cataracts. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for cataracts	.166	0	1

CCW indicator for cerebral palsy: For each person-month, this variable records whether the person meets the CCW clinical criteria for cerebral palsy. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for cerebral palsy	.002	0	1

Indicator for cerebrovascular disease: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for cerebrovascular disease within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for cerebrovascular disease	.09	0	1

CCW indicator for chronic kidney disease: For each person-month, this variable records whether the person meets the CCW clinical criteria for chronic kidney disease. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for chronic kidney disease	.182	0	1

CCW indicator for chronic obstructive pulmonary disease (COPD) and bronchiectasis: For each person-month, this variable records whether the person meets the CCW clinical criteria for chronic obstructive pulmonary disease (COPD) and bronchiectasis. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for chronic obstructive pulmonary disease (COPD) and bronchiectasis	.077	0	1

CCW indicator for colorectal cancer: For each person-month, this variable records whether the person meets the CCW clinical criteria for colorectal cancer. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for colorectal cancer	.009	0	1

CCW indicator for cystic fibrosis and other metabolic developmental disorders: For each person-month, this variable records whether the person meets the CCW

clinical criteria for cystic fibrosis and other metabolic developmental disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for cystic fibrosis and other metabolic developmental disorders	.004	0	1

CCW indicator for depression and depressive disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for depression and depressive disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for depression and depressive disorders	.122	0	1

CCW indicator for diabetes: For each person-month, this variable records whether the person meets the CCW clinical criteria for diabetes. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for diabetes	.251	0	1

Indicator for diabetes with complications: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for diabetes with complications within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for diabetes with complications	.148	0	1

Indicator for diabetic ulcer: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for diabetic ulcer within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for diabetic ulcer	.032	0	1

CCW indicator for drug use disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for drug use disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for drug use disorders	.002	0	1

CCW indicator for endometrial cancer: For each person-month, this variable records whether the person meets the CCW clinical criteria for endometrial cancer. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for endometrial cancer	.004	0	1

CCW indicator for epilepsy: For each person-month, this variable records whether the person meets the CCW clinical criteria for epilepsy. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for epilepsy	.016	0	1

CCW indicator for female/male breast cancer: For each person-month, this variable records whether the person meets the CCW clinical criteria for female/male breast cancer. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for female/male breast cancer	.035	0	1

CCW indicator for fibromyalgia, chronic pain and fatigue: For each person-month, this variable records whether the person meets the CCW clinical criteria for fibromyalgia, chronic pain and fatigue. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for fibromyalgia, chronic pain and fatigue	.154	0	1

Indicator for fluid and electrolyte imbalance: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for fluid and electrolyte imbalance within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for fluid and electrolyte imbalance	.095	0	1

Indicator for gastroesophageal reflux disease: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for gastroesophageal reflux disease within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for gastroesophageal reflux disease	.171	0	1

Indicator for gastroparesis: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for gastroparesis within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for gastroparesis	.003	0	1

CCW indicator for glaucoma: For each person-month, this variable records whether the person meets the CCW clinical criteria for glaucoma. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for glaucoma	.12	0	1

CCW indicator for heart failure: For each person-month, this variable records whether the person meets the CCW clinical criteria for heart failure. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for heart failure	.076	0	1

CCW indicator for hip/pelvic fracture: For each person-month, this variable records whether the person meets the CCW clinical criteria for hip/pelvic fracture. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for hip/pelvic fracture	.003	0	1

CCW indicator for HIV/AIDS: For each person-month, this variable records whether the person meets the CCW clinical criteria for HIV/AIDS. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for HIV/AIDS	.003	0	1

CCW indicator for hyperlipidemia: For each person-month, this variable records whether the person meets the CCW clinical criteria for hyperlipidemia. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for hyperlipidemia	.498	0	1

CCW indicator for hypertension: For each person-month, this variable records whether the person meets the CCW clinical criteria for hypertension. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for hypertension	.565	0	1

CCW indicator for intellectual disabilities and related conditions: For each person-month, this variable records whether the person meets the CCW clinical criteria for intellectual disabilities and related conditions. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for intellectual disabilities and related conditions	.007	0	1

CCW indicator for ischemic heart disease: For each person-month, this variable records whether the person meets the CCW clinical criteria for ischemic heart disease. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for ischemic heart disease	.207	0	1

CCW indicator for learning disabilities: For each person-month, this variable records whether the person meets the CCW clinical criteria for learning disabilities. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for learning disabilities	.001	0	1

CCW indicator for leukemias and lymphomas: For each person-month, this variable records whether the person meets the CCW clinical criteria for leukemias and lymphomas. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for leukemias and lymphomas	.012	0	1

CCW indicator for liver disease, cirrhosis and other liver conditions (except viral hepatitis): For each person-month, this variable records whether the person meets the CCW clinical criteria for liver disease, cirrhosis and other liver conditions (except viral hepatitis). If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for liver disease, cirrhosis and other liver conditions (except viral hepatitis)	.028	0	1

