Using Agent-Based Modeling to Evaluate the Effects of Hurricane Sandy's Recovery Timeline on the Ability to Work

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Research Highlights

- An agent-based model tests the impacts of recovery timelines on the ability to work
- This ABM accounts for commuter adaptation and household characteristics
- Quicker subway/rail system recovery is the most effective for the NYC area
- Power system restoration can increase productivity by allowing teleworking

Abstract

Hurricane Sandy greatly disrupted the New York City (NYC) region's transportation systems, electric power systems, work locations, and schools in 2012. This study uses survey responses from NYC Metropolitan Area residents to develop an agent-based model that depicts commuter travel behavior and adaptation after the disruption. Six scenarios were tested to quantify which systems were more critical to recover for an earlier return to productivity - defined as the ability to work for one's employer. The recommended system restoration order depends on the pattern of normal commuting behavior. In the NYC Metropolitan Area, a larger share of commuters use transit to commute than in any other US metropolitan area. This resulted in the model indicating the subway/rail system recovery as the most important factor for returning the most people to productivity. The second most important factor is widespread power restoration itself, which allows residents to telework while waiting for the transportation system to recover. The next most important factor is the reopening of schools and daycares (with associated infrastructure systems), freeing parents to commute. The remaining expedited system recovery scenarios tested using the agent-based model resulted in a faster return to productivity than the baseline, but to a lesser degree than the subway/rail, power, and childcare systems scenarios. Additional analysis of recovery shows that households with higher annual income benefit more from power recovery compared to those with lower incomes. Moreover, the effectiveness of recovery scenarios can differ based on residential location and the extent of disruption in that location.

Keywords: Agent-based modeling; hurricane Sandy; adaptation

1. Introduction

Although the occurrence of natural disasters cannot be controlled, society can reduce the impacts through effective post-disaster recovery strategies. This study evaluates the disruptions from Hurricane Sandy, system recovery speeds and their effects on household-level economic productivity. Hurricane Sandy, a high-impact natural disaster termed "Superstorm Sandy" due to its intensity, hit the New York City (NYC) area on October 29, 2012. The storm greatly disrupted transportation and power systems Kaufman, Qing et al. (2012), limiting the public's ability to reach employment locations and return to productivity. Returning to productivity, for the purposes of this study, means the "ability to work" for a given job. Some jobs require one to be physically present while others allow employees to work remotely. Those that must be present need the transportation system, while those working remotely may need both the power and communication systems to be functioning. Both groups may face additional constraints, such as childcare obligations due to school and daycare closures, which further influence their ability to be productive.

In the NYC metropolitan area, nearly one-third of workers 16 years and older who leave their homes to work commute using public transit—a transit mode share eight times the average for other metropolitan areas in the US . This high mode share adds complications, since it becomes more important in NYC than in other parts of urban America to restore the transit system and supporting infrastructure. Lower-income households may face even more challenges due to reduced transport options (*e.g.*, not owning a private vehicle) and a lack of financial resources to pay for childcare during school closures or higher-priced private transport options (Masozera, Bailey et al. 2007, 2017, Lowe 2018). Additionally, lower income households can be located in areas more vulnerable to damage. Faber [6], for instance, found that a larger percentage of the households in NYC census tracts flooded by Sandy were below the poverty line than in non-flooded areas. This flooding contributed to the temporary closure of 150 NYC subway stations, curtailing access to the system for residents and workers who normally travel to or from these stations. The sharpest drops in access appeared to be among areas with extremely high poverty rates, although there were not enough such tracts for this claim to show statistical significance (Faber 2015).

Several studies of commuter behavior after a disruption have used survey approaches and statistical models. For example, Kontou, Murray-Tuite, and Wernstedt (Kontou, Murray-Tuite et al. 2017) captured commuters' adaptation after Hurricane Sandy by developing five multi-variable binary logit models for changing mode, canceling a work trip, changing route and changing departure times (earlier or later) for home-to-work trips. Existing literature (Giuliano and Golob 1998, Mokhtarian, Ye et al. 2010, Zhu, Levinson et al. 2010) has noted that changing departure time and changing route are the first two preferred options for commuters facing a transport disruption and can be considered tactical decisions (as opposed to strategic decisions) that do not necessarily involve financial investments or changes in activities and are within the traveler's control. Changing mode is the least preferred option (Giuliano and Golob 1998, Mokhtarian, Ye et al. 2010, Zhu, Levinson et al. 2010), less likely than even canceling the trip altogether (Giuliano and Golob 1998), since a lack of car ownership and limited transit service options constrain the feasibility of a mode change (Zhu, Levinson et al. 2010). The transit service and accessibility are outside the commuter's control while car ownership can be considered a strategic decision, involving a significant financial investment and effort to obtain the vehicle.

Levinson and Zhu's (Levinson and Zhu 2012) review of 16 papers on behavioral responses to transportation network disruptions identifies several limitations of existing studies that restrict their generalizability: (1) lack of detail in route and departure time choices, (2) reliance on single-option commuter adaptation, such as changing routes or departure times, and failure to incorporate multiple options, and (3) failure to consider experience and learning during the course of the disruption. Our research addresses some of these shortcomings by building an agent-based model (ABM). To address issue (1), the ABM considers route and departure time choices for each agent. For subway/rail commuters, we model the complete daily route choice while for other modes, we only consider specific parts of the route used in commuting, such as bridges and tunnels. With regard to issue (2), our ABM allows agents to make multiple changes, such as route and departure time, at the same time. Finally, for issue (3), commuters in our model learn from their previous travel experiences by considering delay and crowding from the previous day so they can adjust their travel decisions accordingly.

ABMs can simulate time-based situations that are complicated and dynamic, such as the disruptions associated with Hurricane Sandy, often employing statistical models. Central to our purposes, agent-based modeling offers an appropriate approach for modeling transportation-related problems (Bernhardt 2007) and incorporating dynamic human decision making that can cause significant differences in total system function (Hager, Rauh et al. 2015). For example, agent-based modeling has been used in studies of travel demand and decision-making behavior throughout an evacuation (Zhang, Spansel et al. 2013, Yin, Murray-Tuite et al. 2014, Zhang and Wolshon 2014, Ukkusuri, Hasan et al. 2017), the minimum evacuation time for Florida Keys (Chen, Meaker et al. 2006), comparing staged and simultaneous evacuation strategies (Chen and Zhan 2006) and the effect of departure time on evacuation (Lammel and Klupfel 2012). Other studies used agent-based modeling techniques to calculate future transportation demand (Huynh, Cao et al. 2011) and evaluate road congestion problems (Rossetti, Bampi et al. 2000).

Our study differs from these pre-impact situations, focusing on the commuters who stay in the impact area and attempt to lead as normal a life as possible after the immediate danger has passed. After Hurricane Sandy, residents were affected by disruptions caused by the storm and recovery measures implemented by various entities. To deal with these disruptions, people changed their commuting patterns. Marsden and Docherty (Marsden and Docherty 2013) stated that travel behavior is far more variable than policy makers allow for and studying behavior after each disruption can reveal new insights. Therefore, to identify potential commuting changes and gain new insights for recovery efforts, this study uses survey data and is informed by prior studies.

This paper presents an original ABM for capturing people's behavior and adaptation after Hurricane Sandy and specifically addresses how different hypothetical recovery scenarios affect the timeframe of when people can return to a productive state. A better understanding of these factors could help officials and agencies decide how to focus their recovery efforts to promote an earlier return to productivity following a disaster, as well as identify the systems most critical to recover first. The remainder of this paper is divided into four sections. Section 2 describes the ABM and the data used to develop it. Section 3 presents the results of the investigation of recovery scenarios that alter the real timeline of system recovery to examine their impact on productivity. Finally, Section 4 outlines the conclusions and Section 5 presents future directions and limitations.

2. Data and Methodology

Each ABM has three major components: (1) agents and their characteristics, (2) environment, and (3) agent behavior and methods of interaction (Macal and North 2010). The ABM was coded in MATLAB. These components are described in Sections 2.1-2.3.

2.1. Agents and their characteristics

We use previously collected data from a post-Hurricane Sandy telephone survey to define the agent characteristics and behavioral responses when adapting to Hurricane Sandy's disruptions. This survey was conducted in January 2013, using 7,828 telephone numbers provided by an independent survey research firm for residents in the 23 counties that constituted the New York (NY-NJ-PA) metropolitan area in 2012. More than 40 percent of the call records proved ineligible for the survey (representing disconnected telephone lines, lines devoted to fax machines or computers, residences located outside of the target area, etc.), yielding roughly 4,600 remaining possibilities. Completed interviews (n = 397 respondents) captured approximately 9 percent of these possibilities, while refusals to participate comprised 34 percent and unreachable numbers (no answer, busy, etc.) comprised 57 percent. Using a proportional allocation method that assumes the same (unknown) proportion of unreachable numbers were eligible to complete the survey as for the reachable numbers, this translates into a 15.9 percent response rate (Smith 2009, 2015, Kontou, Murray-Tuite et al. 2017).

The survey itself included 31 questions about pre-hurricane normal commuting patterns, basic socio-demographic characteristics, post-hurricane commuting patterns and how commuting recovered after the hurricane. Based on the pre- and post-hurricane questions, we identified the six types of commuting changes displayed in Table 1. Table 1 also shows summary statistics for variables from the survey used in this study. Regarding socio-demographic characteristics, average household annual income ($107,694) was higher than the Census estimate of NYC Metropolitan Area mean income ($79,037) for the 2012 American Community Survey (1-year estimates) (2012), but the standard deviation in our data was over $60,000. This can be explained by a higher percentage of respondents with a college degree or above (82%) in the sample than in the Census data (52%). However, it is important to note, the Census statistics of education refer to the whole adult population while our sample is drawn from the working population. The percentage of female respondents is 58%, slightly higher than the Census statistics (48%). Moreover, 81 percent of the respondents were born in the US versus, higher than the 69 percent from the Census estimates (Kontou, Murray-Tuite et al. 2017).

Kaufman's (Kaufman, Qing et al. 2012) findings about people's behavior after Hurricane Sandy demonstrated that New Yorkers used innovative ways to maintain their mobility. Both commuters' adaptability and transportation providers' efforts allowed a large number of New Yorkers to reach their work places after Hurricane Sandy. Results from the NYU Rudin Center's survey (Kaufman, Qing et al. 2012) of 315 commuters showed significant changes in commuting patterns on November 1-2 after Hurricane Sandy. Before the hurricane, almost 46 percent of commuters used subways for transportation, but after the hurricane, this number decreased to 11 percent. On the other hand, the number of people who used other modes of transportation increased. The percentage of people who used telework, bus, and car after the hurricane increased by 20, 3, and 1 percent, respectively. Moreover, 15 percent of respondents did not work on November 1-2 (Kaufman, Qing et al. 2012).

Table 2, based on the survey data used in Kontou et al. (Kontou, Murray-Tuite et al. 2017), shows commuting changes and how they vary by different personal and environmental features. Every day nearly 10 million people rely on the transit network to travel to work in NYC (Kaufman, Qing et al. 2012); therefore, transit disruptions force many people, especially those who are transit dependent, to find alternative travel methods. Of the transit commuters in Kontou et al.'s data (Kontou, Murray-Tuite et al. 2017), 55 percent changed modes while only 9 percent of non-transit commuters changed modes. Transit commuters who own a personal vehicle had the option to shift from transit to their personal cars. Moreover, the New York City Department of Transportation provided alternative services like bus-bridges as an alternative for closed subway lines (Kaufman, Qing et al. 2012). This bus service gave subway commuters without personal vehicles an option for changing modes; however, replacement services were not available for some disrupted routes and changing mode is not always the easiest choice. Therefore, some transit commuters teleworked; 35 percent of transit commuters teleworked versus 22 percent of non-transit commuters. In general, transit commuters changed their commuting pattern more than non-transit commuters. Greater percentages of transit commuters changed routes and departure times and canceled their work trips in comparison to non-transit commuters.

