Figure 1 outlines the timing of the administrative agreement, inspections, and baseline estimates.

Figure 1: Overview of key events The key date is January 31, 2019, the date the administrative agreement went into effect. The goal of the present exercise is to obtain point-in-time estimates of pests immediately after. Ideally, inspections would have been conducted immediately upon the agreement's execution. In reality, the inspections were conducted over a year later in February and March 2020, then paused due to COVID-19. That means the inspections occurred after a year of mitigation efforts, which, depending on the extent of mitigation between January 2019 and February 2020, complicates their interpretation as a measure of baseline issues.

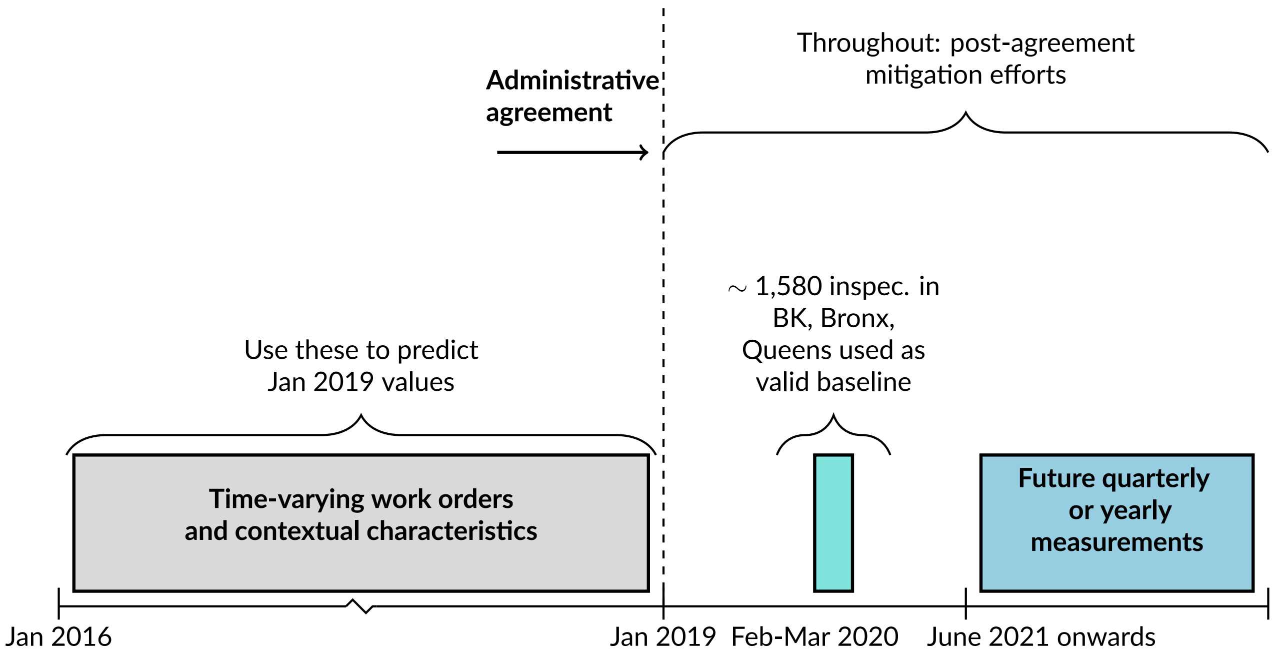

Table 1 highlights four approaches that can be used to generate estimates of pests at baseline and over time. Each approach has benefits and drawbacks. Our collaboration focused on contrasting these benefits and drawbacks.

Table 1: Four approaches to generating baseline and over-time estimates

Approach	How it generates estimates	Pros	Cons	How to mitigate cons
1. Raw inspection results	Calculate rates based on inspections	Does not require modeling the sampling or inspection process	Inaccurate due to two forms of selection: (1) which units were sampled? (e.g., higher odds for top quartile developments), (2) which sampled units were inspected? (demographic variation in opt in rates)	NA; should always reweight
2. Reweighted inspection results	Calculate rates based on inspections; simulate sampling process to get Pr(sampled); predictive model of how work order history/contextual characteristics predict inspection given sampled	Helps generalize from sample ->all units in boroughs with sampling	(1) Most valid as a point-in-time estimate corresponding to when inspections conducted (Feb-March 2020) and issues generalizing beyond that point-in-time, either backwards (to January 2019) or forwards (to measure changes over time); (2) needs new inspection results to generate new estimates	More inspections: inspections in all boroughs and at different times of year
3. Predictive model for inspection results	Uses inspection results as a binary label to predict. Uses time-varying contextual characteristics and work order data to predict the result of an inspection; reweights by sampling probabilities	(1) Helps generalize from sample ->all units in boroughs with sampling; (2) can generate new estimates without new inspection results by fitting a model to a new timespan of predictor/feature data (e.g., present model is work orders Jan 2016-Jan 2019; future could use Jan 2016-Jun 2021)	(1) Even though it can generate new estimates without new inspection results, if there are changes over time in things like which tenants submit work orders, mitigation efforts, and other factors, there may be hidden generalization error; (2) needs large amounts of data to generate predictions that are reliable at the sub-borough level	More inspections: inspections in all boroughs and at different times of year
4. MAXIMO work order data without inspection results	Calculate rates based on the frequency of work orders	Does not require inspections	(1) May suffer not only from general measurement error (e.g., general underestimates of pests if not all tenants with pests submit complaints) but also systematic measurement error (e.g., differential underestimates for groups least likely to submit work orders despite pest presence); (2) skewed distribution of work orders means that over-time improvements could just reflect appropriate responsiveness to high-frequency work order submitters	None