Coordinating Epidemic Control and Economic Support Policies in Cities: An Agent-Based Analysis of Unintended Urban Market Restructuring

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Abstract: This paper looks at urban policy co-ordination and market restructuring under epidemic shocks. Specifically, it explores the trade-offs between public health policy for mitigating epidemics and economic support in cities. While public health policy is geared towards minimizing mobility and interaction, economic support aims to stimulate circulation and contact. The paper contributes to urban policy research by showing how epidemic-control measures and economic-support instruments, when designed without cross-market coordination, can produce enduring and unintended restructuring across urban business, labor, and housing systems. Methodologically, the paper links an epidemiological module to a multi-market urban agent-based model in order to trace cascading interactions across sub-markets at the intra-urban scale. Using the city of Beer Sheba, Israel as a case study, it demonstrates that some support measures, especially business-oriented subsidies, may stabilize short-term activity while intensifying longer-run commercial fragmentation, labor-market contraction, and housing pressure. The urban implications of these findings are discussed.

Keywords: policy analysis, epidemic control, economic support, spatially-explicit agent based modelling, urban market restructuring

Code: The Matlab simulation code used in this paper is available at:
https://github.com/rom1kp/b7ABM-matlab

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1. Introduction

This paper examines the urban consequences of unsynchronized policies. It shows how epidemic control and economic support interventions can reorganize the structure of commercial activity, labor and housing demand and mobility in the city, in ways that are spatially and sectorally interdependent. The Covid pandemic that began in March 2020, generated local urban crises as much as global emergency conditions and highlighted the paradoxical symbiosis between epidemic control measures that restrict mobility and interaction and economic interventions that stimulate activity through contact and circulation. Hitherto these had been considered discrete policy instruments. While much attention has been devoted to the direct effects of these mitigation mechanisms and to measuring the economic costs of lockdowns (Akinwande et al 2025, Fan et al 2022, Wu et al 2023, Zhang et al 2022), their unintended effects on the long-term restructuring of urban markets has been less investigated.

To simulate urban policy coordination under conditions of market restructuring, we employ agent based modeling (ABM). This unravels the web of interactions across closely linked markets as a public health shock creates cascading effects across multiple sub-markets in the city. For example, the effect of an epidemic on labor supply may influence household income, which in turn will affect housing demand and consumption patterns. Business closures will affect employment which alters migration and housing stability. Policy measures aimed at one domain (e.g., lockdowns or wage subsidies) will ripple through connected markets. The ABM capacity to model these cross-market feedbacks makes it especially appropriate for analyzing market restructuring in cities and for producing rich information about cross-market and cascading effects. It disaggregates complex systems (like cities) into their atomic units, i.e. 'agents'. These units are autonomous, independent and pro-active with clearly defined goals, behavioral rules and sensing abilities for deriving information from their environment (Crooks et al 2019). In the advent of epidemic-generated shocks, ABMs have been used to simulate contagion processes (Cuevas 2020, Kerr et al 2021, Grinberger and Felsenstein 2023). However, they have not been fully exploited to deal with the re-organization of urban markets (O'Sullivan et al 2020, Choi and Hohl 2025).

To show how epidemic-control measures and economic-support instruments designed without cross-market co-ordination can produce unintended restructuring across urban systems, we use the city of Beer Sheba, Israel as a study site. We harness a multi-market, spatially-explicit ABM as the modeling framework and addresses three leading research questions pertinent to cities engaged in post-shock reorganization:

- How do epidemic-control and economic-support interventions interact across urban sub-markets?
- Which epidemic-control and economic-support interventions preserve health outcomes with the lowest level of urban system disruption?
- Under what conditions do support measures intensify restructuring rather than stabilize the city?

The paper proceeds as follows. The next section addresses the research gap in the area of policy co-ordination and urban restructuring. Section 3 presents the case study area and data while Section 4 details the modeling framework. The results are presented in Section 5 and their policy implications discussed in Section 6. Some take-home messages and suggestions for future work are presented in the Conclusions.

2. Literature Review and Research Gap

The urban economic costs of pandemic containment measures such as lockdowns, have been well documented. Studies highlight their limited effectiveness and (generally negative) direct impact on household social welfare and economic activity (Aum, Lee and Shin 2021, Deb et al 2020). Other work emphasizes their indirect effects such as business sector revenue contraction in secondary sectors such as commerce, tourism and recreation (Che et al 2023, Skare et al 2021). Attempts by urban governments to mitigate competing policy dissonance via interventions that bolster business sector resilience given the constraining effect of pandemic containment, have also attracted attention. (Bennedsen et al 2020, Rothert et al 2024, Zhang et al 2022). It should be noted however, that while this form of policy non-coordination characterizes pandemic containment (Paul et al 2024), it is also a feature of many other areas of spatial public regulation such as land use planning (Moroni 2012), disaster recovery (Henkel et al 2022) and regional development efforts (Bourdin et al 2025).

While the direct and indirect economic costs of pandemics are well documented (Fan et al 2022), a research gap exists with respect to some of the more subtle urban consequences of epidemiological shocks combining with support policies. The first of these relates to policy coordination and crisis governance. Recent work has highlighted the fragmented policy response of cities when faced with multiple shocks such as pandemic combined with war and concomitant demographic change (Kajdanek and Radzimski 2025). Other studies have looked at the combined shock effects of epidemic control with a housing affordability crisis and a reshaping of residential preferences (Jiao et al 2024, Shin et al 2025). Again, policy response has been uncoordinated and ad hoc as cities struggle to respond to heterogeneous employment and income shocks (Dreesen and Heylen 2023).

ABMs have been proven to be an efficient tool in studying urban epidemiological patterns (O'Sullivan et al 2020, Rothert et al 2020). Pandemic trajectories emanate from mobility patterns which in turn are derived from urban structure. Policy reacts to this by constraining mobility. While intra-urban mobility data is rather limited, the high-resolution intra-urban simulation capacity of an ABM mitigates the obstacles of working in a data-poor environment. A research gap however exists relating to the way urban structure shapes epidemic and (economic) recovery dynamics (Zhang et al 2022). This necessitates an intra-urban simulation capacity generally at the neighborhood or census tract levels. Recent advances have shown how the use of scaling and synthetic data can contribute to understanding the role of urban structure in fashioning urban recovery from shocks by allowing for heterogeneity in mobility-behavior adaptation (Peng and Liu 2024, 2026). In turn, this highlights the non-linear nature of urban recovery dynamics where small changes in initial conditions can expand into unanticipated outcomes. Empirically, neighborhood-level simulation has shown how heterogeneous mobility behavior can be modeled under different pandemic shock scenarios (Peng et al 2023). However, this is achieved on the basis of rigid behavioral assumptions relating to individual-level mobility decisions based on perceptions of costs, benefits and exposure to mobility choices.