Gender is an important factor in defining travel patterns. Men and women have different commuting behavior relative to labor force characteristics and household commitments (Turner and Neimeier 1997). In our data, a lower percentage of females changed modes compared to males (27 percent vs. 40 percent). Moreover, a greater percentage of males teleworked compared to females (32 percent vs. 25 percent).

Mobility can be more challenging for older people and households with lower income (Mattson 2012). A greater percentage of younger people used each of five commuting changes to adapt to post-hurricane conditions compared to older people. This could be because of higher adaptability in younger people. With regards to teleworking, commuters with higher income possibly work in positions that are more likely to have a telework option. Therefore, a higher percentage of them teleworked in comparison to households with lower income. Moreover, higher income commuters more frequently use personal vehicles; based on the survey data, 57 percent of commuters with higher income travel to work with their cars versus 45 percent of people with lower income.

Having children affects parents' travel patterns in many ways. Therefore, greater percentages of families with children changed their modes, routes and departure times, canceled their work trip, and teleworked compared to those without children in the household. Those with children probably canceled their work and teleworked in cases where they could not find caregivers for their children when the school/daycare was closed. Parents also may change their routes and departure times to bring their children to school or care locations in a disrupted transportation network.

When work is far from home, it is harder to reach especially during post disaster conditions with delay, crowding, and transportation system problems; therefore, greater percentages of people who live far from work changed their departure times and routes. Moreover, many of them may prefer to telework or cancel work for the day. Of the commuters who live farther from work, 58 percent canceled work compared to 50 percent of commuters who lived closer to their work locations. In addition, 33 percent of commuters who live farther from work teleworked compared to 22 percent of commuters who live closer to their work locations.

Higher education levels and management occupations indicate mostly office-related jobs and, not surprisingly, a greater percentage of people in these positions teleworked compared to people with lower education levels and other kinds of occupations. Commuters who have the option of flexible working hours and teleworking in normal situations had higher chances of teleworking during the disruption. Many companies allowed their workers to telework after Hurricane Sandy [2], even if teleworking was not an option during regular conditions. (Additional variables and more information about the survey are available in (Kontou, Murray-Tuite et al. 2017)).

Table 1: Description of Variables and Commuting Changes

Variable	Definition	Mean	Standard deviation	Min	Max
Home and work locations	Zip code of home and work location	-------	-------	-------	-------
Transportation mode	Mode of transportation people use for moving from home to work (rail, bus, …)	-------	-------	-------	-------
Age	Continuous (years old)	46.61	13.10	18	83
Income	Continuous ($)	107,694	61,714	5,000	200,000
Gender	Female 1, 0 otherwise	0.58	0.49	0	1
Number of children	Number of children under the age of 15 in the household	0.64	0.97	0	5
Level of education	College and above 1, 0 otherwise	0.82	0.39	0	1
Management, business, and financial occupation	1 yes, 0 no	0.18	0.38	0	1
Computers, engineering, and science occupation	1 yes, 0 no	0.07	0.26	0	1
Departure time	Departure time from home to work	-------	-------	-------	-------
Have option of telecommuting	1 if it is an option, 0 otherwise	0.24	0.43	0	1
Have option of flexible working hour	1 if it is an option, 0 otherwise	0.54	0.5	0	1
Born in US	1 yes, 0 otherwise	0.81	0.39	0	1
First language English	1 yes, 0 otherwise	0.89	0.31	0	1
Travel cost	1 if travel cost from home to work is more than $20, 0 otherwise	0.05	0.21	0	1
Commuting Change					
Change route		0.50	0.50	0	1
Change mode		0.32	0.47	0	1
Change departure time (depart earlier or later)		0.60	0.50	0	1
Telework		0.28	0.45	0	1
Cancel work		0.54	0.50	0	1

n = 397

Table 2: Commuting Changes based on Personal and Environmental Features

Variable	Change Mode		Change Route		Cancel Work		Telework		Change Departure Time	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Transportation Mode										
Transit	0.55	0.50	0.54	0.50	0.76	0.43	0.35	0.48	0.70	0.46
Non-transit	0.09	0.30	0.45	0.50	0.32	0.47	0.22	0.42	0.50	0.50
Gender										
Female	0.27	0.44	0.48	0.50	0.53	0.50	0.25	0.43	0.58	0.49
Male	0.40	0.49	0.52	0.50	0.55	0.50	0.32	0.47	0.61	0.49
Home to Work Distance										
> 10 km	0.32	0.47	0.55	0.50	0.58	0.50	0.33	0.47	0.63	0.48
<=10 km	0.32	0.47	0.44	0.50	0.50	0.50	0.22	0.42	0.56	0.50
Age										
> 46 years	0.26	0.44	0.43	0.50	0.47	0.50	0.26	0.44	0.56	0.50
<= 46 years	0.40	0.49	0.58	0.50	0.64	0.48	0.29	0.46	0.64	0.48
Income										
> $110,000	0.29	0.46	0.49	0.50	0.54	0.50	0.36	0.48	0.54	0.50
<= $110,000	0.35	0.48	0.51	0.50	0.54	0.50	0.18	0.39	0.66	0.47
Number of Children										
> 0	0.35	0.48	0.54	0.50	0.62	0.49	0.31	0.46	0.64	0.48
= 0	0.30	0.46	0.47	0.50	0.49	0.50	0.26	0.44	0.57	0.50
Education Level										
College & Above	0.32	0.47	0.50	0.50	0.56	0.50	0.33	0.47	0.58	0.49
Under College	0.31	0.47	0.50	0.50	0.48	0.50	0.16	0.37	0.64	0.48
Occupation in Management, Business or Finance?										
Yes	0.32	0.47	0.47	0.50	0.66	0.48	0.53	0.50	0.54	0.50
No	0.32	0.47	0.50	0.50	0.51	0.50	0.22	0.42	0.61	0.49
Have the Option of Flexible Working Hours?										
Yes	0.34	047	0.52	0.50	0.58	0.49	0.43	0.50	0.60	0.49
No	0.29	0.46	0.45	0.50	0.49	0.50	0.09	0.29	0.58	0.49
Have the Option of Telecommuting?										
Yes	0.28	0.45	0.51	0.50	0.62	0.49	0.67	0.47	0.49	0.50
No	0.33	0.47	0.49	0.50	0.52	0.50	0.16	0.36	0.63	0.48

Data Source: survey data used by Kontou et al. [7]

Cleaning the survey data involved several assumptions. The home and work location zip codes included some missing responses. If only one of the home or work locations was known, we used ArcGIS and Google Maps to assign the observation a plausible zip code based on the mode of transportation and trip duration. When both of the home and work locations were missing or at least one of the zip codes and the main mode of transportation were missing, these observations were omitted, reducing the total number of observations to 383. For people reporting more than one mode of transportation, we assumed the transit mode was the main mode of transportation and that this person used the non-transit mode to reach the transit station.

Additional steps were completed to fill in missing data. We used the mean substitution method (Enders 2010) to deal with 35 missing ages. Income had 106 missing values. We developed a simple linear regression model to predict missing income values from nine independent variables: level of education, age, log age, occupation, gender, travel cost, US_English (1 if born in the US or first language is English, 0 otherwise), county group I (1 if live in counties with an average income of more than $125,000, 0 otherwise), and county group II (1 if live in a county with an average income less than $80,000, 0 otherwise).

Other agent characteristics used in the ABM included car ownership and family structure. These were not available in the survey responses, so they were based on Census data (PTV 2005, 2012, 2016). In the US, 68 percent of families with children under the age of 18, are married couples and among these married-couple families, 61.1 percent had both parents employed (2016). Based on these percentages, we calculated the number of families that were married couples with both parents working.

2.2. Environment

The modeled environment included the condition of the power system, schools and daycares, transit system, bridges, tunnels, workplace, and policies such as carpool restrictions and gasoline restrictions. The transit system includes the New York and New Jersey transit networks. In this study, the New York transit network consisted of the New York City subway (MTA), Long Island Railroad (LIRR), and Metro North Rail (MNRR) while the New Jersey transit network consisted of NJ Transit and PATH rail.

To obtain the power outage data, the residential zip code of each household was used to determine which power company provided service for this household. Based on the total number of customers (Murray-Tuite and Mahmassani 2004, Division and Quality 2005, U.S. Food and Drug Administration 2005, American Beverage Association 2006) and number of customers without power (2012, 2012, Caroom 2012, Lee 2012, Bloomberg 2013), we estimated the percentage of people without power in each service area. We then used these percentages to determine which households were without power in the modeled population for each day. We used data available from websites (Chakrabarti and Livingston 2012, Rundquist 2012) to calculate school and daycare closure percentages. Survey responses to three questions about the effects of Hurricane Sandy on each respondent's work schedule, reasons for the change in the work schedule, and the day that they returned to their normal work schedule informed the percentage of closed work locations each day after Hurricane Sandy reached the NYC area.

After Hurricane Sandy, many of the bridges and tunnels in New York and New Jersey were either closed or under policies such as carpool restrictions for several days (Kaufman, Qing et al. 2012). Moreover, power and supply outages caused gasoline shortages across the metro area, and open gas stations experienced severe traffic backups (Kaufman, Qing et al. 2012). Gasoline purchase restrictions were implemented to address gas shortage problems (Kaufman, Qing et al. 2012). Transit agencies suspended bus, subway and rail system services and the process of subway and rail system recovery took several days, especially for the New Jersey systems (Kaufman, Qing et al. 2012). Agencies provided some alternative modes to address these disruptions, such as temporary bus shuttles for some disrupted subway lines, including the Manhattan to Brooklyn subway service (2012, Kaufman, Qing et al. 2012). The available infrastructure and services varied day to day and were incorporated into the model.

2.3. Agents' Behavior and Methods of Interaction

We developed a series of if-then rules and statistical models to define agents' behavior and methods of interaction. This ABM simulated nine working days starting the day after the hurricane reached the NYC area (October 30). By the end of the ninth working day, most of the infrastructure and services had recovered, and after this day, the environment did not change significantly on a daily basis. Agents chose from the six different adaptations listed in Table 1 when their usual commuting patterns were disrupted. Agents were able to choose multiple changes (*e.g.*, both routes and departure times on the same day).

2.3.1. Logit Models

The ABM employed six binary logit models to predict the probability of each of these changes. Kontou, Murray-Tuite, and Wernstedt (Kontou, Murray-Tuite et al. 2017) developed five of these multivariable binary logit models for commuting changes (changing mode, canceling work trips, changing routes and changing departure times). We developed the remaining binary logit model to predict the probability of teleworking. Highly correlated independent variables were not used in the same model. The likelihood ratio test was used to identify the overall preferred model, which is presented in Table 3 with all variables significant at the 95 percent (or higher) confidence level. Based on this model, being a transit commuter, having the option of teleworking and flexible working hours during normal situations, having a college degree or above and working in a management, business and financial occupation increases the probability of teleworking during the disruption.

Table 3: Telework Binary Logit Model

Independent variables	β	Std. Error	Pr(>|z|)
Intercept	-3.594	0.467	<0.001***
Transit commuter (binary)	0.831	0.303	0.006***
Have option of telecommuting (binary)	1.699	0.327	<0.001***
Have option of flexible working hour (binary)	1.387	0.354	<0.001***
Level of education (binary)	0.857	0.366	0.019**
Management, business, and financial occupation (binary)	0.708	0.347	0.041**
Model Statistics			
Observations	331	-----------	-----------
Adjusted R-square	0.337	-----------	-----------
Log likelihood restricted	200.46	-----------	-----------
Log likelihood unrestricted	141.66	-----------	-----------

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

The change mode model (Kontou, Murray-Tuite et al. 2017) only calculated the probability of changing modes and did not identify the mode to which people switched. Therefore, a multinomial logit (MNL) model was developed to predict the probability of choosing each mode. Mode options were drive alone, carpool, bus, rail (including subway), taxi, and walk. Table 4 presents the mode choice model with drive alone as the reference alternative.

