Prediction of Hospital Readmission Project Summary– 05/26/2022

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Situational Overview

In 2012, the Centers for Medicare and Medicaid Services (CMS) began reducing Medicare payments for subsection(d) hospitals with excess readmissions, under the Hospital Readmission Reduction Program (HRRP). CMS measures excess readmissions by a ratio, calculated by dividing a hospital's predicted 30-day readmission rate (RR) for heart attack, heart failure, pneumonia, chronic obstructive pulmonary disease, hip/knee replacement, and coronary artery bypass graft surgery by expected RR. CMS derives expected RR itself for a given hospital with a proprietary formula based on an average hospital with similar patients.

We have been approached by the leadership team at Community Medical Center (CMC), a relatively large public hospital in New Jersey (~2,500 inpatient cases/year). In their most recent annual review, CMS flagged CMC for having a higher-than- expected RR, and informed the leadership team the hospital would be subject to reduced payments at the next annual evaluation if this rate (currently ~17%) did not improve by 1% to align with what CMS expects given their own proprietary model's assumptions.

The hospital's leadership wants us to help then conduct their own analysis of factors most related to RR, and then potentially assist them in coming up with a data-driven plan to avoid a CMS penalty. Based on their knowledge of such penalties previously incurred at other similar institutions, they have already determined a similar penalty would substantially affect CMC's ability to provide quality care to their patients across the range of services they provide.

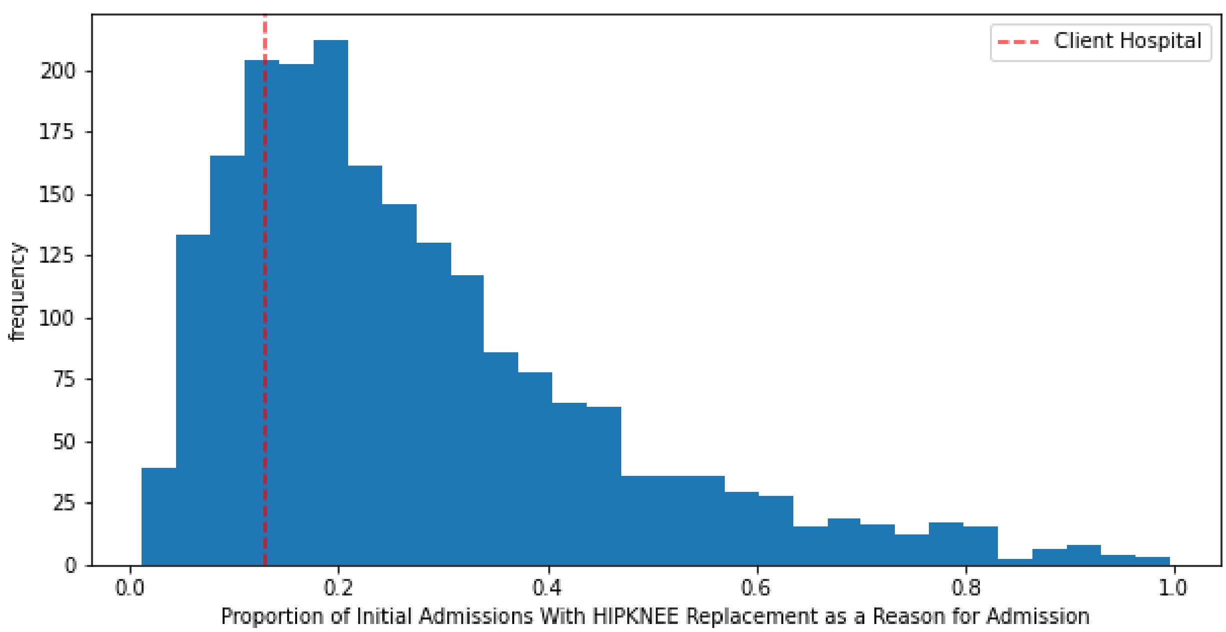
Methodology

Using within-visit inpatient and outpatient outcomes data from ~2,700 US hospitals (minimum number of yearly inpatient admissions of 200) distributed across the CMS data repository, as well as county-level demographic data (e.g., population and age) data from the US Census Bureau and socioeconomic data (e.g., income) from the Bureau of Economic Analysis (BEA), I developed an optimized machine learning model for prediction of 30-day inpatient RR. I then used this optimized model to predict RR for our client (CMC). Finally, the optimized model was deployed to project the effect of putative changes to several feature values for our client hospital on predicted RR. Though the features selected for this final exercise were important to model construction, their inclusion in this scenario projection exercise does *not* imply a causative effect of these features on RR.