The approach presented below charts new territory in simulating post-shock urban policy co-ordination and in explicitly addressing the role of intra-urban heterogeneity and mobility-behavior adaptation. To this end, we simulate a reduced representation of the city of Beer Sheba utilizing an exploratory policy ABM as described below.

3. Study Area and Data Sources

We implement an ABM for the city of Beer Sheba, Israel's fourth largest metropolitan area after Tel Aviv, Jerusalem, and Haifa. The city has 220,000 residents and provides services to around 750,000 residents across the northern Negev region. Nearly 50% of residents are under the age of 40, making it one of the youngest cities in Israel (City of Beer Sheba 2025).

We use Survey of Israel (SoI) building data from 2021 which includes 13,700 buildings, 90% of which are residential and 3% commercial. The city of Beer Sheba includes 59 census tracts (Statistical Areas-SA's), of which our model relates to 30 SAs representing the city's main neighborhoods (Figure 1). The reduction in SA's improves computation times and focusses the simulation effects. The SAs in Figure 1 comprise about 4,900 buildings and

100,000 synthetic residents. The implication is that our simulation world consists of only one settlement which is a reduced representation of the city of Beer Sheba rather than the full metropolitan system. Consequently, while intra-city mobility is considered, inter-urban mobility is deemed outside the purview of the simulation.

The primary data entities used in the model are households, agents (i.e. individual residents of the city), residential assets, buildings and jobs. Appendix 1 describes the characteristic variables used to operationalize these entities and their value ranges. The simulation model requires detailed urban data on agents, assets, and workplaces. As the highest spatial resolution at which socio-economic data are available in Israel is the SA, we use a spatial allocation procedure which disaggregates tract-level data to generate a synthetic agent population assigned to residential buildings (Section 4.5 below). While at the individual level,

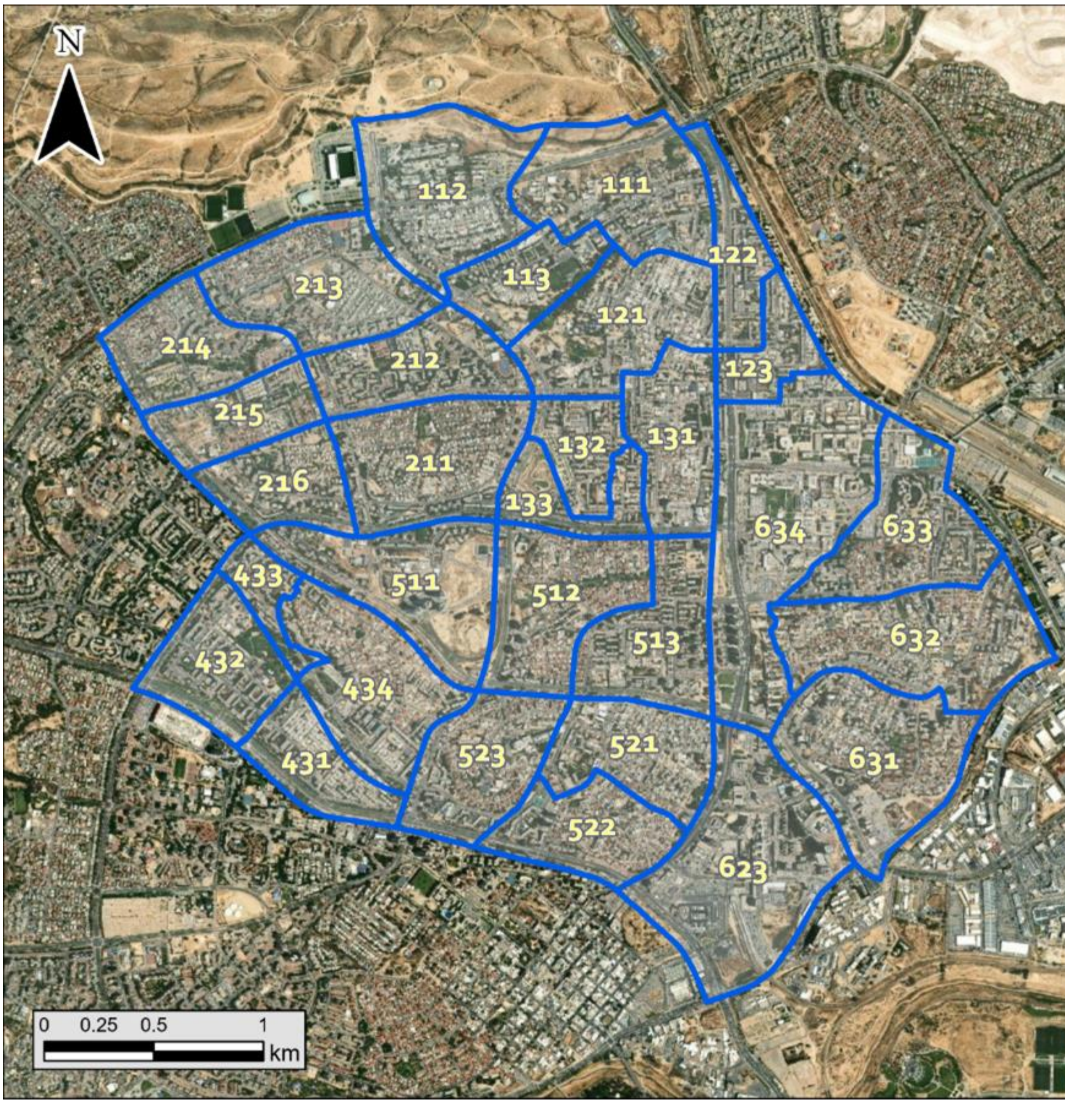

Fig 1: Case Study Area: 30 Statistical Areas in the city of Beersheba

the representation is not necessarily accurate, the entire population recreates SA totals. This kind of allocation procedure is increasingly used in spatially-explicit ABMs (Peng and Liu 2026). Our implementation utilizes the above buildings dataset along with SoI 2021 asset data identification codes that are linked to real-estate transaction data collected by the Israeli Tax Authority, for the years 2008-2021.