CCW indicator for lung cancer: For each person-month, this variable records whether the person meets the CCW clinical criteria for lung cancer. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for lung cancer	.008	0	1

Indicator for metastatic cancer: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for metastatic cancer within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for metastatic cancer	.011	0	1

CCW indicator for migraine and chronic headache: For each person-month, this variable records whether the person meets the CCW clinical criteria for migraine and chronic headache. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for migraine and chronic headache	.024	0	1

CCW indicator for mobility impairments: For each person-month, this variable records whether the person meets the CCW clinical criteria for mobility impairments. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for mobility impairments	.015	0	1

CCW indicator for multiple sclerosis and transverse myelitis: For each person-month, this variable records whether the person meets the CCW clinical criteria for multiple sclerosis and transverse myelitis. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for multiple sclerosis and transverse myelitis	.005	0	1

CCW indicator for muscular dystrophy: For each person-month, this variable records whether the person meets the CCW clinical criteria for muscular dystrophy. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for muscular dystrophy	0	0	1

Indicator for neuropathy: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for neuropathy within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for neuropathy	.051	0	1

CCW indicator for obesity: For each person-month, this variable records whether the person meets the CCW clinical criteria for obesity. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for obesity	.15	0	1

Indicator for occupational exposure to risk factors: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for occupational exposure to risk factors within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for occupational exposure to risk factors	0	0	1

CCW indicator for osteoporosis: For each person-month, this variable records whether the person meets the CCW clinical criteria for osteoporosis. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for osteoporosis	.06	0	1

CCW indicator for other developmental delays: For each person-month, this variable records whether the person meets the CCW clinical criteria for other developmental delays. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for other developmental delays	.001	0	1

Indicator for other problems with primary support group: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for other problems with primary support group within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for other problems with primary support group	.002	0	1

Indicator for pancreatitis: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for pancreatitis within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for pancreatitis	.009	0	1

Indicator for peptic ulcer disease: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for peptic ulcer disease within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for peptic ulcer disease	.008	0	1

Indicator for peripheral and visceral atherosclerosis: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for peripheral and visceral atherosclerosis within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for peripheral and visceral atherosclerosis	.083	0	1

CCW indicator for peripheral vascular disease: For each person-month, this variable records whether the person meets the CCW clinical criteria for peripheral vascular disease. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for peripheral vascular disease	.097	0	1

CCW indicator for personality disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for personality disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for personality disorders	.009	0	1

Indicator for pneumonia: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for pneumonia within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for pneumonia	.033	0	1

CCW indicator for post-traumatic stress disorder: For each person-month, this variable records whether the person meets the CCW clinical criteria for post-traumatic stress disorder. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for post-traumatic stress disorder	.006	0	1

CCW indicator for pressure and chronic ulcers: For each person-month, this variable records whether the person meets the CCW clinical criteria for pressure and chronic ulcers. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for pressure and chronic ulcers	.024	0	1

Indicator for problems with education and literacy: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for problems with education and literacy within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with education and literacy	0	0	1

Indicator for problems with employment and unemployment: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for problems with employment and unemployment within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with employment and unemployment	0	0	1

Indicator for problems with housing and economic conditions: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for problems with housing and economic conditions within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with housing and economic conditions	.001	0	1

Indicator for difficulty with life management: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for difficulty with life management within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for difficulty with life management	.002	0	1

Indicator for lifestyle problems: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for lifestyle problems within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for lifestyle problems	.021	0	1

Indicator for psychosocial problems: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for psychosocial problems within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for psychosocial problems	0	0	1

Indicator for problems with social environment: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for problems with social environment within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with social environment	.002	0	1

Indicator for problems with upbringing: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for problems with upbringing within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with upbringing	0	0	1

Indicator for problems with care provider dependency: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient

claims with any diagnosis for problems with care provider dependency within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for problems with care provider dependency	.047	0	1

CCW indicator for prostate cancer: For each person-month, this variable records whether the person meets the CCW clinical criteria for prostate cancer. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for prostate cancer	.033	0	1

Indicator for protein-calorie malnutrition: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for protein-calorie malnutrition within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for protein-calorie malnutrition	.005	0	1

Indicator for pulmonary circulatory disorder: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for pulmonary circulatory disorder within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for pulmonary circulatory disorder	.028	0	1

CCW indicator for rheumatoid arthritis/osteoarthritis: For each person-month, this variable records whether the person meets the CCW clinical criteria for rheumatoid arthritis/osteoarthritis. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for rheumatoid arthritis/osteoarthritis	.281	0	1

Indicator for respiratory infection: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for respiratory infection within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for respiratory infection	.119	0	1

Indicator for retinopathy: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for retinopathy within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for retinopathy	.001	0	1