The logit and MNL models are embedded in the ABM, and, along with their inputs, are used to determine how the agents adapt to disrupted situations. The models and characteristics of the agents lead to an agent-specific probability of a particular outcome. As in Ukkusuri et al. (Ukkusuri, Hasan et al. 2017), a random number is generated and compared to the cumulative probability distribution for a particular decision to determine the outcome for that agent. Different situations are linked to specific adaptations, and series of if-then rules lead to the appropriate model for making decisions in each situation. In situations where agents have more than one option (e.g., change route and/or mode), logit models are used sequentially (see for example Figures 3 and 4 below) based on previous literature and survey findings.

Table 4: Mode Choice Model

Mode	Alternative Specific Parameters	Estimated value	t-statistics
Carpool	Constant	-2.5076	-1.770*
	Age (continuous)	0.0114	0.498
	Income (continuous)	-0.0005	-0.103
	Distance from home to work (continuous)	-0.0002	-0.167
	Born in US (binary)	-0.525	-0.648
Bus	Constant	0.9263	1.209
	Age (continuous)	-0.0004	-0.031
	Income (continuous)	-0.0177	-4.646***
	Distance from home to work (continuous)	-0.0006	-0.417
	Born in US (binary)	-0.8032	-1.691*
Rail	Constant	2.1692	3.672***
	Age (continuous)	-0.0361	-3.441***
	Income (continuous)	0.0031	1.352
	Distance from home to work (continuous)	-0.0006	-0.412
	Born in US (binary)	-1.4421	-4.208***
Taxi	Constant	-8.0799	-0.912
	Age (continuous)	-0.0962	-1.251
	Income (continuous)	0.0721	1.403
	Distance from home to work (continuous)	-0.5085	-1.600*
	Born in US (binary)	-2.5165	-1.597*
Walk	Constant	2.7774	1.863**
	Age (continuous)	-0.0089	-0.300
	Income (continuous)	-0.0105	-1.478*
	Distance from home to work (continuous)	-0.6023	-2.370**
	Born in US (binary)	-2.7752	-3.417***
Model Statistics	Log likelihood at zero	-628.819	------
	Log likelihood at constants	-454.4771	------
	Log likelihood at convergence	-405.5537	--------
	R-squared w.r.t. zero	0.3551	--------
	R-squared w.r.t. constants	0.1076	--------
	Adjusted R-squared w.r.t. zero	0.3153	--------
	Adjusted R-squared w.r.t. constants	0.0629	--------

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$

2.3.2. Decision Frameworks

Decision flow-charts detailed the agent behavior estimation for the post-Hurricane Sandy period.

As shown in Figure 1, at the start of each day, agents checked their work location's condition to see whether it was closed or open. If it was closed, some agents may telework, and all others were considered unproductive that day. Even if work were open, agents were permitted to telework if their main mode of transportation was disrupted, but they needed power to do so. If power was available, the ABM calculated the probability of teleworking based on the telework model. On the other hand, if work was open, the agents checked the condition of their main mode of transportation. However, agents with children, even if their work was open, could not go to work when daycares and schools were closed unless they made other care arrangements, as illustrated in Figure 2. If schools and daycares were closed, households with two parents working outside the home needed to find an alternative caregiver or have one parent stay home to take care of their children while the other one went to work. Single parents needed to find another caregiver if they wanted to go to work. Therefore, for households with all parents working, if daycares and schools were closed, the ABM first calculated the probability of canceling work based on the cancel work model. If a particular agent did not cancel work, the ABM compared the square of the cancel work probability to another random number to determine whether they found another caregiver. If another caregiver was not found, in households with both parents working, the agent's spouse cared for the children, while in single-parent households, the agent canceled the work trip.

When their work was open and there was not an issue with childcare, agents were grouped based on their main mode of transportation: (1) rail and subway commuters, (2) car, carpool, and taxi commuters, and (3) bus commuters. When making trips, agents first checked the condition of their normal transportation mode.

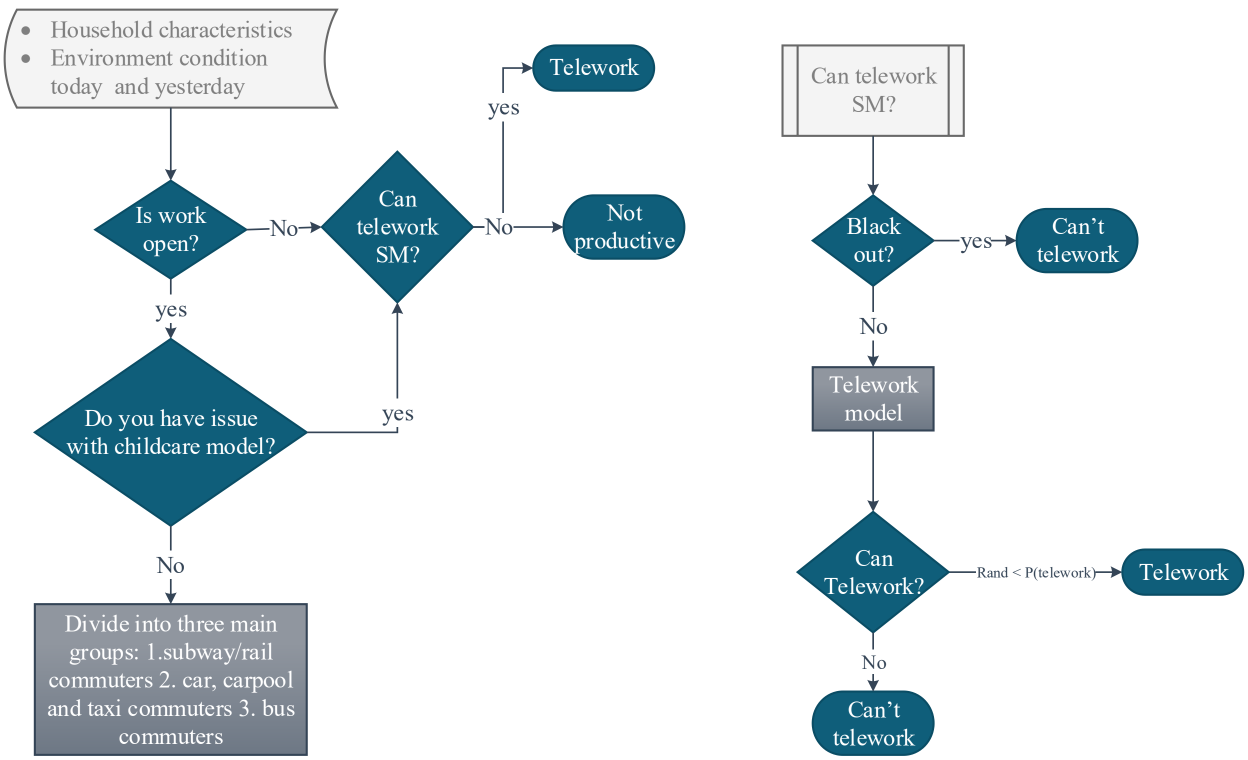

Figure 1: Work Condition and Telework Flow Charts

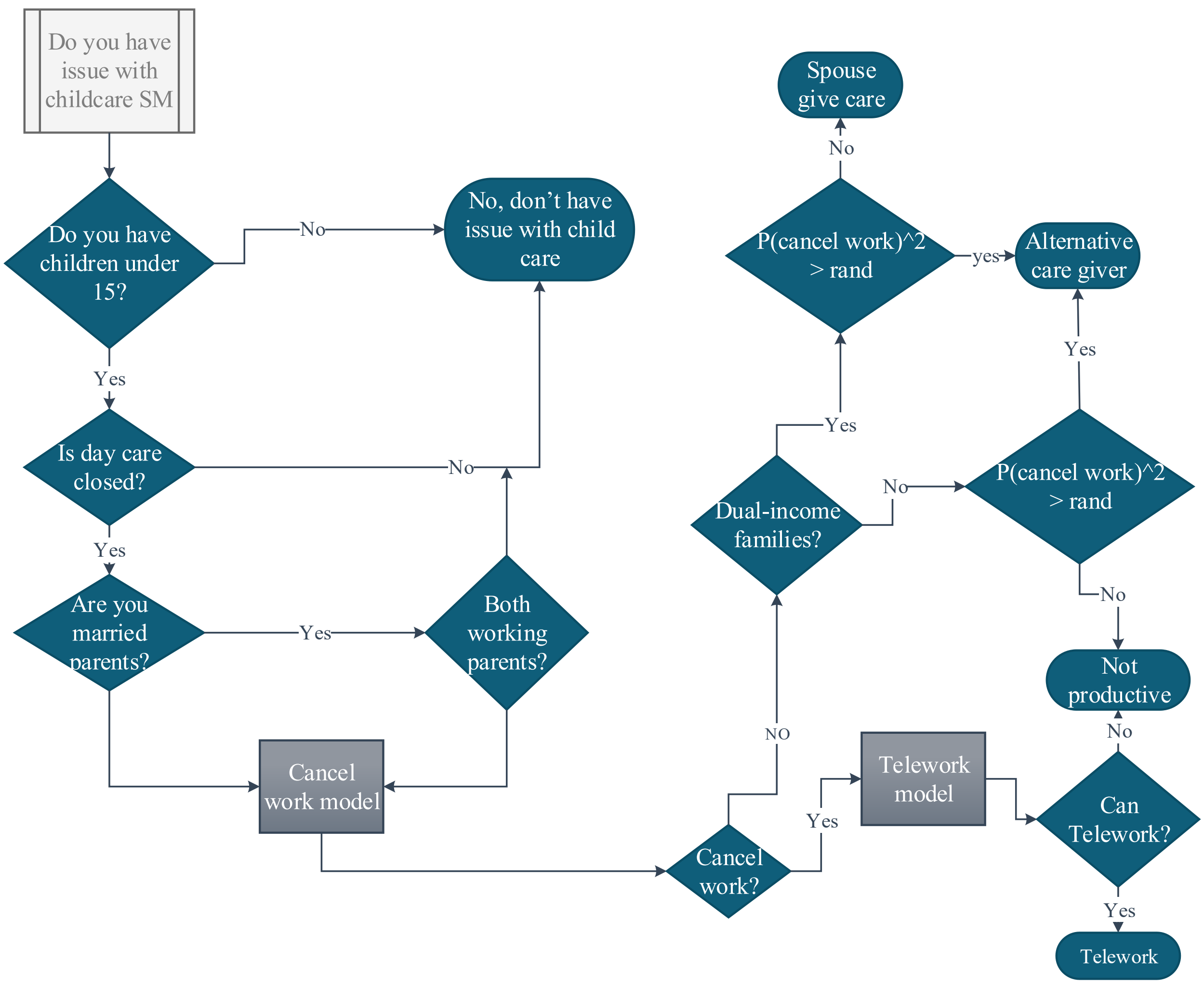

Figure 2: Issue with Childcare Flow Chart

2.3.2.1 Rail and Subway Commuters

Figure 3 presents the decision flowchart for subway/rail commuters. Each subway/rail system consists of different lines, and each of these lines can have different recovery durations. Therefore, the subway/rail line that each agent used while traveling from home to work daily was needed. From the available shapefiles of subway/rail stations (2017), the latitude and longitude of each subway/rail stop were converted to x y coordinates. The ABM calculated the Euclidean distance between each home/work location and subway/rail stops: the two closest stations to home were chosen as the probable origins, and the two closest stations to the work location were chosen as the probable destinations for each person. To find the subway lines that agents used to move from their origins to destinations, the ABM employed Dijkstra's algorithm (shortest path). The algorithm’s input files included the origin, destination, edge connections (links), and their costs, where the cost of each line was the length of each link in the actual network. Lengths of subway/rail lines and the station locations were obtained using shapefiles (Romalewski 2010, 2017, 2017) and the closest facility tool in ArcGIS. A walkable path was added between the stations with distance less than 0.3 miles in subway and rail systems, so that agents could change their subway/rail lines if needed. The ABM ran the shortest path algorithm for all four combinations of origins and destinations for each agent in the normal situation. The model selected the shortest path as the normal commuting path for each agent.