We simulate 8 policy scenarios for the city in the wake of a Covid-19 outbreak: a combination of two epidemic control policies (no intervention and full lockdown) and four economic policies (no intervention, business wage subsidy only, household cash transfer only and both economic support policies together; see Section 4.4 below). Additionally, we simulate a no-epidemic scenario as a baseline, showing the urban development trajectory under business-as-usual. The hands-off (no-epidemic control, no economic support) scenario is used to identify the effect of the epidemic by itself and to gauge the impact of policy decisions.

4. Modeling Framework

4.1 Urban System Architecture

The structure of the modeling system is depicted in Figure 2. The model simulates an urban system comprising three basic markets: housing, labor and the business sector. These are subject to policy stimuli in terms of household support and business support instruments. Model outputs relate to number of businesses, their revenues and expenditure and attributes of the housing and labor markets. This urban module is augmented by an epidemiological module, itself subject to mitigation policies (Grinberger and Felsenstein 2023). Outputs here relate to numbers of infected, quarantined and hospitalized agents and their relevance to urban economic performance in terms of labor supply and business survival.

Agents represent the smallest unit that can exert an impact on the system, even if the impact is local and temporary. In the case of cities, contagion patterns and markets such as the labor market, the smallest unit is the individual resident. In the housing market context, the relevant unit is the household and individual agents are therefore grouped into households that collectively make housing decisions. In the business sector, the relevant unit is the individual firm or business. This is represented in the model by the commercial building which is essentially a quasi-agent. This conceptual simplification means we can replace specifying the firms' profit function with the volume of building level visits in order to represent business sector demand (see Section 4.3 for further elaboration)

Businesses differ from residents and households in terms of their mobility. While relocation is a rare event for a business, individuals move as part of their daily routine.

Businesses however also possess the traits typical of an agent, i.e. the ability to proactively make decisions. The model assumes that the system includes five main land-use types – empty, residential, commercial, industrial, and public. It further assumes that each commercial building houses a single business, meaning that a business is represented in the model as a single commercial building and the jobs assigned to it. The actions of the different agent classes feed into the three aforementioned markets (Figure 2). The sections below describe the model's dynamics conceptually. Formal dynamics are articulated in Appendices A3.1-A3.6 where the equation listing for the supply and demand schedules for each of the sub-markets in the simulation model are presented in detail.

4.2 The Simulation as a System

The sequence of cascading effects begins in the epidemiological sub-model where contagion processes affect consumption patterns (Section 4.4). This impact is accentuated when epidemic-control policy mandates a total cessation of non-residential activities upon the expansion of contagion. This immediately disrupts demand in the business sector demand side, through the restriction of agents' daily routines. Since business revenue in the model is proxied by volume of visits, the sudden absence of traffic causes a sharp decline in potential profitability. Commercial collapse directly impacts the labor market, shifting the crisis from a public health issue to an economic one as firms are forced to shed staff to reduce their wage bills and if the effect is substantial, to close down. This results in a significant drop in demand for labor which in turn triggers a city-wide downward pressure on salaries. For the individual agent, the loss of employment initiates a search for work. However, the systemic lack of available jobs due to layoffs and business closures increases the duration of unemployment, exponentially raising the probability that an agent will drop out of the workforce entirely.

The feedback loop eventually reaches the housing market (Section 4.3) where the economic strain on households begins to alter the city's residential landscape. As household incomes drop due to unemployment, their ability to afford rent is compromised. Simultaneously neighborhood-level housing values begin to fluctuate as local service levels decline and vacancy rates rise due to business closures. These financial pressures force households looking to relocate to move away from their home neighborhood, sometimes leaving the simulation world entirely, and affects in-migration patterns.

These changes are however not deterministic nor global. The geographic specificities of residence and workplace change, leading to new intra-urban mobility driven by changes in consumption and providing opportunities for businesses to emerge in new places. This drives up service levels and hence house values, creating new constraints for relocation and in-migration. New businesses also mean new jobs, animating an increase in demand for labor and hence an increase in income and willingness to pay[1].