Indicator for rheumatoid arthritis/collagen vascular disease: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for rheumatoid arthritis/collagen vascular disease within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for rheumatoid arthritis/collagen vascular disease	.048	0	1

CCW indicator for schizophrenia and other psychotic disorders: For each person-month, this variable records whether the person meets the CCW clinical criteria for schizophrenia and other psychotic disorders. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for schizophrenia and other psychotic disorders	.012	0	1

CCW indicator for sensory (blindness and visual) impairment: For each person-month, this variable records whether the person meets the CCW clinical criteria for sensory (blindness and visual) impairment. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for sensory (blindness and visual) impairment	.003	0	1

CCW indicator for sensory (deafness and hearing) impairment: For each person-month, this variable records whether the person meets the CCW clinical criteria for sensory (deafness and hearing) impairment. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for sensory (deafness and hearing) impairment	.046	0	1

Indicator for sepsis: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for sepsis within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for sepsis	.018	0	1

Indicator for sleep apnea: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for sleep apnea within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for sleep apnea	.108	0	1

Indicator for solid tumor without metastasis: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for solid tumor without metastasis within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for solid tumor without metastasis	.094	0	1

CCW indicator for spina bifida and other congenital anomalies of the nervous system: For each person-month, this variable records whether the person meets the CCW clinical criteria for spina bifida and other congenital anomalies of the nervous system. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for spina bifida and other congenital anomalies of the nervous system	.001	0	1

CCW indicator for spinal cord injury: For each person-month, this variable records whether the person meets the CCW clinical criteria for spinal cord injury. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for spinal cord injury	.003	0	1

CCW indicator for stroke/ischemic transient attack: For each person-month, this variable records whether the person meets the CCW clinical criteria for stroke/ischemic transient attack. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for stroke/ischemic transient attack	.032	0	1

CCW indicator for tobacco use: For each person-month, this variable records whether the person meets the CCW clinical criteria for tobacco use. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for tobacco use	.054	0	1

CCW indicator for traumatic brain injury and nonpsychotic mental disorders due to brain damage: For each person-month, this variable records whether the person meets the CCW clinical criteria for traumatic brain injury and nonpsychotic mental disorders due to brain damage. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for traumatic brain injury and nonpsychotic mental disorders due to brain damage	.002	0	1

Indicator for urinary tract infection: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for urinary tract infection within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for urinary tract infection	.083	0	1

CCW indicator for viral hepatitis: For each person-month, this variable records whether the person meets the CCW clinical criteria for viral hepatitis. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
CCW indicator for viral hepatitis	.009	0	1

Indicator for cilostazol use: For each person-month, this variable takes the value of 1 if a person incurred a claim for cilostazol within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for cilostazol use	.002	0	1

General internists per 1000 residents: For each person, this variable records the number of general internists per 1000 residents in the county containing the ZCTA. If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes, with weights being the fraction of the ZCTA population residing within each county.

Source: Area Health Resources File

Risk Factor	Mean	Minimum	Maximum
General internists per 1000 residents	.577	0	1.953442

Physician diversity: For each person, this variable records the percentage of medical doctors who are minorities (African Americans, Hispanics, and others, but excluding Asian-Americans). If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes, with weights being the fraction of the ZCTA population residing within each county.

Source: American Community Survey (2017, individual)

Risk Factor	Mean	Minimum	Maximum
Physician diversity	18.872	0	73.88705

Social workers per 1000 residents: For each person, this variable records the number of social workers per 1000 residents in the county containing the person's ZIP code tabulation area of residence. If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes, with weights being the fraction of the ZCTA population residing within each county.

Source: American Community Survey (2017, individual)

Risk Factor	Mean	Minimum	Maximum
Social workers per 1000 residents	3.772	0	6.382436

Indicator for frailty: For each person-month, this variable takes the value of 1 if a person meets the definition for frailty within the past twelve months, and 0 otherwise. The clinical definition for frailty is derived from Kim and Schneeweiss (2014).

Source: Part A, B, and Part B DME claims

Risk Factor	Mean	Minimum	Maximum
Indicator for frailty	.268	0	1

Indicator for sickle cell anemia: For each person-month, this variable records whether the person has incurred at least one inpatient or two non-inpatient claims with any diagnosis for sickle cell anemia within the past two years. If so, this variable takes the value 1; if not, then 0.

Source: Part A and B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for sickle cell anemia	0	0	1

Indicator for durable medical equipment (DME) use: For each person-month, this variable takes the value of 1 if a person used any durable medical equipment in the previous 12 months, and 0 otherwise.