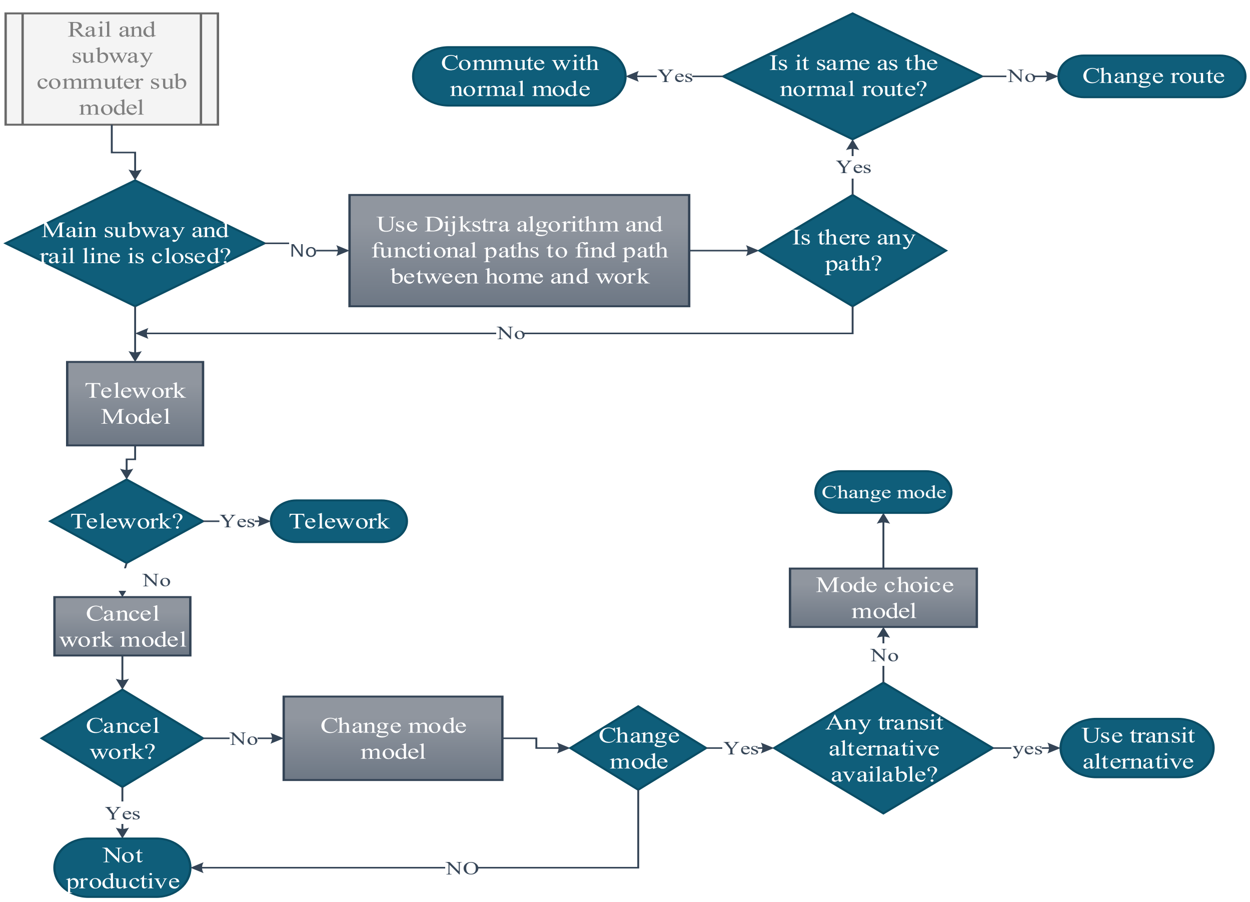

Figure 3: Rail and Subway Commuters Flowchart

At the start of each post-Hurricane Sandy day, the subway/rail lines that were closed were omitted from the edge connection (link file). Then the shortest path algorithm was used again with the updated edge connections. If Dijkstra's algorithm was not able to find a path from home to work, agents could not use their regular transportation mode for commuting. If a path was found and the chosen path was the same as the agent's normal path, the agent traveled with the regular route, but if the paths were different, the agent adapted to a new situation by changing routes.

Agents who could not use their regular modes of transportation could change their modes, not work at all, or telework. Based on (Giuliano and Golob 1998, Mokhtarian, Ye et al. 2010, Zhu, Levinson et al. 2010), the order from most- to least-preferred is to cancel their work trip, telework and change mode. This ABM considered telework before canceling work because people can telework even if they cancel their work trips. Therefore, the probabilities of teleworking, not working, and changing mode were calculated sequentially by using logit models. If they changed modes, agents in this commuting group used the transit alternative if it was feasible for them based on their home and work locations, otherwise the mode choice model was used to determine which mode they chose. Based on this model, the probability of choosing each of the six modes was calculated for each agent, subject to the availability of each option. For instance, drive alone was not considered an option if the agent did not own a car and walking was not feasible if work was far from home. The ABM calculated the probability of choosing the remaining modes and, based on a random number, identified the selected mode.

2.3.2.2 Car, Carpool, and Taxi Commuters

Figure 4 shows the decision framework for car, carpool or taxi commuters. Several major tunnels and bridges were closed after Hurricane Sandy. Therefore, if an agent had one of these tunnels or bridges on her/his way to work, s/he needed to change routes or modes to be able to reach the destination. The sum of distances between home and each of these tunnels and bridges and work and each of these tunnels and bridges was calculated, and the closest bridge to the home and work locations was chosen as the first priority for each agent, and all other bridges and tunnels were listed as alternatives based on their distance.

Agents checked, daily, the closure status of the bridges and tunnels they used in a normal commute to work and, if it was closed, the probability of changing routes was calculated based on the change route model. If they changed routes, agents moved from home to work with the next closest open bridge or tunnel. If not, they first considered teleworking, then canceling work, and finally changing mode, similar to the rail/subway group.

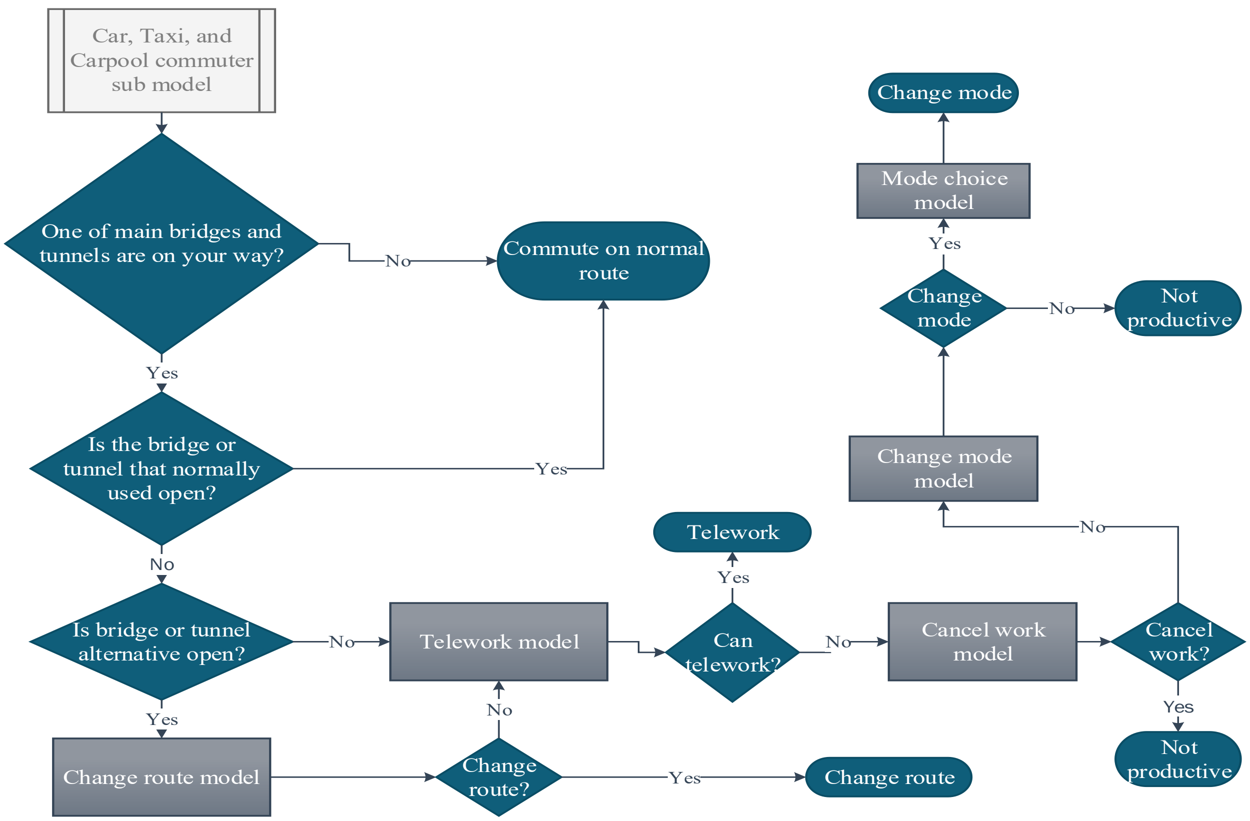

Figure 4: Car, Carpool or Taxi Commuter Decision Framework

2.3.2.3 Bus Commuters

If an agent's main mode of transportation was bus, the framework followed was similar to that of for the car, carpool and taxi group. At the beginning of each day, the agent checked the status of the bus system. All bus services were closed for the first day of the simulation (October 30), and all of them were restored by October 31. The distances between a home and all of the bus stops was calculated, and the closest stop to the home location was considered as the bus stop from which this agent started his/her trip. If the bus service was disrupted, these commuters considered teleworking, canceling work, and changing mode, in that order.

2.3.2.4 Modeling Considerations for All Agents

Some of the variables used in the logit models depended on the agent characteristics and environment, which needed to be updated daily. These included tunnel closure, carpool restrictions, gasoline restrictions, and delay and crowding conditions. At the start of the day, if the bridge/tunnel that an agent normally used for commuting was closed or carpool restrictions were in place, it was assumed that the commuter encountered a tunnel closure and carpool restriction that day. Based on typical gasoline consumption of a car (2018), fuel capacity (McGhee and Grimes 2006), and the roundtrip distance from home to work, the ABM calculated the next day that each agent would need fuel. If on that day, the gasoline restriction policy was in effect and their plate number was opposite the accepted number (*e.g.*, even- rather than odd-numbered), gasoline restrictions constrained the agent on that day.

At the end of each day, agents who were able to travel to work learned from their experience, which could affect their decisions for the next day. Based on the survey data, respondents preferred to change routes and leave earlier more than all of the other changes, when they faced delays and crowding. The ABM compared the number of agents who used each tunnel, bridge, public transit link, and bus stop before the disruption to the number of agents who used each of them after disruption. If any of the elements was used more than in the normal situation, that part of the route/service was considered crowded. All agents who used one of those crowded subway lines, bridges, tunnels, or bus stations on their way considered delay and crowding for the next day.