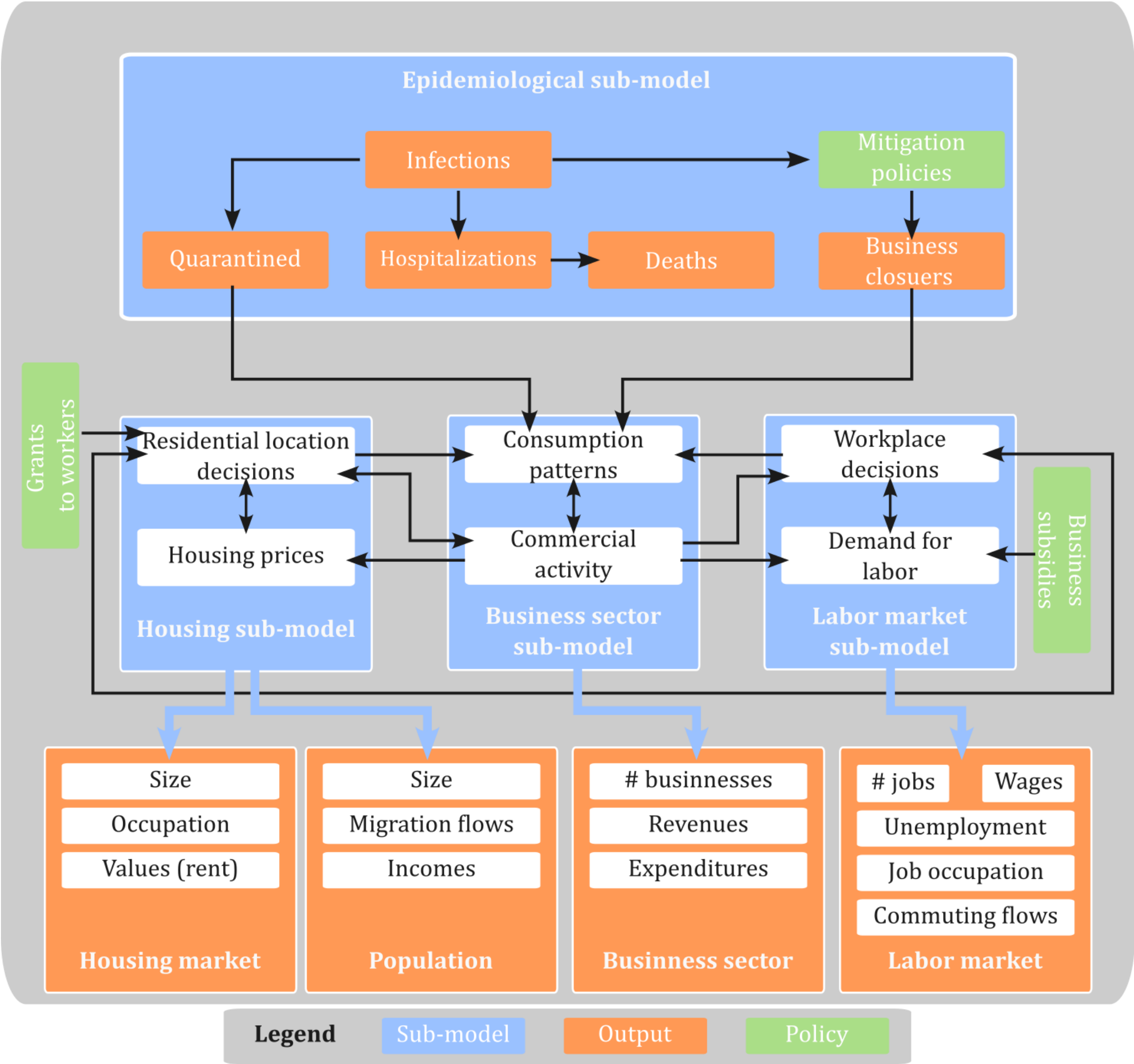

Figure 2. The policy simulation model

[1] Note that given the agent behavior and interactions driving the model, equilibrium is not defined as a closed-form analytical solution (ie a Walrasian equilibrium with market clearing). Rather it is emergent, stochastic, and generated by decentralized agent interactions and not simultaneous market-clearing conditions. In this dynamic, steady-state world, house prices, employment rates, wages, business composition, population distribution and infection levels remain statistically stationary over time because no endogenous behavioral mechanism produces systematic net change in any market. Housing rents, employment rates, wage levels, business

Whatever direction these cyclical and geographic (local) impacts take, they lead to the destabilization of the system. To mitigate this systemic effect, economic policy interventions are designed to target specific destabilization points within these interactions (Section 4.3). Business wage subsidies aim to bolster business profitability by financing the lowest-paying jobs. This prevents mass layoffs that would otherwise flood the labor market. Concurrently, household cash injections provide a buffer that allows relocating and in-migrating households to find suitable housing solutions despite the temporary loss of wages. By stabilizing these economic variables, the policy interventions attempt to preserve the urban structure until the epidemiological module indicates that the reproduction rate has stabilized, allowing for a phased return to normal daily routines.

4.3 Housing, Business and Labor Market Sub-Models

The simulation begins with the *housing market*, where the primary actors are households represented by clusters of individual agents sharing a residence. The behavior of a household is dictated by the combined attributes of its members, particularly their total income and average age. Every day within the simulation, households evaluate their living situation through a three-stage probabilistic sequence. They first consider relocating within their current neighborhood, then look at other neighborhoods, and finally consider moving to a different city entirely. The selection of a new home involves a scoring system where households rank potential areas based on proximity to work and demographic preferences, such as the age and income profile of the neighborhood, as defined in Appendix. A3.1. Once an area is selected, the household randomly selects one of the available assets (dwellings) it can afford, based on rents (Appendix. A3.2,), household income, and the willingness to pay parameter value. In case no such asset exists in the area, the household extends its search to the next level, i.e. to other neighborhoods or cities. This process also considers empty buildings, even if initially non-residential. In case an empty building is chosen, it becomes residential and new jobs are generated according to the jobs per sq. meter value for residential land uses. If a household fails to find a suitable home across the entire simulated world, it is removed from the system.

On the supply side, housing is treated as a "trickle-down" system (Emmi and Magnusson 1994). Neighborhood-level residential values per sqm fluctuate based on changes in population and local services (Appendix. A3.2). Values increase when demand (population

composition, and population distribution do not exhibit systematic upward or downward trends and random fluctuations may persist.

size, number of businesses) increase, or when housing supply decreases. This subsequently scales the value of individual buildings, based on whether their local accessibility to services is above or below the neighborhood total. Finally, the specific monthly rent for an apartment is calculated by balancing the household's willingness to pay against the standardized value of building floor space (App. A3.2).

The *business sector* operates through a similar interplay of supply and demand. Demand is generated by the daily routines of agents represented by the sequence of buildings they visit each day. The number of activities an agent performs each day, i.e. number of visited buildings, is calculated based on their employment status, age, and mobility constraints like disability or car ownership level (Appendix. A3.3). Agents choose where to go next in their routine by scoring neighborhoods and specific buildings based on distance from current location and the "attractiveness" of the destination, which is a function of building size and existing use (Appendix. A3.3). Agent routines are stable, unless the agent moves or changes employment status.

Because the model does not track monetary transactions, business "revenue" is represented by the volume of visits a building receives. The model generates building-level visit volumes from locations visited under agent routines and commercial buildings are considered business quasi-agents. Using this conceptualization, we do not need a fully articulated profit function for firms. Rather, they follow a reduced-form behavioral adjustment rule based on sustained local demand, proxied by a rolling average visit intensity. The model therefore does not include explicit firm profit and uses the rolling 30-day average of local visits as a proxy for business sector demand.

Business health is measured by its "potential profitability," which compares the percentile of its visits against the percentile of the wages it must pay (Appendix. A3.4). If profitability drops too low, the business will shed staff, or close entirely if its total workforce falls below half of its capacity. In this instance, the commercial asset converts into an empty building and the status of the agents it employed converts to unemployed. High potential profitability in a residential or empty building can trigger a commercial takeover, leading to the eviction of residents to make room for new jobs. Some of these can be occupied by in-commuters and the extent to this process is determined probabilistically based on in-commuting probabilities.

In the *labor market* sub-model, job availability is determined by the floor space and land-use type of city buildings, as well as by business response to changing economic conditions, as described above. The economic environment is highly sensitive to the "Occupied

Jobs Ratio" (Appendix. A3.5) which tracks the percentage of available positions that are filled. This ratio drives the "Wage Change Ratio" meaning wages rise when labor is scarce and fall (down to a set minimum) when unemployment is high. On the supply side, unemployed agents search for work by scoring available jobs based on how well the salary matches their expectations and how far they must commute (Appendix. A3.6). If an agent remains unemployed for an extended period, the psychological and financial strain is modeled as a "Drop-out Probability", where the likelihood of the agent giving up or opting for commuting outside of the simulated world increases exponentially over time.