Source: Part B DME claims

Risk Factor	Mean	Minimum	Maximum
Indicator for durable medical equipment (DME) use	.257	0	1

Indicator for dual eligibility with Medicaid: For each person-month, this variable takes the value of 1 if a person was dually eligible for both Medicaid and Medicare within the past 12 months, and 0 otherwise.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Indicator for dual eligibility with Medicaid	.134	0	1

Number of emergency department visits within the past 6 months: For each person-month, this variable counts the number of emergency department visits incurred within the prior 6 months.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Number of emergency department visits within the past 6 months	.176	0	100

Indicator for endocrinologist visit: For each person-month, this variable takes the value of 1 if a person visited an endocrinologist within the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for endocrinologist visit	.07	0	1

Avoidable hospitalization/ED visit: For each person-month, this variable records whether the individual incurred an avoidable hospitalization or ED visits in that month. We use the AHRQ's definition of avoidable hospitalization in defining this outcome. Please see the section 3.2.1 of the documentation for additional detail.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Avoidable hospitalization/ED visit	.006	0	1

Indicator for diabetic foot procedure: For each person-month, this variable takes the value of 1 if a person incurred an inpatient diabetic foot procedure over the last 12 months and 0 otherwise.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Indicator for diabetic foot procedure	.001	0	1

Number of HbA1c tests: For each person-month, this variable counts the number of visits within the past 12 months in which a person received a Hemoglobin A1C (HbA1c) test. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of HbA1c tests	.552	0	12

Number of heart-related procedures: For each person-month, this variable counts the number of heart-related procedures incurred over the past year.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Number of heart-related procedures	.019	0	13

Number of home health visits: For each person-month, this variable counts the number of home health visits incurred within the past 12 months. We apply a logarithmic transformation to non-zero values. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of home health visits	.015	0	5.56068

Indicator for hospice enrollment: For each person-month, this variable takes the value of 1 if a person enrolled in hospice within the past 12 months, and 0 otherwise.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Indicator for hospice enrollment	.001	0	1

Indicator for insulin use: For each person-month, this variable takes the value of 1 if a person incurred a claim for insulin within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for insulin use	.04	0	1

Indicator for leukotriene receptor modifier use: For each person-month, this variable takes the value of 1 if a person incurred a claim for leukotriene receptor modifiers within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for leukotriene receptor modifier use	.03	0	1

Indicator for no losartan use: For each person-month, this variable takes the value of 1 if a person did not incur a claim for losartan within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no losartan use	.892	0	1

Indicator for original Medicare eligibility for a non-age related cause: Beneficiary was originally eligible for Medicare for a reason other than age.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Indicator for original Medicare eligibility for a non-age related cause	.166	0	1

Total health spending: For each person-month, this variable measures the total health spending incurred within the past 12 months. We define this as the sum of claim total charge amount (Part A), claim payment amount (Part B claim lines, aggregated to the claim level), and claim line beneficiary payment amount (part D).

Source: Part A, B, and D claims

Risk Factor	Mean	Minimum	Maximum
Total health spending	10712.08	0	3267903

Indicator for no mental health use: For each person-month, this variable takes the value of 1 if a person did not incur a visit with a mental health professional over the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no mental health use	.948	0	1

Number of medications: For each person-month, this variable counts the number of distinct medications (as measured by NDC codes) for which there are part D claims within the past 12 months.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Number of medications	6.934	0	146

Indicator for oncologist visit: For each person-month, this variable takes the value of 1 if a person visited an oncologist within the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for oncologist visit	.095	0	1

Indicator for oral antibiotic use: For each person-month, this variable takes the value of 1 if a person incurred a claim for oral antibiotics within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for oral antibiotic use	.301	0	1

Indicator for oral corticosteroid use: For each person-month, this variable takes the value of 1 if a person incurred a claim for oral corticosteroids within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for oral corticosteroid use	.055	0	1

Number of outpatient visits: For each person-month, this variable counts the number of visits in an outpatient setting incurred within the past 12 months. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of outpatient visits	14.125	0	384

Continuity of primary care - Duration: For each person-month, this variable calculates the average time interval between primary care visits over the past 12 months. Visits that occur within 14 days are aggregated. Individuals with no primary care visits over the past 12 months are assigned a value of 365. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Continuity of primary care - Duration	130.616	15.20833	365

Discontinuity of primary care - Index: For each person-month, this variable calculates (1 - the continuity of care index), from Boxerman and Bice (1977). This score ranges from 0 to 1 and is intended to measure dispersion in person-provider contact. If the person sees the same provider for all visits, indicating highly continuous care, the index score is 0; if the person sees a different physician for every visit, indicating fragmented care, the index score is 1. If a person has no primary care visits within the past year, they are assigned a value of 0. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Discontinuity of primary care - Index	.62	0	1

Discontinuity of primary care - Proportion: For each person-month, this variable estimates (1 - the fraction of primary care visits within the past 12 months provided by the same provider). For example, if a person had 10 primary care visits over the past 12 months, and four visits were with the same provider, then this measure would take a value of (1 - .4) = .6. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Discontinuity of primary care - Proportion	.545	0	1