Key Findings

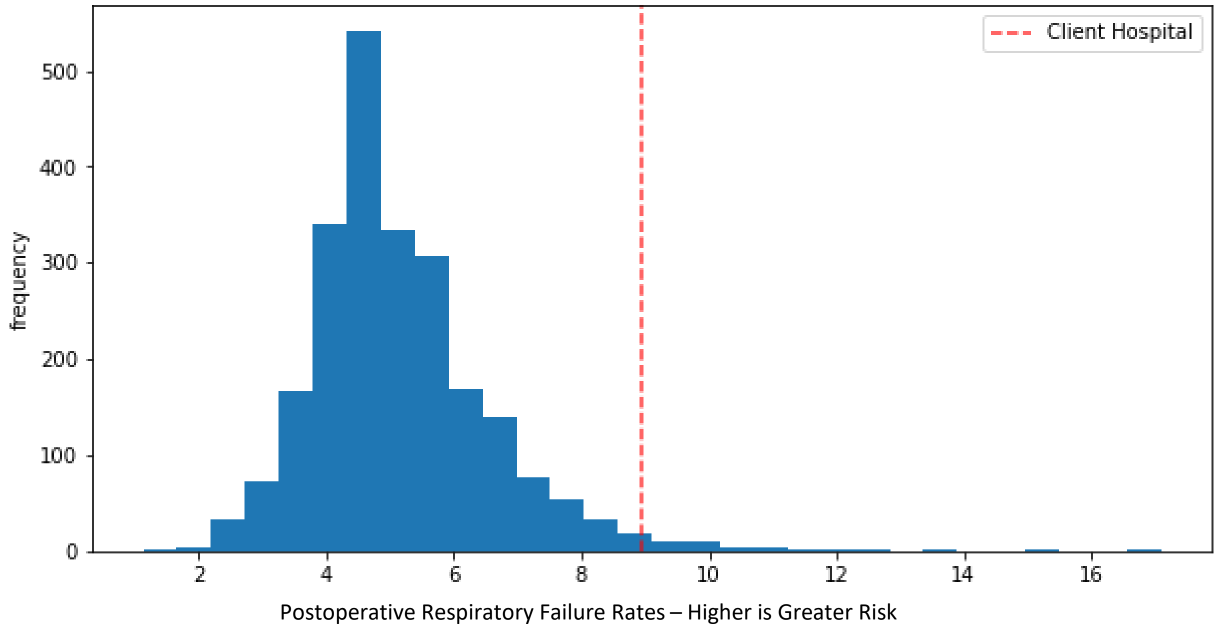
- Modeling results indicated that CMC can reasonably expect a 1% reduction in RR over the next year simply by chance without making any policy, procedural, or business changes. The model predicts a current RR of 15.5% (+-.7%), while the actual RR is 16.8%.
- CMC had a proportion of inpatient cases due to elective hip and knee replacement well below the overall hospital sample median (**Figure 1**).
- CMC was at the high (poor health) end of the hospital sample in two measures of patient respiratory health; postoperative respiratory failure rate (**Figure 2**) and case rate involving COPD at admission (**Figure 3**). Across the sample of hospitals surveyed, higher COPD case rates at admission was associated with higher postoperative respiratory failure rate (**Figure 5**).
- The three features highlighted in the previous key findings points, and in the figures below, stood out both for their relatively strong correlations to RR in exploratory data analysis, as well as in their relative importance to model generation. (**Figure 4**)