4.4 Epidemiological Sub-model and Policy Triggers

The epidemiological module introduces a biological layer to the above urban mechanics. Sixty days into the simulation, a virus is introduced to a small group of agents. The disease spreads when a susceptible agent and an infectious agent visit the same building. The probability of transmission involves the susceptibility of the host's age group, the current infectiousness of the spreader based on how long they have been sick, and a social interaction factor that assumes people with similar demographics are more likely to interact closely (Appendix.A3.7). This process is based on generic parameters related to epidemic contagion in the case of first-wave Covid19 (Appendix A2). It is also adjusted for the form and spatio-temporal resolution of our ABM which does not model intra-building movements.

Newly infected agents remain unaware of their status for the first week, continuing to spread the virus until they and their entire household are forced into a 14-day home quarantine. This means that their routine is reduced to include their home building only. Quarantined agents may become infected but still be undiagnosed when released back to perform their daily routines. The model tracks the progression from infection to recovery, hospitalization, or death.

The policy triggers are represented foremost by a lockdown that is activated automatically if the 'Effective Reproduction Rate', i.e. the average number of people to whom an infected person will transmit the virus, rises above 1.0 (Appendix. A3.7). This stylized policy rule means that a lockdown halts non-residential activities, which immediately impacts routines and hence business profitability and employment[2]. To counter this, the model includes economic policy triggers. These are exemplified by a business wage subsidy that covers the cost of a business's lowest-paying jobs and a household cash transfer of 750 NIS directly to

[2] Routines change in that agents do not visit buildings that are closed down

household incomes. Together these are envisaged as helping stabilize the housing and labor markets during and after the health crisis.

4.5 Initialization, Calibration and Validation

Initialization: the spatial allocation procedure follows three broad stages (Lichter et al 2015): extracting the external (real world) spatial data for buildings and assets; creating synthetic households and agents and creating synthetic workplaces. Note that many of the calculated allocation steps use normal distribution functions or random values to incorporate uncertainty and natural variability into the process. This probabilistic approach prevents rigid, deterministic allocations and enhances the robustness of the model by better reflecting real world heterogeneity. A single set of agents is generated and used in all simulations, for the sake of comparability.

The first stage uses real-world real estate transactions data to produce housing values, converts detailed land use categories into the general types considered in the model, and creates synthetic asset records. These create mean house values for each SA, based on building footprint area and considering floor height as 4 meters and minimum asset area as above 30 meters. In the second stage, household structures are generated based on SA-level probabilities, derived from Central Bureau of Statistics data on the distribution of household sizes and number of households by number of children per SA (Appendix. A2). Along with these, household characteristics are drawn based on data regarding the presence of disabled members, car ownership rates, and distribution of household incomes by socioeconomic percentile. To assign households to residential assets, we use household incomes, asset prices, and distances to the city center to compute utilities offered by each asset in relation to each household. These are formalized in Appendix. A3.8.

Finally, workplaces are generated, and agents are assigned to them. This entails first generating jobs in each building based on the jobs per square meter (job density) parameter, derived for each land use. Some jobs start off as occupied by an in-commuting non-agent, determined probabilistically by the in-commuting probability parameter value. Agents are distributed to each available job based on the census tract they live in and commuting probabilities, derived from a commuting matrix describing the share of residents in every metropolitan region in the simulation world. This matrix includes the probability to commute outside of the world, and hence an agent may probabilistically choose to commute out. The procedure is done iteratively, one agent at a time, until either all agents participating in the workforce are employed or all jobs are occupied. In the case of the former, the remaining jobs continue to be unoccupied. In the case of the latter, the remaining agents' work status is set to unemployed. Finally, the wages of occupied jobs are set to be equivalent to the occupying agents' income. Wages for unoccupied jobs are drawn based on the mean income and standard deviation neighborhood values.

Validation: the results of a validity check for the synthetic population are presented in Appendix A4. As can be seen, in most cases, the allocation procedure reproduces SA-level totals for key variables such as household size, age, income group, disabilities, car ownership etc, at a high level of accuracy. Correlation coefficients are generally >0.7 and the error indicators (MAE and RSME) all report low margins. The few cases where the allocation model does not perform satisfactorily (eg percentage households with children/elderly, percentage in labor force), can be ascribed to lack of synchronization between model categories and source-data categories.

Epidemiological plausibility: note that the epidemiological module is stylized rather than predictive and is therefore validated against stylized empirical regularities. These are presented in Appendix A6. In general, these are derived from the empirical literature (eg Roimi et al. 2021) and institutional benchmark values used for pandemic contagion (eg CDC 2021). We test against a large range of values for epidemiological variables such as probabilities of infection, hospitalization and mortality (see Appendix A5).

Baseline Urban Validity: this is important as the no-epidemic system needs to stabilize in a reasonable stationary range before the shock. The contagion process starts on day 90 and the economic models activate after 30 days. Sixty days are therefore needed to stabilize the model. Baseline stability is evaluated over the pre-contagion interval, i.e. between the start of economic stabilization at day 30 and the introduction of contagion at day 90. Stability is assessed by identifying the first day for which each main urban-economic indicator remains within ±1% of its day-90 value.

Table 1 shows that most of the model variables and scenarios experience the earliest stable first day around day 34 for most metrics and scenarios. In contrast the latest stabilization day for most variables shows more variation and ranges from days 34-57 and from days 47-57 for all scenarios. Note that the idle workforce ratio is listed but excluded from the system-level stabilization day because its absolute values are near zero and relative changes are therefore misleading. In sum, while the first 90 days are not numerically identical across the variables and scenarios, the stabilization pattern is consistent across scenarios. The economic system begins stabilizing after day 30 and reaches a narrow pre-contagion stationary range before day

90. The system therefore reaches a stable pre-contagion urban-economic state more than 30 days before the epidemiological shock begins.

	Earliest first stable day	**Latest first stable day**
Variable		
Households / occupied assets	47	57
Residential stock	34	34
Service / commercial buildings	34	34
Workplaces / jobs	36	48
Mean wage	34	44
Mean housing price / rent	36	40
Jobs occupancy ratio	34	34
Idle workforce ratio	89	90
Business outcome	37	41
Scenario		
No epidemic baseline	34	57
Lockdown + household subsidy	34	48
No lockdown + household subsidy	34	47
Lockdown + both subsidies	34	48
No lockdown + both subsidies	34	48
No lockdown + business subsidy	34	48

Table 1: Stability-Variables and Scenarios

5. Results

5.1 Epidemiological Outcomes

The epidemiological module produces multiple simulated public health measures for the city over time: the daily and total number of infections, hospitalizations, and quarantines, along with the active number of infections, hospitalizations, and quarantines. Figure 3 presents a representative sample of these. We present epidemiological outcomes with both public health and economic policy measures and without them. All epidemiological outcomes display the same general picture of a rapid increase when no lockdown is enforced, regardless of government assistance, which peaks after about 20-40 days (depending on the measure) and is followed by an equally rapid decline.