Number of primary care visits: For each person-month, this variable counts the number of primary care visits within the past 12 months. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of primary care visits	8.799	0	315

Indicator for previous conservative diabetic wound procedure: For each person-month, this variable takes the value of 1 if a person underwent at least one conservative diabetic procedure within the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for previous conservative diabetic wound procedure	.011	0	1

Number of prior admissions: For each person-month, this variable counts the number of all inpatient hospital admissions incurred within the past twelve months.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Number of prior admissions	.15	0	28

Prior admission length of stay: For each person-month, this variable calculates the length of the most recently incurred hospital inpatient stay over the past 12 months. For individuals without a previous inpatient stay, this value is set to zero.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Prior admission length of stay	.456	0	436

Prior hospitalization admission source - none: For each person-month, this variable indicates the individual did not incur an inpatient hospital stay within the past 12 month.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission source - none	.898	0	1

Prior hospitalization admission source - other: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission source was: other.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission source - other	0	0	0

Prior hospitalization admission source - physician referral: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission source was: physician referral.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission source - physician referral	.091	0	1

Prior hospitalization admission source - transferred from facility: For each person-month, this variable indicates that for the individual's most recently incurred inpatient

hospital stay within the past 12 months, the individual's admission source was: transferred from facility.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission source - transferred from facility	.011	0	1

Prior hospitalization admission type - elective: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission type was: elective.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - elective	.031	0	1

Prior hospitalization admission type - emergency: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission type was: emergency.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - emergency	.066	0	1

Prior hospitalization admission type - none: For each person-month, this variable indicates the individual did not incur an inpatient hospital stay within the past 12 month.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - none	.898	0	1

Prior hospitalization admission type - other: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission type was: other.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - other	0	0	1

Prior hospitalization admission type - trauma center: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission type was: trauma center.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - trauma center	.001	0	1

Prior hospitalization admission type - urgent: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's admission type was: urgent.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization admission type - urgent	.004	0	1

Prior hospitalization discharge status - home: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's discharge status was: home.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization discharge status - home	.082	0	1

Prior hospitalization discharge status - none: For each person-month, this variable indicates the individual did not incur an inpatient hospital stay within the past 12 month.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization discharge status - none	.898	0	1

Prior hospitalization discharge status - other: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's discharge status was: other.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization discharge status - other	0	0	1

Prior hospitalization discharge status - transferred to inpatient care: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's discharge status was: transferred to inpatient care.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization discharge status - transferred to inpatient care	0	0	0

Prior hospitalization discharge status - transferred to post-acute care: For each person-month, this variable indicates that for the individual's most recently incurred inpatient hospital stay within the past 12 months, the individual's discharge status was: transferred to post-acute care.

Source: Part A Claims

Risk Factor	Mean	Minimum	Maximum
Prior hospitalization discharge status - transferred to post-acute care	0	0	0

Indicator for prior nursing home stay: For each person-month, this variable takes the value of 1 if a person incurred a nursing home stay within the last 12 months, and 0 otherwise.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Indicator for prior nursing home stay	.024	0	1

Indicator for prior readmission: For each person-month, this variable takes the value of 1 if a person incurred an all-cause 30-day hospital readmission within the last 12 months, and 0 otherwise. We define readmission as two inpatient stays occurring fewer than 30 days apart.

Source: Part A claims

Risk Factor	Mean	Minimum	Maximum
Indicator for prior readmission	.018	0	1

Indicator for prior surgery: For each person-month, this variable takes the value of 1 if a person underwent a surgery within the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for prior surgery	.563	0	1

Indicator for provider administered drug: For each person-month, this variable takes the value of 1 if a person received a provider-administered drug as defined by a 'J code' in the past 12 months, and 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for provider administered drug	.214	0	1

Beneficiary race - Asian: Beneficiary's Research Triangle Institute (RTI) race code is Asian.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Asian	.019	0	1

Beneficiary race - Black: Beneficiary's Research Triangle Institute (RTI) race code is Black.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Black	.215	0	1

Beneficiary race - Hispanic: Beneficiary's Research Triangle Institute (RTI) race code is Hispanic.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Hispanic	.009	0	1

Beneficiary race - Native American: Beneficiary's Research Triangle Institute (RTI) race code is Native American.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Native American	.001	0	1

Beneficiary race - Other: Beneficiary's Research Triangle Institute (RTI) race code is Other.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Other	.016	0	1

Beneficiary race - Unknown: Beneficiary's Research Triangle Institute (RTI) race code is Unknown.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - Unknown	.024	0	1

Beneficiary race - White: Beneficiary's Research Triangle Institute (RTI) race code is White.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary race - White	.717	0	1

Indicator for rivaroxaban use: For each person-month, this variable takes the value of 1 if a person incurred a claim for rivaroxaban within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for rivaroxaban use	.017	0	1

Number of rural clinic visits: For each person-month, this variable counts the number of rural clinic visits incurred within the past 12 months. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of rural clinic visits	0	0	1

Beneficiary gender - female: Beneficiary gender is female.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary gender - female	.596	0	1

Beneficiary gender - male: Beneficiary gender is male.