On each day, agents chose a departure time. Agents who encountered delay and crowding, carpool restrictions, tunnel closure, or gasoline restriction may decide to depart earlier or later. The ABM used depart earlier and depart later logit models sequentially (i.e., later departure was considered only if the agent did not choose to depart earlier) to decide whether to change their departure time or not. When agents decided to change departure time, the new departure time was chosen based on the distribution of the change in departure time from the survey data. The change in departure time distribution was only used for the first time that they decided to make this change. For the next time, they changed departure time only one time step (half an hour) at a time to avoid large jumps. For the first day of work after the disruption, agents considered news (2012, Kaufman, Qing et al. 2012) about the delay and crowding on the roads as prior information for their departure time decision.

2.4 Population Generation

The PopulationSim package was used to generate a synthetic population for the modeling region. The synthesized population includes information about all age ranges, but our model considered only employed people. Therefore, all unemployed people were omitted, which reduced the total number of people from 19 million to 8 million. Many of the people who were car, carpool, taxi and bus commuters did not have any disrupted bridges and tunnels impeding their normal commute path; that is, they could commute normally even after the transportation disruption (assuming that their work was open and schools were in session). Therefore, people whose commuting patterns were not affected by Hurricane Sandy were omitted as well (to reduce computation time). In the end, after the population synthesis, the simulation included 2,828,751 total agents. Table 5 shows the breakdown by transportation mode for the total population, as well as the subset of this total living in affected areas.

To deal with high computing cost, only agents affected by transportation system disruption were modeled. First, the model was run for normal conditions and the outputs like the path that subway/rail commuters used normally and bridges and tunnels that agents used for traveling to work were saved for input in other scenarios. Also, subway/rail commuters were grouped based on their origins and destinations. Agents with the same origin and destination were placed in one group and the shortest path algorithm was only run once for each group.

Table 5: Agents' Normal Transportation Modes

Mode of Transportation	Total Number of people	Number of people in the affected area
Car	4,649,517	256,477
Carpool	257,418	22,014
Taxi	54,086	3,059
Bus	701,585	191,985
Subway/Rail	1,983,300	1,983,300
Telework	371,916	371,916
Total	**8,017,822**	**2,828,751**

3. Scenarios and Results

The simulation model was run for the normal (undisrupted) condition, the base disrupted situation and six different recovery scenarios. These recovery scenarios allow testing the role of different infrastructures on the ability to return to productivity. In particular, they represent various recovery rates of the transportation system to support commuting, infrastructure supporting teleworking alternatives, and disruptions to childcare infrastructure that constrain working parents. Because of the importance of transit in the NYC Metropolitan Area and the fact that NYC's transit system recovered at a different rate from the New Jersey system serving the commuting area, three out of six recovery scenarios were about subway and rail recovery.

Teleworking options are under the control of the employer, provided that the type of work is appropriate for teleworking and the supporting infrastructure is available. With severe transportation disruptions, some office workers teleworked for the first time, despite a 2010 federal mandate that requires all government agencies to develop strategies for promoting telework in normal and emergency situations like Hurricane Sandy [51]. However, more than 8 million homes and businesses lost power after Hurricane Sandy(Green 2012). The power utilities often work separately from transportation providers during restoration of power, especially for residential areas (although rail operations and fuel pumps depend on power). Therefore, another recovery scenario tested effects of faster power restoration.

Manhattan is connected to New Jersey via the Lincoln Tunnel, Holland Tunnel, and George Washington Bridge from one side and it is connected to Queens and Brooklyn with the Queensborough Bridge, Queens Midtown Tunnel, Williamsburg Bridge, Manhattan Bridge, Brooklyn Bridge, Hugh L. Carey Tunnel, and Robert Kennedy Bridge from the other side. After Hurricane Sandy, many of these bridges and tunnels were either closed or were under policies like carpool restrictions. Many people use these tunnels and bridges daily for commuting from home to work. In another scenario, effects of faster recovery of these tunnels and bridges were examined.

Even if the transportation system recovers completely, there is no guarantee that all people instantly return to their normal commuting patterns because of competing responsibilities, such as care giving. Daycare and school closure can shift parents' behavior. To examine the effect of earlier recovery of school and daycares, another scenario was considered.

In each scenario, only one factor varied and all other factors remained the same as the base scenario. In the base disrupted situation, the environment used the actual recovery events (2012, Kaufman, Qing et al. 2012). In the first scenario, the electrical system recovered one day earlier compared to the base case. In the second scenario, the schools and daycares recovered one day faster than the base case. In the third scenario, the tunnels reopened one day faster and carpool restrictions started and ended one day earlier. In the fourth scenario, all subway/rail links reopened one day earlier. In the fifth scenario, the New Jersey area rail/subway followed the same timeline as the New York area rail/subway (*e.g.*, if on day 1, 20 percent of the New York area rail/subway system recovered, 20 percent of the New Jersey area rail/subway would be recovered too). In absolute terms, the actual extent of such partial restoration depends on the number of links in the two systems. The number of links in the New York transit network (including MTA subway, LIRR, and MNRR) is 2.82 times the New Jersey transit network links (including NJ Transit and Path rail). Therefore, if 282 links were recovered in the New York rail/subway on day 3, 100 links would recover in the New Jersey rail/subway on that day; with links sequenced for recovery based on the order of their actual recovery. In the sixth scenario, the New York area rail/subway recovered on the same timeline as the New Jersey area rail/subway. For instance, if 100 links were recovered in New Jersey rail/subway on day 3, 282 links would recover in the New York rail/subway system on that day, with links sequenced for recovery based on the real condition. The results include the analyses in the following order: 1) base condition (actual recovery), and 2) other scenarios.

3.1. Base Condition

Figure 5 shows the agents' adaptation in the base condition for the first nine weekdays. Although changing departure time and changing route were the first two preferred options (Giuliano and Golob 1998, Mokhtarian, Ye et al. 2010, Zhu, Levinson et al. 2010), on days 1 and 2, the transportation systems were mostly disrupted, forcing many commuters to change their transport mode or telework to remain productive. Otherwise, they canceled work. Because of this, the most common to least common options on these first two days were to cancel work (not work at all), telework, and change mode. Beginning on the third day, the subway/rail system started to recover, so the number of agents who changed departure time and changed route increased while the number of agents who changed mode decreased.

On the fifth day of the simulation, the number of agents who either teleworked or did not work at all decreased because this was the day when most of the schools reopened, allowing families with children to return to more normal work patterns. In addition, many agents traveled to work using the recovered subway/rail system instead of teleworking or not working since a substantial proportion of rail/subway links had recovered by this day.

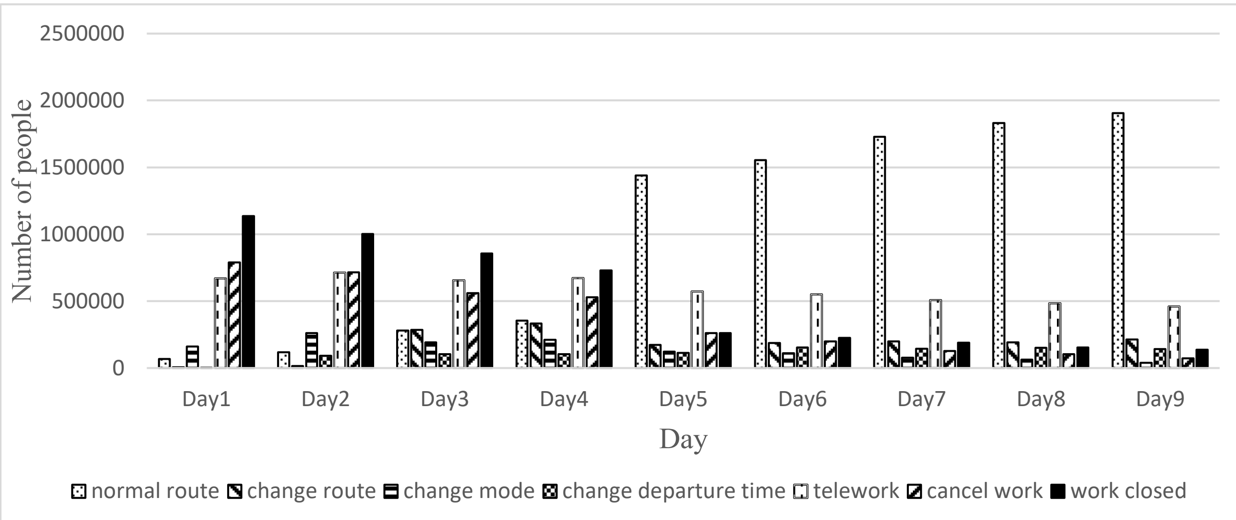

Figure 5: Agents' Adaptation Choices for the First Nine Days under Base Conditions

Figure 6 shows the departure time distribution of agents in normal conditions and the first nine days in the base recovery condition. Until day 5, many of the work places and school/daycares were closed and the rail/subway system was greatly disrupted. Fewer people were moving from home to work, so departure times spread out, with no distinct peak. Starting at day 5, the number of agents commuting from home to work increased, but the transportation systems were not recovered completely. Therefore, commuters experienced delay and crowding while traveling from home to work. Consequently, the number of agents who departed in earlier time periods was more in the base recovery condition compared to the normal condition because agents sought to avoid delay and crowding. The number of agents who moved from home to work in the peak hours (7 to 9 am) were still more than other times even in the base recovery condition, and the overall trend of the departure time distribution in the base recovery condition is similar to the normal condition.

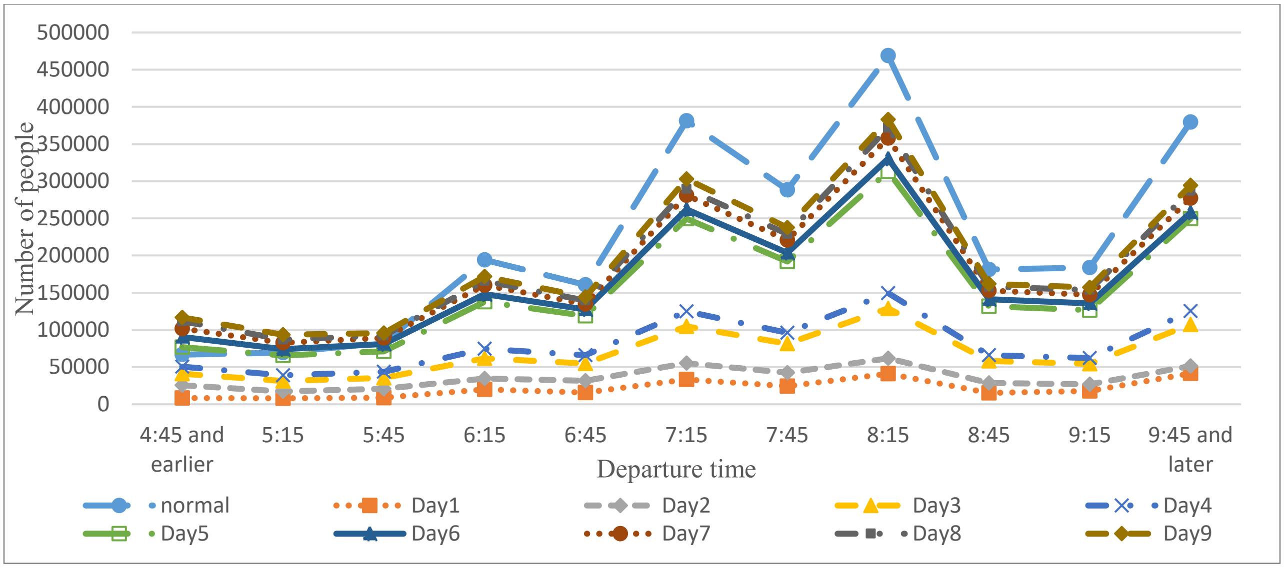

Figure 6: Departure Time Distribution

3.2. Other Scenarios

Results of the base condition and six different scenarios are compared in this section. Figure 7 shows the cumulative lost person-work days in the different scenarios from the most effective recovery scenario to the least effective one in regards to productivity, reading left to right. As noted earlier, nearly one-third of commuters in the New York Metropolitan Area use transit. After Hurricane Sandy reached the NYC metro area, the subway and rail systems were completely disrupted for two days and NJ Transit recovered more slowly. Not all of the transit commuters owned a car or were able to travel to work with the other available modes of transportation, forcing many to cancel their work trips. As a result, when the rail/subway system recovered faster, productivity increased. Moreover, recovering the NJ rail/subway system as fast as the NY rail/subway system was the third most effective scenario.

