

Appendix 1. Detailing the algorithm developed to identify viable commercial properties

A1. Test case study: New York City (NYC)

Because our focus is on converting brown office buildings to green apartment buildings, we begin by studying NYC, where we can observe GHG emissions at the building level, allowing us to layer in environmental considerations. We then scale up the analysis to the entire U.S. We use the procedures outlined in section A2 of this Appendix.

1. Identifying conversion targets in NYC

We use building-level energy use data from the Energy and Water Data Disclosure for Local Law 84 and convert energy use to carbon equivalents. Emissions include both direct (on-site fossil fuel) and indirect (electricity use) emissions. We then compare emissions to the emission limits under Local Law 97. Passed as a part of the Climate Mobilization Act by the New York City Council in 2019, this local regulation aims to reduce emissions by 40 percent by 2030, and by 80 percent by 2050, and imposes steeply increasing carbon taxes to implement these goals. We find that 16 percent of large office buildings (i.e., above the 25,000 square foot threshold) are over the limits set for 2024, and that 72 percent of large office buildings are over the limits set for 2030. The emissions dataset contains 1,867 office properties in NYC (second column in table A-1). It shows that 70.5 percent of properties in this sample were built before World War II and 92.7 percent of properties were built before 1990. The former group accounts for 44.8 percent of aggregate GHG emission fines that will need to be paid under the status quo after 2030, and the latter group accounts for 89.4 percent of total fines.

We merge the emissions data with CompStak, a dataset that contains detailed property and leasing characteristics for office buildings. The intersection

with the GHG emission data set contains 1,014 properties. This sample has similar age and emissions distributions (columns “CompStak” in table A-1).

2. The conversion selection algorithm

To arrive at a sample of plausible office conversion candidates, we winnow down our sample of properties in a series of steps.

First, we impose a location requirement and keep only buildings located in midtown and downtown Manhattan built before 1990. The rationale here is to focus on the locations where the negative externalities from office vacancies are the strongest, as well as to focus on locations with strong transportation amenities. Because the transportation network was originally built to move workers into the central office district, residents in converted buildings will enjoy the benefit of network centrality in accessing other areas of the city, which is a desired and valued residential amenity.

Second, we keep only buildings built before 1990. This is consistent with the recommendation by the NYC Office Adaptive Reuse Study (New York City Department of City Planning 2023). We drop buildings smaller than 25,000 square feet, which may lack scale economies for conversion. Such projects may be attractive for smaller conversions but are unlikely to attract institutional capital. The administrative cost-benefit analysis of approving or subsidizing small projects may be unfavorable as well.

We drop buildings with deep floor plates. Specifically, we remove buildings with a distance from the window to the core that is more than 60 feet. In the NYC data, we observe building width and depth from the PLUTO data set (New York City Department of City Planning n.d.). This allows us to calculate the distance from the core of the building to the window as the width divided by two or the depth divided by two. We define distance to the core as the smaller of these two

TABLE A-1.

Descriptive statistics for office buildings subject to LL97

Year built	Count		2024 fine (million \$)		2030 fine (million \$)	
	Full	CompStak	Full	CompStak	Full	Compstak
Pre-War	1317	741	21.70	15.87	61.38	45.07
1945–1959	129	65	1.75	1.25	15.19	9.34
1960–1979	189	101	5.40	2.20	37.57	30.16
1980–1989	96	63	2.60	0.94	8.34	5.97
1990–1999	33	16	0.41	0.07	2.58	2.02
2000–2009	63	11	3.00	0.04	7.97	1.27
2010–2019	38	17	0.96	2.52	3.92	7.05
2020+	2	0	0.00	0.00	0.06	0.00
Total	1,867	1,014	35.81	22.88	137.01	100.88

Source: Energy and Water Data Disclosure for Local Law 84; CompStak



numbers. Many modern office buildings have physical attributes that are unfavorable for apartment conversion. In particular, many massive full-block glass-and-steel office buildings feature deep floor plates that make it difficult to bring enough light and air into the interior of the structure. They would therefore require at least one core drilled in the middle or side of the structure to create enough natural light, which greatly adds to the cost of conversion. They typically also have inadequate plumbing to accommodate many bathrooms on each floor, might not have windows that can be opened, feature too many elevators, and otherwise present physical obstacles to conversion.

These first screening criteria ensure that we focus on properties in the urban core, which have sufficient scale, reasonable floor plate depth, and are older and of lower quality than average. Such buildings are both browner and less expensive, making them better candidates for conversion to green apartments. At this stage of the selection process, we have 611 NYC buildings in the candidate set.

After we restrict the sample to buildings with limited long-term leases and remaining lease durations of less than two years, we are left with 401 plausible conversion candidates. Finally, we remove green buildings and select high-emission properties; approximately 76 percent of the conversion target list exceeds the 2030 GHG limit. This leaves us with 307 brown office-to-green apartment conversion candidates.

Our final candidate sample represents 30 percent of the initial 1,010 NYC office properties and 14.6 percent of the initial square footage. This sample accounts for a total of \$17.5 million in GHG emission fines under

the 2030 limit, or 15.3 percent of total emissions, and 17.3 percent of total fines for the initial sample.

A2. Scaling up conversions nationally

Having selected conversion candidates for NYC, we can scale up the exercise to the entire U.S. We apply the same selection criteria we used for NYC to all 105 office markets covered by the CompStak dataset. That is, we identify older, lower-quality office buildings of sufficient scale and with small enough floorplates located in downtown areas.

To implement the location requirement (step 1), we select office properties located in ZIP codes with at least 1,000 residents per square mile. This helps us select commercial districts rather than suburban office clusters. Since the national algorithm does not condition on the availability of GHG emission data and considers other dense neighborhoods besides midtown and downtown Manhattan, the initial set of buildings for NYC is about 50 percent larger than in the previous exercise. We apply the national algorithm to NYC in the second column of table 1. To implement the low distance-to-core requirement (step 5) in the national sample, we select office buildings with floor plates below 14,400 square feet. For the national sample, we proxy for the size of the average floor plate as the total building size divided by the number of floors.

Table 1 shows how, starting with the CompStak universe of office buildings, each step of the algorithm reduces the number of conversion candidates. This

results in 2,874 conversion candidates nationally, of which 573 properties are located in NYC.

We do not have data on GHG emissions for buildings outside NYC, complicating step 7 of our algorithm. We can impute a GHG emission level for each building, however, based on that building's characteristics. To do so, we estimate the relationship between emissions

and building characteristics in the NYC sample of conversion candidates and use the estimated regression coefficients for this imputation. We select the properties with imputed emissions in excess of the imputed emissions limit according to the 2030–34 NYC parameters.