Source: Beneficiary Demographics

Risk Factor	Mean	Minimum	Maximum
Beneficiary gender - male	.404	0	1

Number of specialist visits: For each person-month, this variable counts the number of specialist visits incurred within the past 12 months. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of specialist visits	4.889	0	365

Indicator for no statin use: For each person-month, this variable takes the value of 1 if a person did not incur a claim for statins within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no statin use	.644	0	1

Number of lab tests: For each person-month, this variable counts the number of visits within the past 12 months in which a person received any laboratory test. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of lab tests	.146	0	53

Number of urgent care visits: For each person-month, this variable counts the number of urgent care visits incurred within the past 12 months. We define visits as unique combinations of person-provider-day.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Number of urgent care visits	.148	0	79

Indicator for no vaccination (flu or pneumonia): For each person-month, this variable takes the value of 1 if a person did not receive a vaccination (flu or pneumonia) within the past 12 months, 0 otherwise.

Source: Part B claims

Risk Factor	Mean	Minimum	Maximum
Indicator for no vaccination (flu or pneumonia)	.482	0	1

Indicator for warfarin use: For each person-month, this variable takes the value of 1 if a person incurred a claim for warfarin within the past 12 months, and 0 otherwise.

Source: Part D claims

Risk Factor	Mean	Minimum	Maximum
Indicator for warfarin use	.024	0	1

Number of hospital beds per 1000 residents: For each person, this variable records the number of active (short term or critical access or transplant) hospital beds per 1000 residents in the person's ZIP code tabulation area of residence.

Source: CMS Provider of Service Files (December 2018) American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Number of hospital beds per 1000 residents	1.782	0	69.72138

National ranking of deprivation: For each person, this variable records the national ranking of deprivation for the person's ZIP code tabulation area of residence. This index 'includes factors for the theoretical domains of income, education, employment, and housing quality.' See https://www.neighborhoodatlas.medicine.wisc.edu/ for additional detail. Higher values indicate a greater degree of deprivation.

Source: Neighborhood Atlas

Risk Factor	Mean	Minimum	Maximum
National ranking of deprivation	28.595	0	94.28051

Indicator for presence of a for-profit hospital: For each person, this variable records whether the person's ZIP code tabulation area of residence contains at least one active (short term or critical access or transplant) for-profit hospital.

Source: CMS Provider of Service Files (December 2018)

Risk Factor	Mean	Minimum	Maximum
Indicator for presence of a for-profit hospital	.004	0	1

Indicator for no federally qualified health center: For each person, this variable records whether the person's ZIP code tabulation area of residence does not contain at least one active federally qualified health center.

Source: CMS Provider of Service Files (December 2018)

Risk Factor	Mean	Minimum	Maximum
Indicator for no federally qualified health center	.752	0	1

Indicator for no mental health center: For each person, this variable records whether the person's ZIP code tabulation area of residence does not contain at least one active community mental health center.

Source: CMS Provider of Service Files (December 2018)

Risk Factor	Mean	Minimum	Maximum
Indicator for no mental health center	.978	0	1

Indicator for no rural health clinic: For each person, this variable records whether the person's ZIP code tabulation area of residence does not contain at least one active rural health clinic.

Source: CMS Provider of Service Files (December 2018)

Risk Factor	Mean	Minimum	Maximum
Indicator for no rural health clinic	1	0	1

Indicator for no VA clinic or VA medical center: For each person, this variable records whether the person's ZIP code tabulation area of residence does not contain at least one VA clinic or medical center.

Source: Veterans Affairs Facility Listing

Risk Factor	Mean	Minimum	Maximum
Indicator for no VA clinic or VA medical center	.936	0	1

Number of hospitals per 1000 residents: For each person, this variable records the number of active (short term or critical access or transplant) hospitals per 1000 residents in the person's ZIP code tabulation area of residence.

Source: CMS Provider of Service Files (December 2018) American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Number of hospitals per 1000 residents	.009	0	.3377237

Median household income: For each person, this variable records the median household income in the person's ZIP code tabulation area of residence (pooled from 2013-2017).

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Median household income	84094.19	16188	218638

Located in partial county mental health care shortage area: For each person, this variable takes the value of 1 if the person's ZIP code tabulation area of residence is located in a county that is designated by HRSA in 2018 to be a partial-county mental health care shortage area. The variable takes the value of 0, otherwise. If the ZIP code tabulation area lies in two counties, the value is estimated as a weighted average of the county-level attributes.