Under the lockdown scenarios, the increase is much less sharp. The peak in infections appears later and is much lower, and the epidemic continues for a longer duration. Interestingly, the peak and the duration for daily hospitalizations and deaths are not affected, while the absolute numbers decrease. This is because lockdowns act on exposure while hospitalization and death are downstream states governed by fixed rules and age-based probabilities. A lockdown therefore reduces how many cases reach those states. Some measures, e.g. daily infections and quarantines, show a double-peak pattern, suggesting that the delay in contagion caused by the lockdown allows it to potentially exist for longer periods than in the no-lockdown scenarios. Under these scenarios, it seems that 'herd immunity' is reached quickly but with a greater burden on the health system and with a higher death toll. This all fits well with general epidemiological knowledge and with trends observed during the Covid-19 pandemic (Arbel et al 2024).

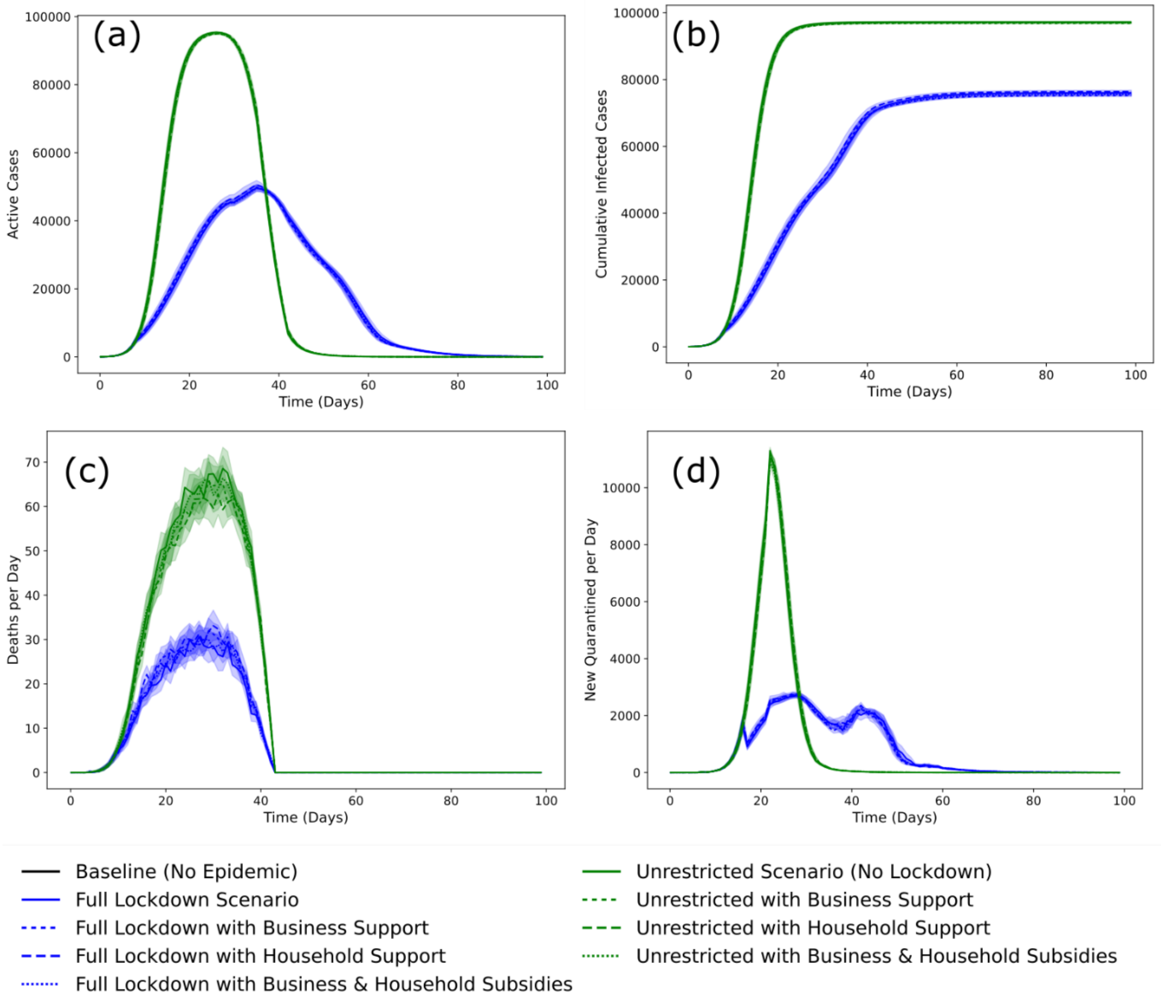

Figure 3. (a) Active infections, (b) total infected, (c) daily deaths, and (d) quarantined over time, by public health and economic policy scenarios.

5.2 Business and Labor Restructuring

The trajectories of the no support and the household, business and combined support policies observed under the lockdown scenarios are also prominent when the long-term impacts on the business sector are observed (Figure 4). However a more striking outcome is that under most scenarios and in relation to the no-epidemic baseline, the epidemic leads to a major disruption of the business sector derailing its pre-epidemic development path and leading to economic restructuring over the longer term. This reorganization is characterized by an increased number of businesses (Figure 4b), paying on average less wages (Figure 4a) and offering less jobs (Figure 4d). The income of residents however tends to increase under most scenarios, although it is questionable whether this produces significant differences from the baseline scenario (Figure 4c). Most of the change happens within the first 120 days of the simulation, after which a steady state emerges or, in the case of income, a clear development pattern emerges.