Figure 1. Distribution of Proportion of Inpatient Cases that Were Hip-Knee Replacements Across Hospitals



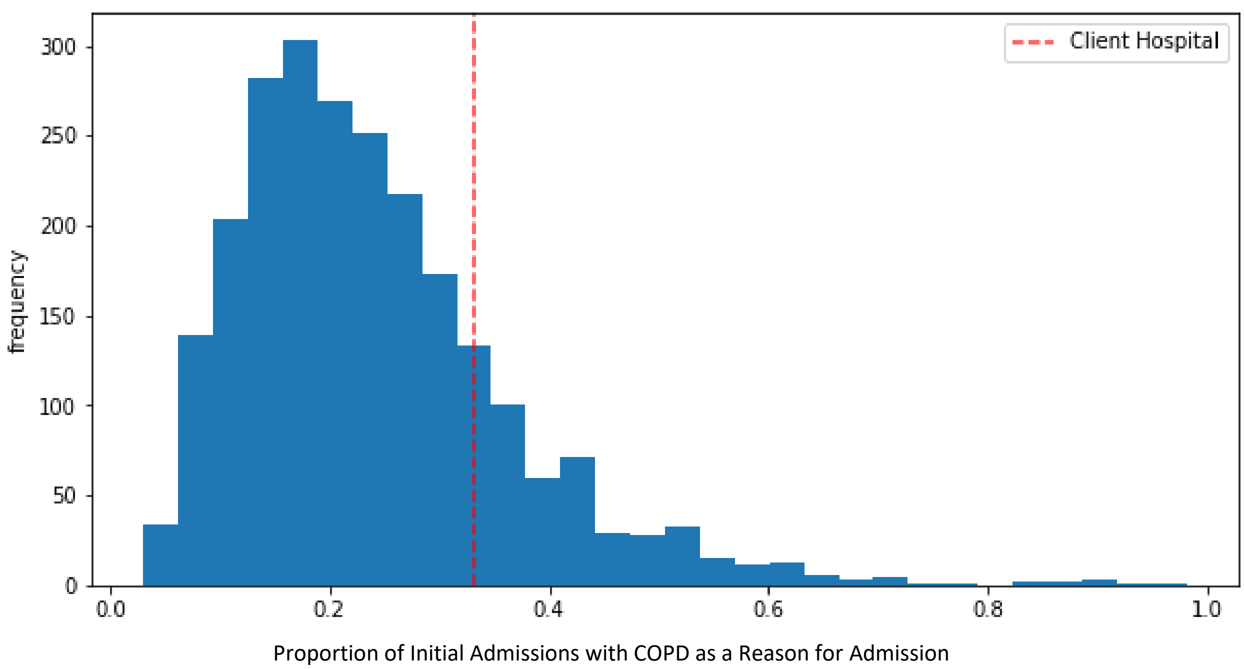
Our client hospital (CMC; dashed red line) had a proportion of inpatient cases that were Hip-Knee Replacements that was in the lower third of hospitals in the sample.

Figure 2. Distribution of Postoperative Respiratory Failure Rates Across Hospitals