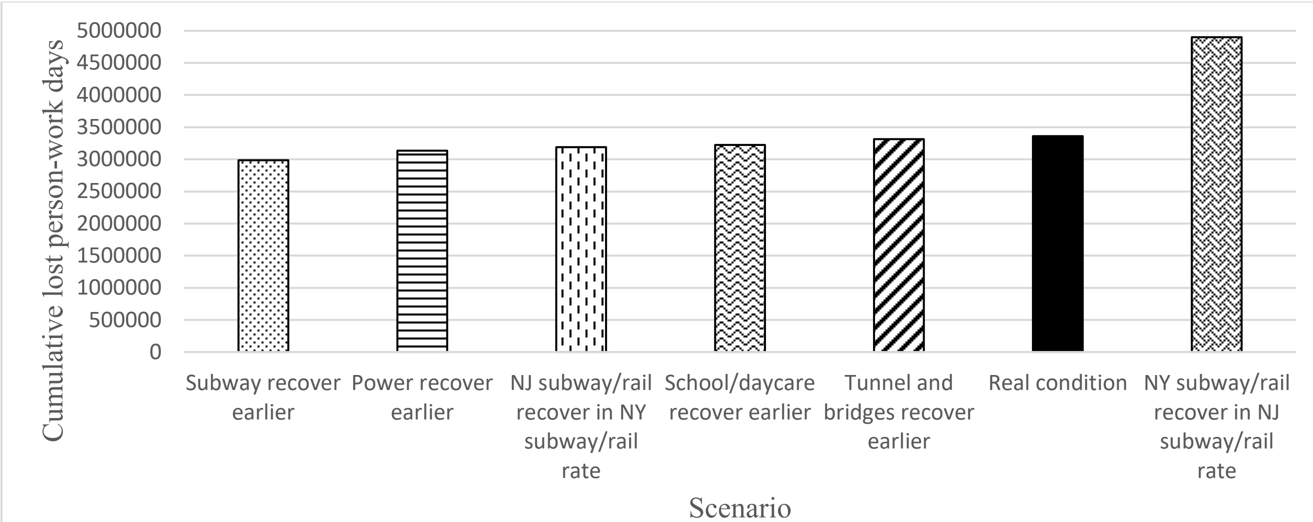

Figure 7: Cumulative Lost Person-Work Days Over the Nine Work Day Period

Figure 8 shows the number of agents who did not work on each day after disruption. When the subway/rail recovered one day earlier, the number of agents who failed to work at all decreased noticeably on the second day. This occurred because in all other scenarios there was no subway/rail service on the second day, while in this scenario some subway/rail service appeared.

The second most effective scenario was recovering the power systems one day earlier. Some agents telework in normal conditions, so they need power to be productive. Moreover, after the disruption, many companies allowed their employees to telework. If power is available, teleworking can be a substitute for commuting to work, and it avoids traffic, delay, and crowding. Moreover, agents do not need to shift to other modes. In addition, teleworking furnishes a potentially viable work option for families that have children while schools and daycares are closed.

The fourth most effective strategy was accelerating the recovery of school/daycare by one day. Although schools and daycares are not part of the transportation system, they directly affect the behavior of agents who are transportation system users. When schools and daycares are closed, parents cannot travel to their work unless they can find another caregiver. The first day that most of the schools reopened after the hurricane was day 5 of the simulation, which allowed the number of people who canceled their work trips to decrease. However, in the scenario where schools and daycares recovered one day earlier, the number of agents who did not work decreased noticeably from day 4. These numbers show how important schools' and daycares' conditions are in the recovery process.

The fifth most effective scenario entailed tunnels recovering one day earlier and carpool restrictions starting and ending one day earlier. This scenario was not as effective as the prior ones because the number of agents driving through one of the bridges and tunnels was less than the number of rail/subway commuters. In addition, not all the bridges and tunnels were closed due to the hurricane's impacts. Therefore, agents could reach their work locations by simply changing routes.

The least effective hypothetical scenario, the one where the NY subway/rail recovered at the NJ subway/rail rate, was much worse than even the base condition. In this case, there were no rail/subway lines available for many agents to move from home to work; therefore, more agents did not work at all.

Almost 70 percent of commuters modeled in this ABM used subway/rail as their main mode of transportation (recall that those who faced no disruptions were not modeled). Therefore, because of the high number of subway/rail users, and the fact that subway/rail system was closed completely for two days and, in other systems (e.g., power), some percentage of people always had service (e.g., power), the earlier subway/rail recovery stands out. Moreover, a functional subway/rail system also gave other commuters (e.g., drive alone) an alternative when they were not able to use their regular mode. For instance, commuters with a car as their main mode of transportation who faced tunnel closures or carpool restrictions could use the functional rail/subway system regardless of their occupation type. However, other scenarios like earlier power restoration or daycare and school restoration were not useful for all commuters. First, only 13 percent of agents teleworked during normal conditions. Second, even if power was restored earlier, some employers might not allow telework and teleworking is not applicable to some occupations. A similar situation arose for the school and daycare restoration scenario. Not all agents had children and were in households with all parents working and depending on school/daycare to be productive. Thus, all scenarios other than subway/rail recovery scenarios had effects on smaller populations of agents which is why their results seem similar.

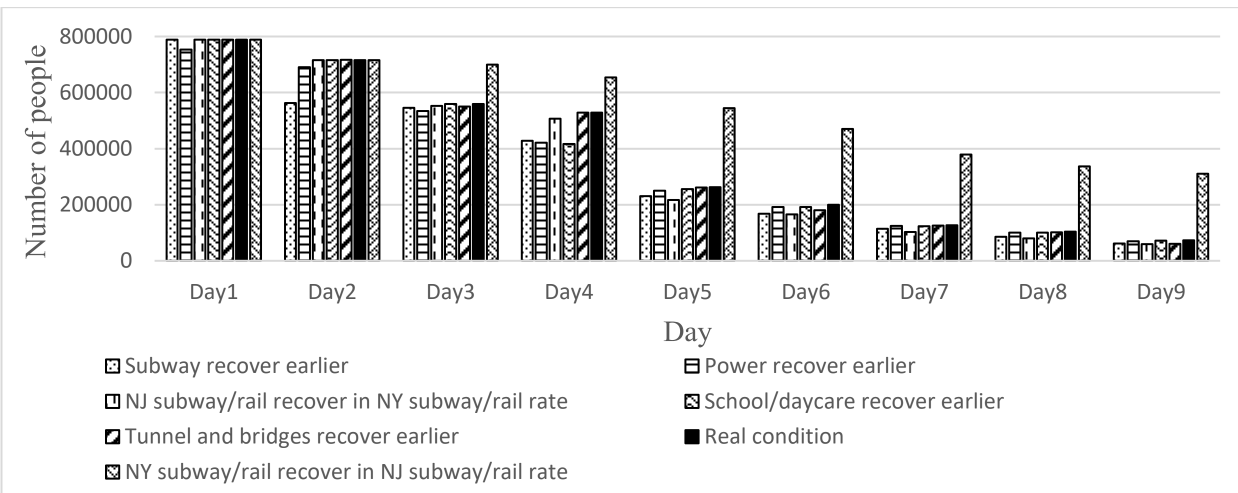

Figure 8: Number of Agents who Did Not Work on Each Day

Turning from these aggregate results to differences broken out by income, Figure 9 presents cumulative lost person-work days in five different household income groups. In all of the income levels, the scenario entailing an earlier subway recovery was the most effective except for households with more than a $200,000 annual household income. For these high-income households, the most effective scenario was the one involving an earlier power recovery, with accelerated subway recovery the second most effective scenario. Members of households with higher income levels may have occupations that allow teleworking and do not require them to be on-site, so recovering power earlier can increase the productivity of this group by making the telework option available. Moreover, this group is less dependent on the subway/rail system for transportation and, therefore, recovering the subway/rail system earlier is not as effective as for other income levels in increasing productivity.

At the other end of the income scale, for households with annual incomes below $25,000, recovering the schools/daycares earlier was more effective than recovering power because people with lower income usually work in occupations that do not permit teleworking. Therefore, recovering power in this group was not as effective as in the households with higher income levels. The relative effectiveness of scenarios in terms of lost person-work days for the other income levels (those not at either end of the income scale) remained the same as for the aggregate results.

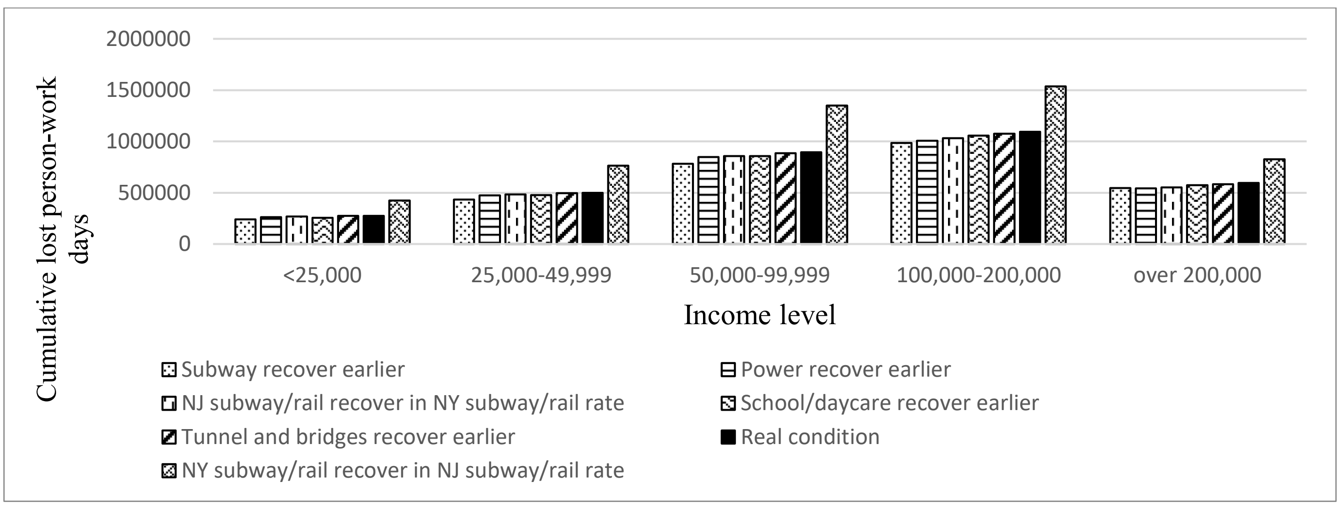

Figure 9: Cumulative Lost Person-Work Days by Income Level

Figure 10 presents cumulative lost person-work days in different residential locations. As indicated earlier, the most effective recovery scenario across the aggregated NYC area entailed the earlier recovery of the subway, and this holds true for all subareas except New Jersey, Staten Island, and Long Island. New Jersey Transit recovered relatively slowly, so recovering it one day earlier but at the same slow pace as the baseline was not as effective as recovering it at the quicker pace of the NY subway/rail recovery rate. For people living in New Jersey, the most effective recovery scenarios (in order of decreasing effectiveness) were NJ subway/rail recovery at the NY subway/rail recovery rate, earlier power recovery and earlier subway recovery. For people living in Staten Island, the most effective scenario was to recover tunnels and bridges earlier. This derives from the reliance on the Hugh L. Carey tunnel—a main route for commuters from Staten Island to Manhattan—that was closed for several days. Recovering it one day earlier significantly decreased the number of people who did not work at all. On Long Island, earlier power recovery was the most effective scenario, since a high percentage of households there were without power. In contrast, the percentage of households experiencing a power outage was not as high in Queens, Bronx, and Kings, so the scenario with an earlier recovery of schools/daycare was more effective at reinstating the lost person-work days than the one with earlier power recovery. In all other locations, power recovery was more effective than earlier school/daycare reopening (allowing teleworking), while the worst recovery scenarios in all locations entailed the recovery of the NY subway/rail system at the NJ subway/rail recovery rate and the baseline recovery.