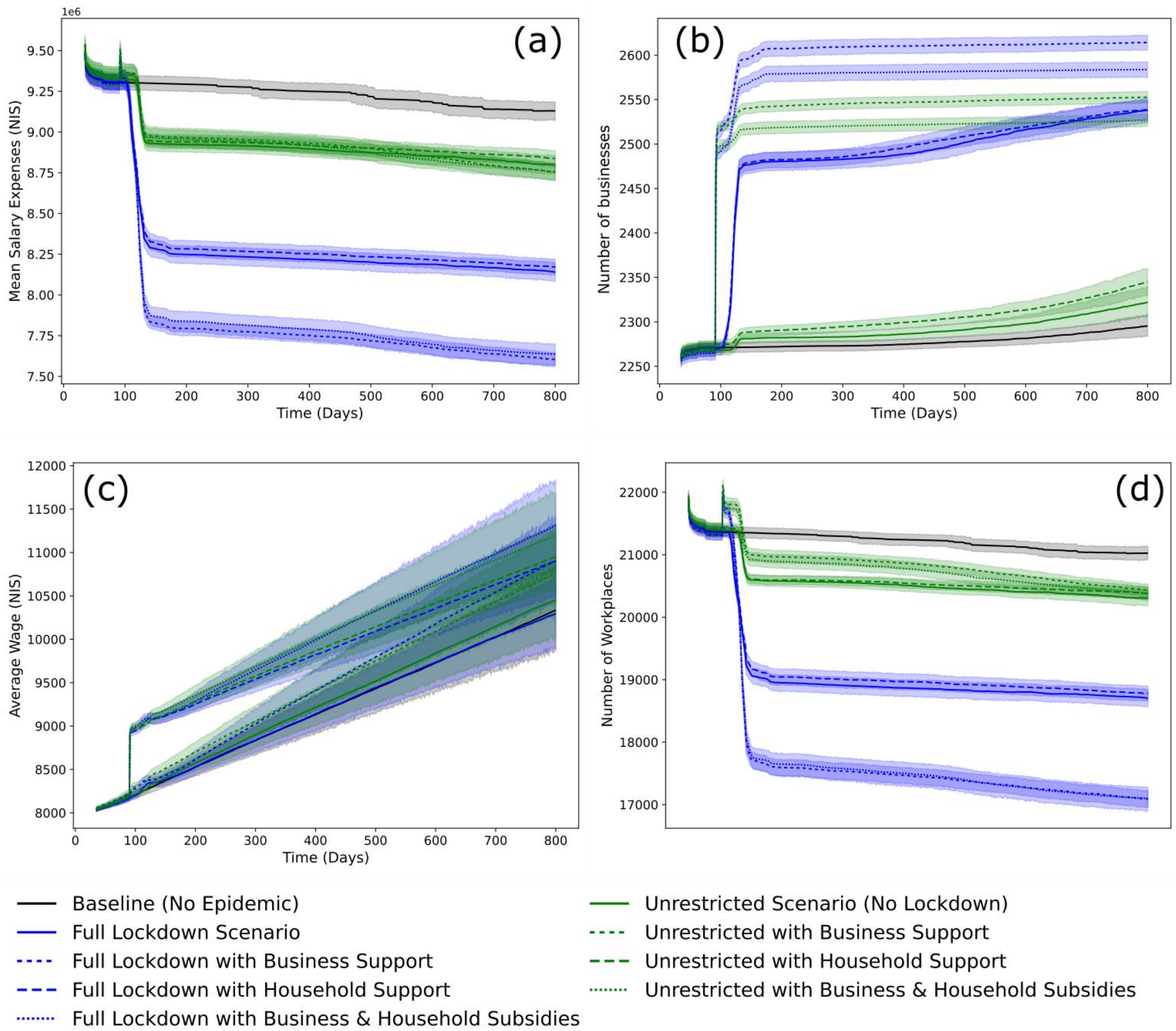

Figure 4. Change in (a) mean wage per business, (b) number of businesses, (c) mean income, and (d) number of jobs over time, by epidemiological and support scenario.

This overall trend is true for most scenarios with the exact extent of impact varying across the scenarios. Lockdown has a long-term disrupting impact on the business sector, showing a significant increase in number of businesses (mean change ranging from 1929 to 2005 across scenarios). In contrast, the no-lockdown scenarios do not surpass 1943 (Table 2). A lockdown also depresses wages and number of workplaces with the change in total wage bill ranging from -106.25 to -123.71 NIS M with lockdown and from -86.62 to -89.69 NIS M without. Similarly, the change in number of workplaces ranges from -2502 to -4189 with lockdown and from -851 to -973 without (Table 3), regardless of the type of the economic intervention policy.

This does not mean however that economic support policies have no impact. Business wage subsidies clearly do have an effect whether alone or combined with household cash transfers. This is not necessarily an impact that aligns with policy objectives as the impact only increases when these policies are in place. Income is unique in that it shows an increase relative to the baseline scenario, regardless of the type of support, with the most pronounced impact in the combined support scenario (Table 2).

Scenario		Number of businesses	Number of workplaces	Total wage bill (NIS M)	Avg. agent income (NIS)
Baseline		1686.27 (34.00)	-255.04 (305.95)	-77.90 (4.46)	3069.65 (1362.98)
No Lockdown	No support	1713.00 (47.48)	-973.33 (347.91)	-87.71 (4.87)	3188.28 (1286.86)
	Household subsidies	1735.63 (42.07)	-896.07 (276.31)	-86.62 (4.01)	3691.30 (1046.64)
	Business subsidies	1943.70 (18.32)	-851.87 (284.04)	-89.69 (4.43)	3490.26 (1383.48)
	Both subsidies	1917.87 (19.64)	-904.13 (302.50)	-89.39 (4.59)	3933.10 (1392.70)
Lockdown	No support	1929.03 (38.05)	-2573.87 (390.83)	-107.39 (4.98)	3031.52 (1131.82)
	Household subsidies	1929.77 (30.13)	-2502.17 (335.21)	-106.25 (4.33)	3641.96 (1161.85)
	Business subsidies	2005.27 (23.52)	-4189.73 (376.56)	-123.71 (3.77)	3641.36 (1416.40)
	Both subsidies	1974.80 (24.38)	-4180.33 (538.81)	-122.67 (5.95)	4052.17 (1482.78)

Table 2. Mean (and standard deviation) change per in values of business-related outcome variables, by scenario. NIS= New Israeli Shekels

This seemingly points to lockdowns as the culprit in the derailment of the business sector. Yet some of the results in Figure 5 point to the very appearance of the epidemic as the cause, even when no lockdown is instituted. The outcome may result in significant change in the various indicators contingent upon the support policy. This is true for the number of businesses when business wage subsidies (with or without household support) result in a larger volume of businesses (comprising 1943 and 1917 firms respectively) than the baseline scenario. In terms of income as well, business wage subsidies result in larger average incomes (Table 3).

On the other hand, the results also suggest that economic policies can undermine efforts to mitigate the impacts of the epidemic. Only those scenarios where businesses subsidies are not offered show numbers of businesses very close to those observed under the baseline scenario, i.e. 1713 businesses without support, 1735 with only household cash transfers and 1686 under the baseline scenario.