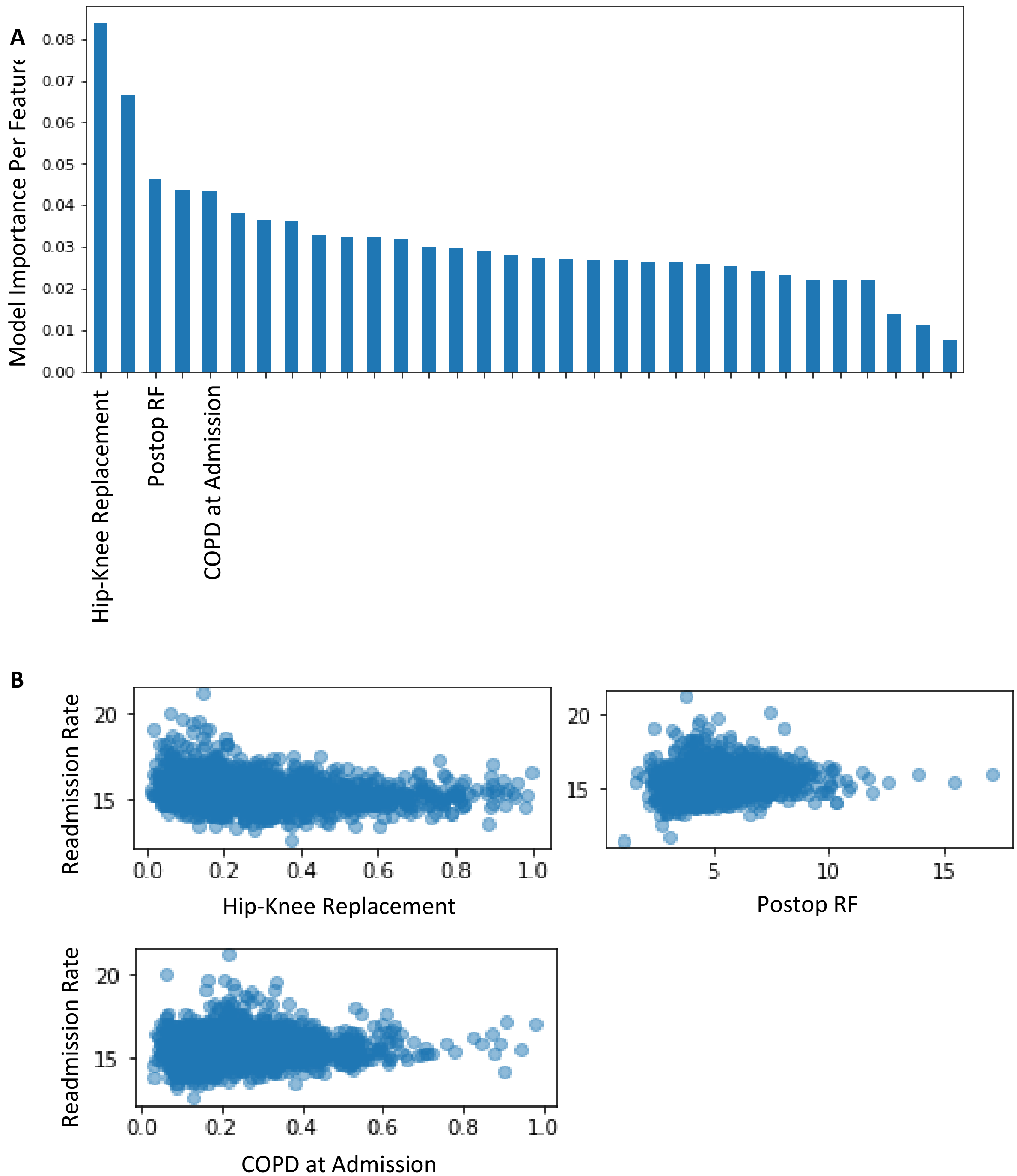
CMC (dashed red line) had a postoperative respiratory failure rate in the top few percent of hospitals in the sample

Figure 3. Rate of Cases Involving COPD at Admission Across Hospitals



The previous figure (Figure 2) showed that CMC had a postoperative respiratory failure rate in the top several percent of hospitals in the sample. In addition, and perhaps related to this, CMC was in the top third of the sample in terms of COPD as a reason for inpatient admission.

Figure 4. Prominent Features in Exploratory Data Analysis and Modeling



A: Proportion of inpatient cases that were hip-knee replacements (Hip-Knee Replacement), postoperative respiratory failure rate (Postop RF) and proportion of cases involving COPD at admission (COPD at Admission) were 3 of the 5 most important features in the best model.

B: These features showed moderate negative (Hip-Knee Replacement), positive (Postop RF and COPD at Admission) correlations, respectively, with RR across the hospital sample. Hip-Knee Replacement had the strongest correlation to RR of any single feature in the data set.

Recommendations to Client

1) **Not making any changes in hospital processes, procedures, or general business practices may still result in the 1% decrease in RR required to avoid CMS penalty, simply due to regression toward mean expectation**.