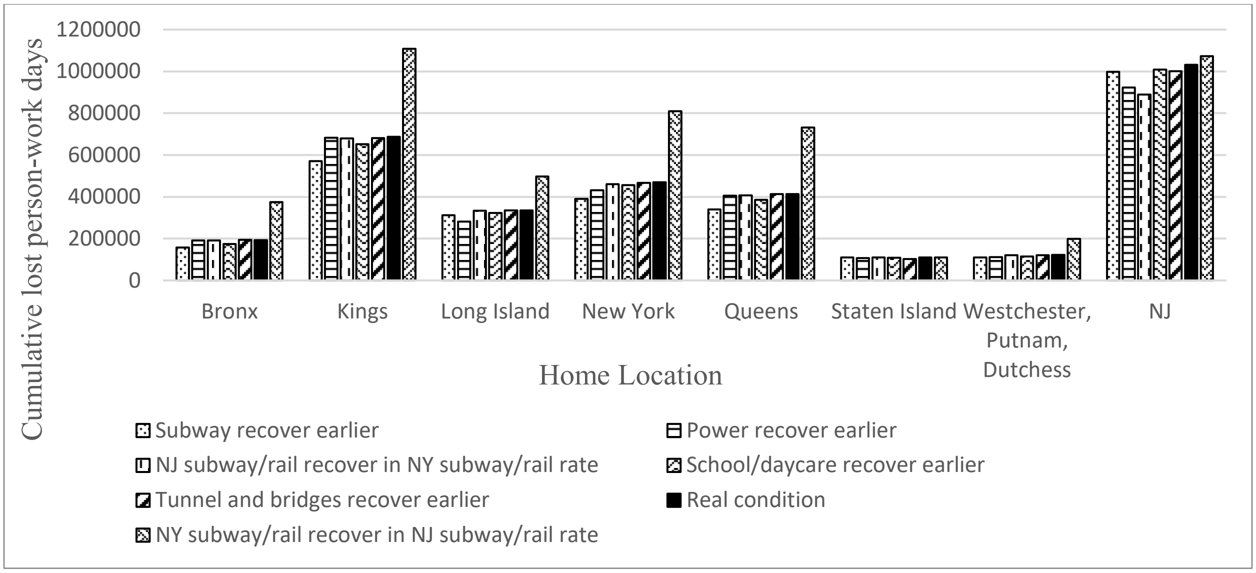

Figure 10: Cumulative Lost Person-Work Days by Home Location

Figure 11 presents the total number of agents who teleworked in different scenarios. Until day 5, the number of agents who teleworked in the scenario with power recovered one day earlier exceeded all of the other scenarios. Because teleworking depends on the power condition (and other factors not modeled here), when more people have power, the number of people who can telework increases. Starting on day 5, the number of agents who teleworked decreased in all scenarios except for the one where the NY subway/rail recovered at the NJ subway/rail system's pace (last scenario). Since, in all of the scenarios, the transportation system condition improved by day 5, agents traveled to work except in the last scenario where, even on day 5, many of the subway/links were not functional. Therefore, agents had to telework, not work at all, change modes, or change routes. Fewer people teleworked in the scenarios where the subway recovered earlier and NJ subway/rail recovered in NY subway/rail rate compared to other scenarios because, with faster subway/rail recovery, more people were able to travel to work.

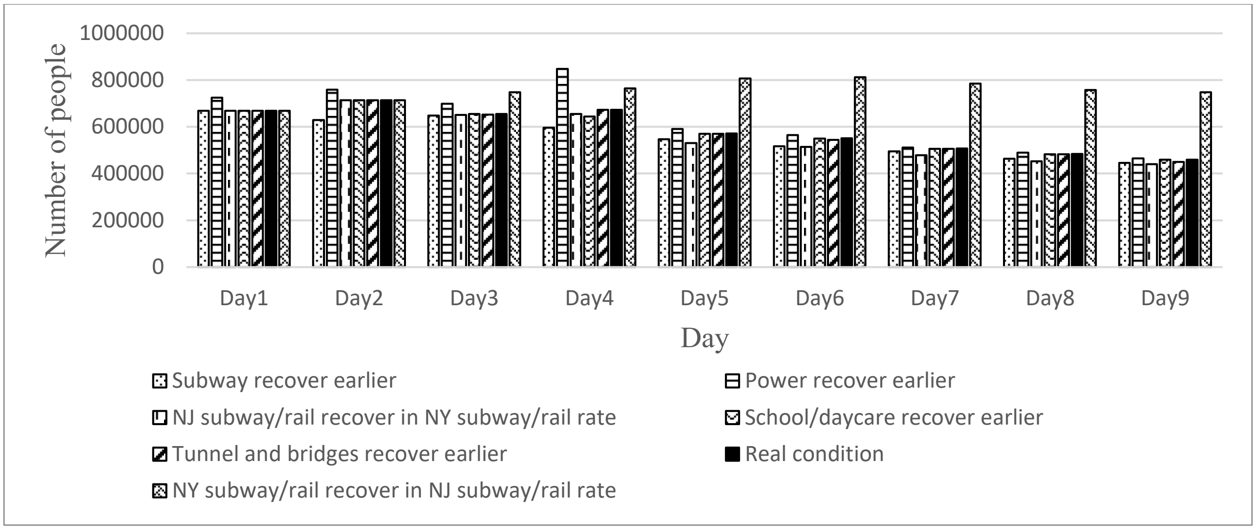

Figure 11: Number of Agents who Telework on Each Day

Figures 12 and 13 show the number of agents who changed modes and changed routes in different scenarios. Starting on day 5, the number of agents who changed modes and changed routes decreased in all of the scenarios except for the last where the number of agents who changed their modes and routes remained high. Fewer agents changed modes when the subway recovered earlier, NJ subway/rail recovered at the NY subway/rail rate, or power recovered sooner. In the first two scenarios, agents were able to travel to work with their normal modes more because the subway/rail system recovered faster. In the third scenario, agents were able to telework more, so they did not need to change modes as much. In the last scenario, the transportation system took longer to recover and with work locations being open, more people tried to reach their work using the disrupted transportation system; therefore, the number of agents who changed modes and routes was high even on day 9 in the last scenario.

In all scenarios, few people changed their routes on days 1 and 2 because of the degree of transportation disruptions. For example, the subway/rail system was completely disrupted; therefore many people with subway/rail as their main mode of transportation did not have the option of changing route and they needed to change modes if they wanted to travel to work. As a result, the number of agents who changed modes in the first two days was much more than the number of agents who changed routes. On the second day, the number of agents who changed routes increased substantially in the subway recover earlier scenario because this was the only scenario with some functional subway/rail lines. Commuters tried to reach their work places by using the few open subway/rail lines so many of them had to change their routes. Reopened subway/rail lines gave more people the chance to reach their work places by using their normal commute modes, so the number of agents who changed modes decreased on the second day in the earlier subway recovery scenario.