Source: Area Health Resources File

Risk Factor	Mean	Minimum	Maximum
Located in partial county mental health care shortage area	.65	0	1.0001

Located in whole county mental health care shortage area: For each person, this variable takes the value of 1 if the person's ZIP code tabulation area of residence is located in a county that is designated by HRSA in 2018 to be a whole-county mental health care shortage area. The variable takes the value of 0, otherwise. If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes.

Source: Area Health Resources File

Risk Factor	Mean	Minimum	Maximum
Located in whole county mental health care shortage area	.218	0	1.0001

Number of hospitals: For each person, this variable records the number of active (short term or critical access or transplant) hospitals in the person's ZIP code tabulation area of residence.

Source: CMS Provider of Service Files (December 2018)

Risk Factor	Mean	Minimum	Maximum
Number of hospitals	.259	0	4

Number of primary care physicians per 1000 residents: For each person, this variable records the number of primary care physicians per 1000 residents in the person's ZIP code tabulation area of residence.

Source: AMA, American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Number of primary care physicians per 1000 residents	.857	0	11.47018

Percent aged 65 and over: For each person, this variable records the percentage of individuals in the person's ZIP code tabulation area of residence aged 65 and over (pooled from 2013-2017).

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent aged 65 and over	15.774	0	100

Percent with less than high school education, ages 65+: For each person, this variable records the percent of the population aged 65 and above in the person's ZIP code tabulation area that has less than a high school diploma.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent with less than high school education, ages 65+	15.032	0	100

Percent live alone, ages 65+: For each person, this variable records the percent of the population aged 65 and above in the person's ZIP code tabulation area that lives alone.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent live alone, ages 65+	26.364	0	100

Percent speak Spanish, aged 65+: For each person, this variable records the percent of the population aged 65 and above in the person's ZIP code tabulation area that speaks Spanish.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent speak Spanish, aged 65+	2.363	0	92.90981

Percent in poverty age 65+: For each person, this variable records the percentage of people age 65+ whose income in the past 12 months is below the poverty level in the person's ZIP code tabulation area of residence (pooled from 2013-2017).

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent in poverty age 65+	7.646	0	100

Percent foreign born: For each person, this variable records the percent of individuals who are foreign-born in the person's ZIP code tabulation area of residence.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent foreign born	12.233	0	66.4828

Percent Hispanic, ages 65+: For each person, this variable records the percent of the population aged 65 and above in the person's ZIP code tabulation area that is Hispanic.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent Hispanic, ages 65+	2.551	0	100

Percent with less than high school education: For each person, this variable records the percent of individuals age 18 and older with less than a high school diploma in the person's ZIP code tabulation area of residence.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent with less than high school education	9.564	0	48

Percent married: For each person, this variable records the percent of the population aged 15+ in the person's ZIP code tabulation area of residence that is currently married (pooled from 2013-2017).

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent married	49.078	0	100

Percent Native American: For each person, this variable records the percent of the population in the person's ZIP code tabulation area that is Native American.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent Native American	.242	0	17.21282

Percent non-English speakers: For each person, this variable records the percent of individuals who speak Spanish or other languages and who speak English less than 'very well' in the person's ZIP code tabulation area of residence.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent non-English speakers	5.284	0	48.36707

Percent non-white, ages 65+: For each person, this variable records the percent of the population aged 65 and above in the person's ZIP code tabulation area that is non-white.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent non-white, ages 65+	26.864	0	100

Percent in poverty: For each person, this variable records the percentage of families whose income in the past 12 months is below the poverty level in the person's ZIP code tabulation area of residence (pooled from 2013-2017) .

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent in poverty	6.563	0	50

Percent single mothers: For each person, this variable records the percent of women aged 15-50 giving birth within the past 12 months who are not married in the person's ZIP code tabulation area

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent single mothers	32.162	0	100

Percent aged 0-4: For each person, this variable records the percentage of individuals in the person's ZIP code tabulation area of residence aged 0-4 (pooled from 2013-2017) .

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Percent aged 0-4	5.803	0	33.15217

Number of pharmacies per 1000 population: For each person, this variable records the number of active pharmacies per 1000 population in the person's ZIP code tabulation area of residence.

Source: Maryland Board of Pharmacies

Risk Factor	Mean	Minimum	Maximum
Number of pharmacies per 1000 population	.23	0	1.205182

Air pollution level: For each person, this variable records the average daily fine particulate matter (PM 2.5) concentration from the EPA's Downscaler Model for 2011-2014 in the person's ZIP code tabulation area of residence.

Source: Environmental Protection Agency

Risk Factor	Mean	Minimum	Maximum
Air pollution level	9.689	0	12.41805

Population: For each person, this variable records the population of the person's ZIP code tabulation area of residence.