Rationale: The model predicts an RR of 15.5% (+-.7%) for CMC, while the actual RR last year was 16.8%. Considering the mean difference and margin of error, such a decrease is well within the range of probable outcomes.

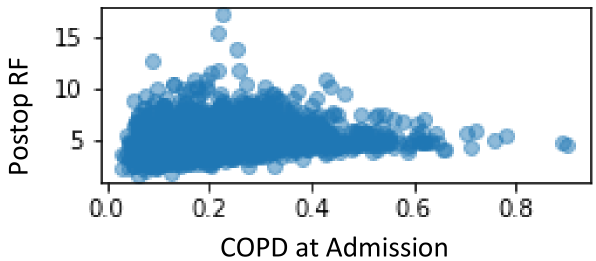
2) If CMC is inclined to make several rapid, low-investment changes that may have an impact in RR, a combination of modestly expanding capacity for hip-knee replacement surgeries and focusing on improving existing protocols for detection and treatment of post-operative respiratory failure is worth exploring.

Rationale: The proportion of hip-knee replacements in the case mix has a negative correlation with RR (**see Figures 1 and 4B**). Additionally, though not implying a causative effect on RR, this feature was also the most important of all in model generation. CMC is currently on the low end of the hospital sample distribution in terms of hip-knee replacements in the case mix. In contrast, CMC is at the extreme high end of the distribution for postoperative respiratory failure rate, a feature with a positive correlation with RR (**see Figures 2 and 4B**). As with hip-knee replacement, post-operative respiratory failure rate was also one of the most important features in model generation (which, again, does not imply causation of RR).

To this end, a scenario in which both of the aforementioned features are brought to hospital sample median level for CMC yields a prediction of RR reduction of 0.32%, which is 32% of the goal reduction of 1%. For hip-knee replacement rate, getting to the sample median would mean an increase from 13% of total inpatient cases to 27% of total inpatient cases. For postoperative respiratory failure rate, getting to the sample median would mean a decrease from 9% to 5%. Though these reductions in full may be infeasible within a year, modest movement in the right direction for each, coupled to regression toward mean expectation (*see Recommendation #1*), may be sufficient to achieve the goal reduction.

Though potentially not possible to modify in an ethical way, and thus not included in this modeling scenario, it is worth noting that CMC also has a case rate involving COPD at admission in the upper-third of the sample distribution. As with postoperative respiratory failure rate, this is a respiratory feature that has a positive correlation with RR (and, likewise, was one of the most important features in model generation; **see Figures 3 and 4B**). The relatively high postoperative failure rate for CMC may, in fact, be closely related to the well higher-than-average proportion of patients who are admitted as inpatients at CMC already with breathing problems (COPD; **see Figure 5**). Therefore, extra vigilance for patients in the post-operative period who presented with COPD at admission may make attempts to globally reduce postoperative respiratory failure rate more effective.

Figure 5. Relationship Between COPD at Admission and Postoperative Respiratory Failure



Proportion of inpatient cases involving COPD at admission (COPD at Admission) was positively correlated to postoperative respiratory failure rate (Postop RF) across the hospital sample.

Future Directions

Though the feature-rich machine learning model is substantially more accurate in prediction of hospital readmission rates (RR) than simple methods, such as prediction with the sample mean, such prediction remains a challenging task. One of the main reasons for this is that RRs are relatively tightly clustered within a few percentage point range. And, as we saw with prediction of the client hospital RR, margin of error for a given hospital in a given year can be a substantial proportion of this overall distribution (see Figure 6).