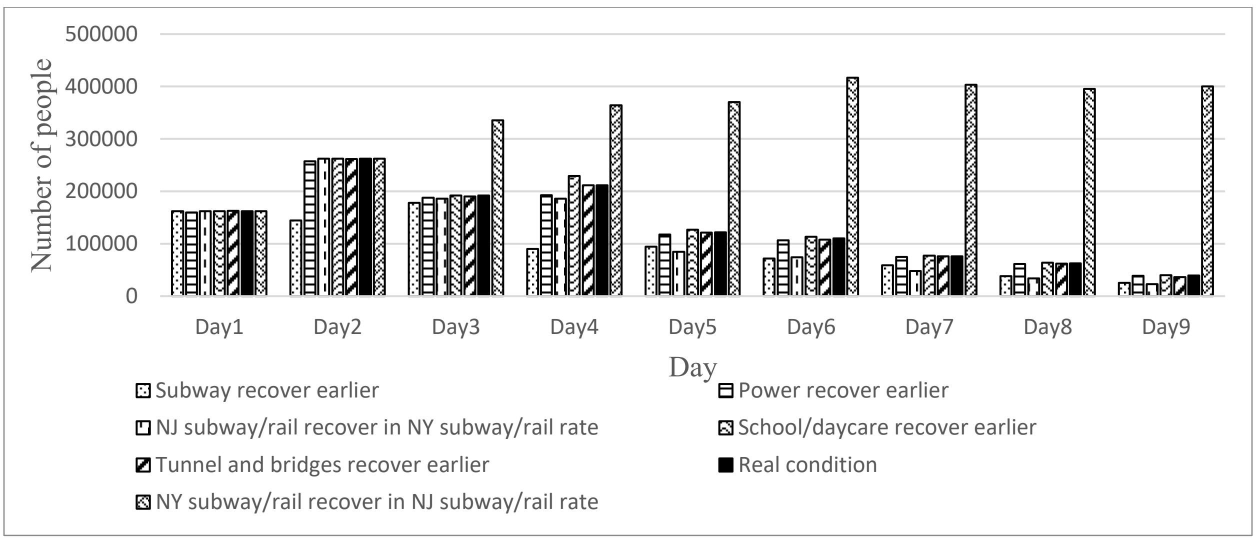

Figure 12: Number of Agents who Change Modes on Each Day

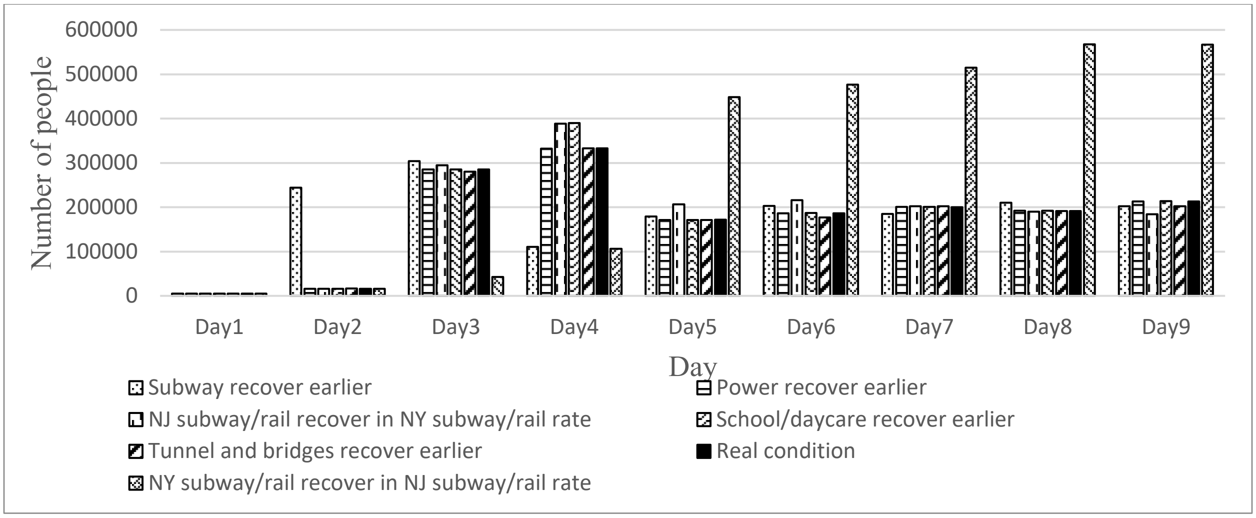

Figure 13: Number of Agents who Change Routes on Each Day

Finally, Figure 14 shows the number of agents who changed their departure times in each scenario. Agents changed their departure times in most of the cases because of delays and crowding. On day 1, more people changed their departure times in the earlier tunnel and bridge recovery scenario compared to all other scenarios. In this scenario carpool restrictions started from day 1 on bridges, therefore some people changed their departure time to deal with carpool restrictions. Starting from day 5, the percentage of school and work places that were closed decreased substantially; therefore, more agents attempted to travel through the disrupted transportation system. To avoid some of the delays and crowding encountered in the disrupted system, many agents changed their departure times. On day 9, when the transportation systems' conditions improved and delays and crowding decreased, the number of agents who changed their departure times decreased, with a gradual return to normal routines. In the last scenario, the transportation system took longer to recover and congestion/crowding occurred more often than the other scenarios. Therefore, more agents changed their departure times in the last scenario.

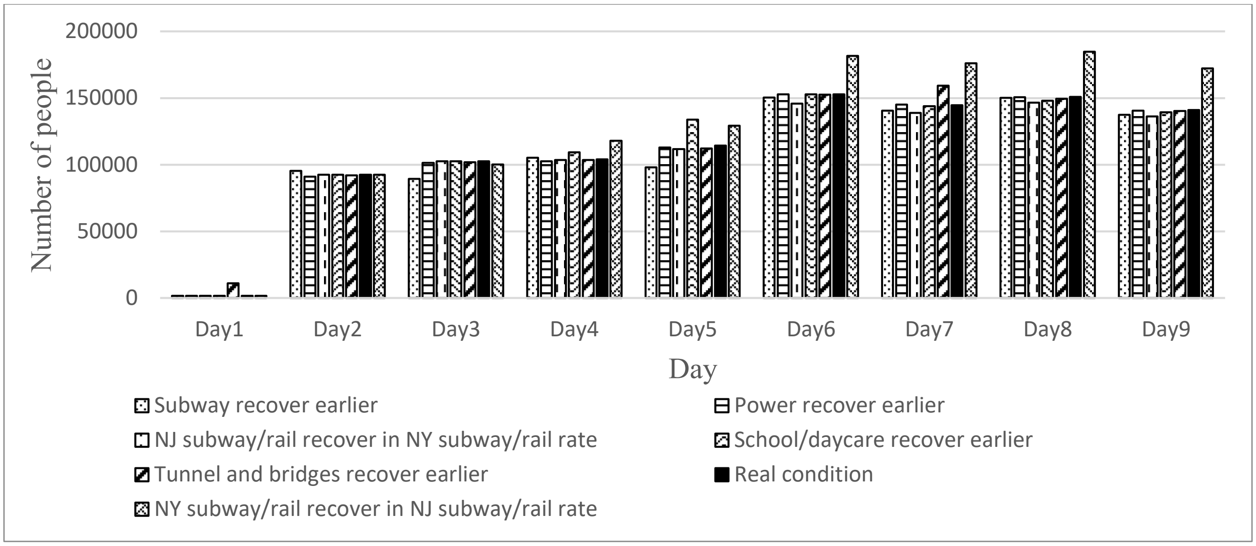

Figure 14: Number of Agents who Changed Departure Times on each Day

4. Conclusion

In this research, data from a NYC Metropolitan Area survey was used to develop an ABM that captured commuter behavior and adaptation and simulated their behavior for nine working days after Hurricane Sandy reached the metropolitan area. A series of if-then rules and logit models defined agents' behavior and methods of interaction. A description of route, mode and departure time choice was presented that allowed each agent to change their behavior based on their experience (e.g., delay and crowding), which addresses an earlier gap (i.e., lack of accounting for experience and learning) in the transportation disruption literature (Levinson and Zhu 2012). In this model, each agent was able to adapt to each day's constraints by changing their route, changing departure time, changing mode, teleworking, and/or not working at all.

Six different recovery scenarios were tested by using this model to find critical factors that promote a faster return to productivity. These scenarios represent changes in recovery speeds of different components of the transportation system (under control of different entities); power, which represents teleworking support infrastructure and an alternative to physically commuting, provided the employer allows telecommuting; and school/daycare recovery, which poses constraints on working parents, regardless of whether the transportation system has recovered. Cumulative lost person-work days were calculated for all six scenarios and the base condition. The change in productivity was calculated based on the percentage change in cumulative lost person-work days in each recovery scenario in comparison to the base recovery condition.

After Hurricane Sandy, the New York transit network was completely disrupted for two days and some subsystems took over a week to recover. The recovery of NJ Transit and Path rail took longer. These disruptions affected almost 70 percent of the agents modeled (recall, agents not affected by any disruptions were not included to save computation time). Therefore, three out of six recovery scenarios focused on the recovery of the metropolitan area's subway and rail system. In the first, all subway/rail systems recovered one day earlier. In the second, the NJ rail/subway network recovered at the same rate as the NY rail/subway network, while in the last one, the NY rail/subway network recovered at the same rate as the NJ rail/subway network. The first two scenarios were the first and third most effective in promoting productivity by 12.2 and 5.1 percent, respectively while the last one was the worst scenario that decreased productivity by 49 percent compared to base recovery condition.

After the disruption, an increase in teleworking could partially offset the decreased ability for physical movement. By teleworking, people can be productive while avoiding delays and crowding and struggling with a disrupted transportation network, but this requires the availability of power and communication networks. The scenario that recovered power one day earlier and, therefore, allowed teleworking increased productivity by 6.7 percent compared to the base recovery condition. This represents a less dramatic improvement than earlier subway/rail recovery because not everyone faced power outages and teleworking is not applicable to all jobs, making the improvement applicable to a smaller agent population group. However, the productivity increase still contributes to a faster recovery, suggesting that coordination among infrastructures (as well as greater broadband coverage and cooperation of employers allowing telecommuting) could be beneficial for returning different population segments (e.g., income groups, geography) to productivity faster as discussed below.

It is important to consider users' preferences and needs while planning for recovery. Humans are adaptive and many factors can change their behaviors and reactions. For example, the recovery process for working parents is not the same as families without children. Childcare responsibilities may cause household members to cancel their work trips even if the transportation system has completely recovered, so the other recovery scenario examined the effect of school and daycare closure on recovery. Earlier recovery of these systems promoted productivity by 4.1 percent compared to the base recovery condition. While constituting only the fourth best scenario in terms of improvement across the entire population, it has greater importance for lower-income segments of the population.

Closure of tunnels and carpool restrictions affected commuting patterns after Hurricane Sandy, but the effect was not as great as subway/rail disruption in this study because there were some open bridges that agents could use by changing routes. However, people who did not want to change routes could change modes, telework, or not work that day. In another scenario, all tunnels were opened one day earlier and carpool restrictions started and ended one day earlier. In this scenario, productivity increased by 1.4 percent compared to the base condition.

The above-mentioned percentages show the effectiveness of different recovery scenarios compared to the base recovery condition for the whole population; however, the best recovery situations for the population as a whole are not necessarily the best for each population subgroup. For example, differences exist by income level. In households with more than $200,000 in annual income, power restoration is the most effective scenario, while in households with annual income below $25,000, power restoration is the third most effective scenario after subway recovery and daycare/school recovery scenarios. Effectiveness of recovery scenarios can also differ based on geographic location and extent of disruption in that area. For instance, some NJ residents depend on the NJ transit/rail system for commuting to work and the NJ transit/rail system was disrupted greatly after Hurricane Sandy. Therefore, for NJ residents the most effective scenario is the one involving a quicker NJ rail/subway system recovery. In Staten Island, recovering tunnel and bridges earlier was the most effective scenario because of reliance on the Hugh L. Carey tunnel for commuting from Staten Island to Manhattan. Effectiveness of power recovery depends on the magnitude of power outages in different locations. For example, on Long Island, earlier power recovery was the most effective scenario because of a high percentage of power outages, while in Queens, the Bronx, and Kings, power recovery was not as effective because of lower percentages of the outage.

The geographic and socio-demographic differences that arise in recovery options highlight the political calculus in deciding among efficiency and equity objectives and among different parts of a metro region. For example, a focus on power restoration at the expense of transport recovery would support residential customers across the region, but particularly benefit those able to telecommute, typically a higher-income group (Lister and Harnish 2011, Kossek and Lautsch

2017). In contrast, lower-income households have less access to telecommuting options and also depend more on the reopening of schools and child care to allow parents to return to work.

Similarly, recovery priorities also may face a tradeoff between actions that maximize aggregate, society-wide benefits and benefits to individual decision-making units or geographic areas, particularly if the incidence of costs differs from that of benefits. For example, in this study, most of the scenarios changed the recovery timeline uniformly by one day. Accelerated transport recovery could come at an additional cost (e.g., from additional crews working overtime or more rapid parts delivery) and different decision agents may weigh these higher costs differently depending on whether the productivity gains associated with them accrue to the area for which the agent takes responsibility (New York State vs. New York City vs. New Jersey State vs. a private firm, for instance). Possible prepositioning of materials and restoration crews mobilized from neighboring areas, which have costs and potential productivity gains that may be spatially concentrated, face a similar dynamic.

Our reluctance to make more dramatic changes in the recovery scenarios reflects an acknowledgement that recovery can be politically charged and complex, with infrastructure systems that are interdependent. For instance, without power, it was difficult to pump out water from tunnels and begin restoration activities (Bloomberg 2013). On the other hand, this subway system was 108 years old and had unique parts that required extensive time and cost to replace (Kaufman, Qing et al. 2012). Hurricane Sandy caused damage to power system generation, transmission, and distribution that was spatially uneven across the metropolitan area. As a system, there has to be recovery coordination, activity sequencing, and prioritization of specific areas.

5. Limitations and Future Research Directions

This ABM is one of the first to allow examination of post-disaster commuter adaptation during a rapid and dynamic recovery process. This ABM was developed for the NYC metropolitan area, which has the largest transit usage of any city in the US. The behavior models would need to be adjusted prior to applying the ABM to a different location. To save computation time, this study also omitted agents not encountering disruptions and did not involve detailed traffic simulation. Future efforts could remove these limitations to quantify delays and more thoroughly explore the effects of delay on adaptation.

A handful of additional avenues for further investigation and improvements exist. First, a larger sample size and more comprehensive survey that yields higher resolution spatial coordinates of home and work locations could allow for a more robust representation of commuter behavior and decision framework across space. Second, more streams of information on delay and crowding could be fed into the decision process for the beginning of each day. Third, the dependencies of the transit system on power could be better captured in the scenarios. Fourth, transportation service providers, utility decision-makers, and other infrastructure providers could be added as new types of agents, responsive to the public and responding to lost work days. Fifth, the distribution of outages and recovery across space and different subpopulations (*e.g.,* income groups) warrants considerably more attention. All of these extensions will enhance the utility of the ABM.

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