Source: American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Population	30658.23	0	119204

Population growth: For each person, this variable records the percent population growth recorded in the person's ZIP code tabulation area of residence from 2011 - 2017.

Source: American Community Survey (2011 and 2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Population growth	4.705	-100	475

Population density: For each person, this variable records the population per square mile in the person's ZIP code tabulation area of residence.

Source: American Community Survey (2017, 5 year estimates), Census

Risk Factor	Mean	Minimum	Maximum
Population density	2614.176	0	97473.26

Located in partial county primary care shortage area: For each person, this variable takes the value of 1 if the person's ZIP code tabulation area of residence is located in a county that is designated by HRSA in 2018 to be a partial-county primary care shortage area. The variable takes the value of 0, otherwise. If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes.

Source: Area Health Resources File

Risk Factor	Mean	Minimum	Maximum
Located in partial county primary care shortage area	.888	0	1.0001

Located in whole county primary care shortage area: For each person, this variable takes the value of 1 if the person's ZIP code tabulation area of residence is located in a county that is designated by HRSA in 2018 to be a whole-county primary care shortage area. The variable takes the value of 0, otherwise. If the ZIP code tabulation area lies in two or more counties, the value is estimated as a weighted average of the county-level attributes.

Source: Area Health Resources File

Risk Factor	Mean	Minimum	Maximum
Located in whole county primary care shortage area	0	0	1

Rurality index: For each person, this variable records the rural/urban index for the person's ZIP code tabulation area of residence. This data is comprised of 10 codes which "delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows." Higher values indicate a greater degree of rurality.

Source: USDA Rural-Urban Commuting Area Codes

Risk Factor	Mean	Minimum	Maximum
Rurality index	1.438	0	10

Number of specialty care physicians per 1000 residents: For each person, this variable records the number of specialty care physicians per 1000 residents in the person's ZIP code tabulation area of residence.

Source: AMA, American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Number of specialty care physicians per 1000 residents	1.682	0	44.88318

Taxable interest per capita: For each person, this variable records taxable interest (tax year 2016) per person in the person's ZIP code tabulation area of residence.

Source: IRS Statistics of Income and American Community Survey (2017, 5 year estimates)

Risk Factor	Mean	Minimum	Maximum
Taxable interest per capita	225.267	0	5886.03

Walkability index: For each person, this variable records the value of the National Walkability Index for the person's ZIP code tabulation area of residence.

Source: Environmental Protection Agency

Risk Factor	Mean	Minimum	Maximum
Walkability index	9.801	0	18.98414

Appendix 2. HEDIS Antibiotics Tables

Source: HEDIS, Volume 2, pages 395-396.

Antibiotics of Concern by NCQA Drug Class Medications

Description	Prescriptions		
Quinolone	• Ciprofloxacin • Gemifloxacin	• Levofloxacin • Moxifloxacin	• Norfloxacin • Ofloxacin
Azithromycin and clarithromycin	• Azithromycin	• Clarithromycin	
Cephalosporin (second, third, fourth generation)	• Cefaclor • Cefdinir • Cefditoren • Cefepime • Cefixime	• Cefotaxime • Cefotetan • Cefoxitin • Cefpodoxime • Cefprozil	• Ceftriaxone • Cefuroxime • Ceftazidime • Ceftibuten
Amoxicillin/clavulanate	• Amoxicillin-clavulanate		
Ketolide	• Telithromycin		
Clindamycin	• Clindamycin		
Miscellaneous antibiotics of concern	• Aztreonam • Chloramphenicol	• Dalfopristin-quinupristin • Linezolid	• Telavancin • Vancomycin

All Other Antibiotics by NCQA Drug Class Medications

Description	Prescriptions	
Absorbable sulfonamide	• Sulfadiazine	• Sulfamethoxazole-trimethoprim
Aminoglycoside	• Amikacin • Gentamicin	• Streptomycin • Tobramycin
Cephalosporin (first generation)	• Cefadroxil • Cefazolin	• Cephalexin
Lincosamide (other than clindamycin)	• Lincomycin	
Macrolide (other than azithromycin and clarithromycin)	• Erythromycin • Erythromycin ethylsuccinate • Erythromycin lactobionate	• Erythromycin stearate • Erythromycin-sulfisoxazole
Penicillin (other than amoxicillin/clavulanate)	• Ampicillin • Ampicillin-sulbactam • Amoxicillin • Dicloxacillin • Nafcillin	• Penicillin G potassium • Penicillin G procaine • Penicillin G sodium • Penicillin V potassium • Piperacillin-tazobactam

	• Oxacillin • Penicillin G benzathine	• Ticarcillin-clavulanate
Tetracyclines	• Doxycycline • Minocycline	• Tetracycline
Miscellaneous antibiotics	• Daptomycin • Fosfomycin • Metronidazole • Nitrofurantoin	• Nitrofurantoin macrocrystals • Rifampin • Trimethoprim

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