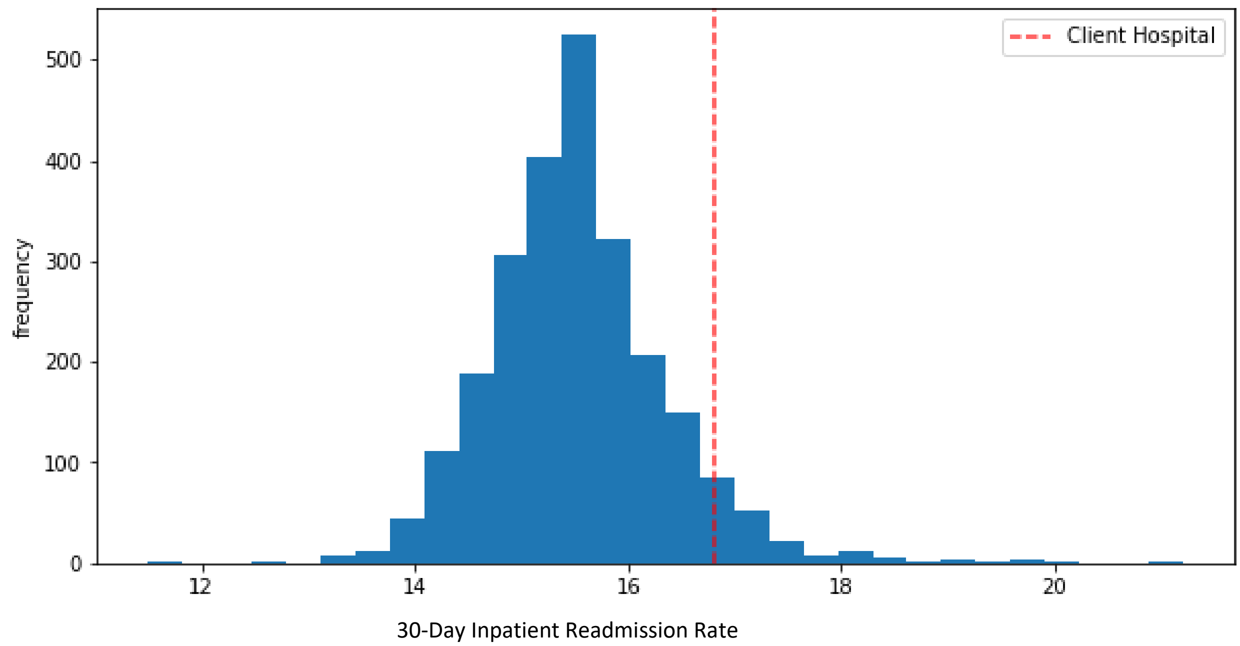
With the above said, there are several clear avenues to pursue in trying to improve model prediction of RR accuracy:

1) **Conduct non-supervised analyses, such as Cluster Analysis,** to initially classify hospitals in the overall sample by properties such as size, private vs public status, network affiliation status, case volume/mix, and demographic/socioeconomic context in which the hospital operates. Each of the resultant clusters can then be modeled separately, and prediction accuracy can be compared to that of the full, highly heterogenous sample (as was conducted presently).

2) **Seek and obtain better data on facility resourcing at the hospital level**. One of the main data holes in the present analysis is that hospital resourcing had to be measured indirectly. This was done several ways, for example by creating features that considered county-level population, hospital density and facility case load together to infer aspects of " facility burden". Much more optimal would be to have raw data, and be able to compute derivative features, for hospital-level resources directly. The raw data would include numbers of doctors and nurses, number of operating rooms, number of intensive care unit beds, and all of the previous in relation to number of patient numbers.

3) **Seek and obtain patient-level data at the hospital level.** Additionally, though I created patient features involving socioeconomics (such as median income) and demographic features (such as median age) for the present study, these features were generated per hospital with county-level data. Much more ideal would be to obtain (anonymized, of course) hospital-level patient data from which to generate features characterizing patients at each hospital. This could perhaps facilitate "normalization" of hospital level outcomes metrics by baseline patient characteristics in a manner that would lead to improved prediction quality.

Figure 6. Readmission Rate Distribution Across Hospitals



The overall sample (n=2,472 facilities with minimum most recent yearly inpatient admissions of >200) had a fairly tight range of RRs, with most of the mass density falling between RRs of 14-17%. The client hospital, CMC, can be seen to fall toward the high end of this range (most recent yearly RR of 16.8%).