These results provide insights into the effectiveness of economic support policies. But to understand the nature of the emerging dynamics, deeper exploration is required. Some hints

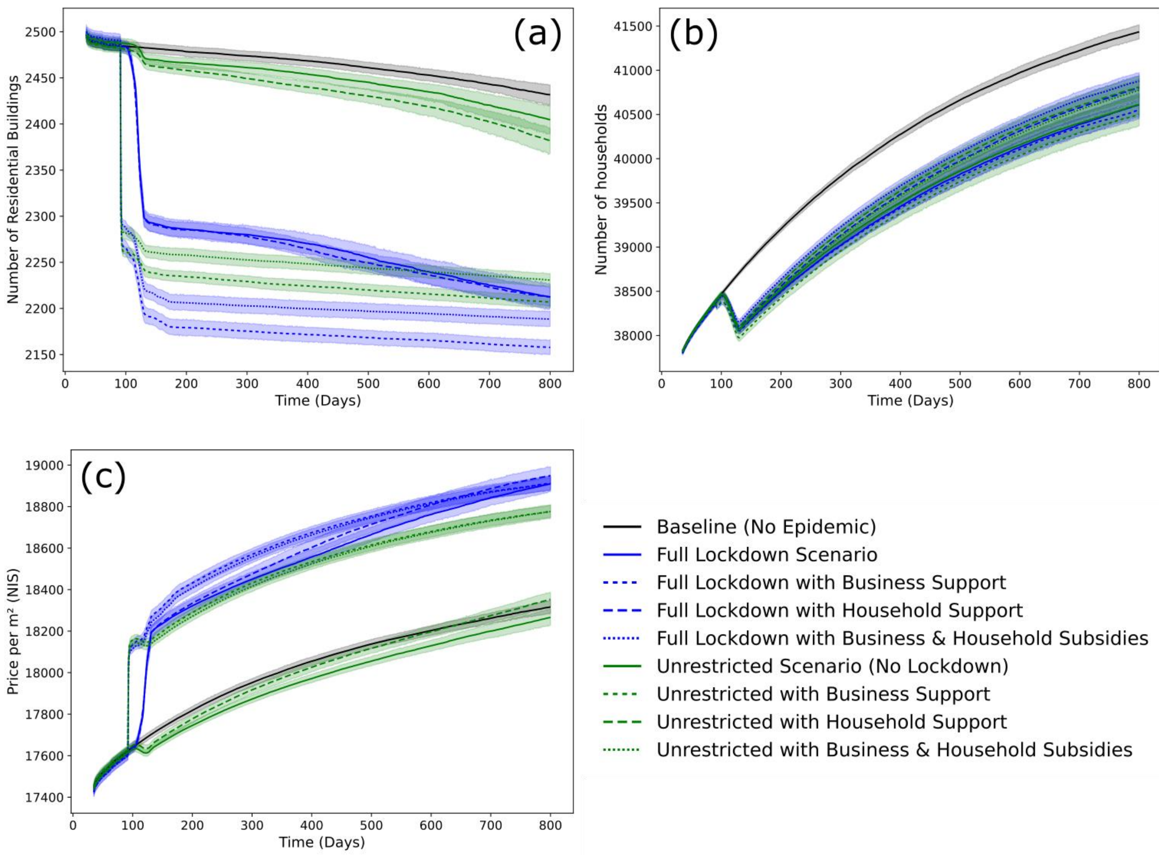

Figure 5. Change in (a) number of residential assets, (b) number of households (occupied assets), and (c) mean residential asset monthly rent per meter, by epidemic control and economic support policies.

are already available in the trends observed in Figure 5. These expose the mechanism driving this pattern of post-shock urban reorganization. Combined with the decrease in the number of jobs, the rising number of businesses indicates that smaller businesses, characterized by smaller floorspace and hence less demand for labor, replace larger businesses.

5.3 Housing and Population Effects

The results for the housing market and the supply side of the labor market (Figure 5) support this conjecture. First, as one would expect given model dynamics, it is clear that the expansion of the commercial buildings stock comes at the expense of the residential buildings stock with the number of residential units decreasing (Fig. 5a). This should have caused a decline in population size, yet the number of households only increases over time even if it does not reach the expected increase under the baseline scenario (Fig. 5b). Interestingly, no differentiation by economic or epidemic control policy is observed, meaning that population size is sensitive only to the very appearance of the epidemic. A smaller residential stock with a larger volume of population indicates that on average, residential buildings increase in floorspace volume thereby offering more housing units for the additional population. These results provide additional information regarding the restructuring of the city in which the addition of multiple small businesses is complemented by the replacement of larger commercial uses with residential uses.

These dynamics provide a clear explanation for other observed phenomena. As residential locations become scarce and demand only increases, the only possible outcome is an increase in housing prices. This also explains the lower wages offered by businesses: a large supply surplus emerges thereby pushing wages down (Fig. 5a). Ostensibly, this seems contradictory to the increase in wages observed for most scenarios (Fig. 5c). However, it may be explained by many agents resorting to commuting to workplaces located outside the simulation world, a space unaffected by local labor market dynamics. This flexibility however is not enough to counter the combination of three conditions – the epidemic, lockdowns, and business support – which lead to a decrease in agent incomes. In sum, the results point to urban restructuring characterized by more but smaller businesses, fewer jobs, lower wage bills, rising rents and the possibility that business subsidies intensify rather than dampen reorganization by generating more commercial units but worse labor and housing outcomes.

5.4 Trade-off Analysis

Decision makers are often required to prioritize interventions. Therefore, developing a metric to assess the trade-off between different types of policy can be instructive. To this end, we define measures for measuring the trade-off between epidemic control and economic support. Both measures are based on a min-max normalization of the outcomes for a given scenario in relation to scenarios defined as the minimal impact and maximum impact scenarios.

From the epidemic control perspective, when measuring outcomes as total number of infections, minimum impact is expected for the maximal policy intervention i.e. lockdown combined with support to both households and businesses. Similarly, maximum impact is expected for the minimal intervention scenario, i.e. no lockdowns or subsidies. Values close to 1 indicate that the extent of contagion is closer to that observed when no interventions are implemented, i.e. a greater public health impact. Note also that values greater than 1 and below 0 are possible, as minimum/maximum impact are defined conceptually, by the extent of intervention, and not empirically, based on results. For example, it is possible that a scenario other than the no lockdowns and subsidies would present the highest contagion rates and accordingly, the value of the measure for this scenario would be greater than 1.

Economic policy is more complex, as it includes multiple performance measures such as number of jobs, total wage bill of businesses, number of businesses, number of residential buildings, population size, average agent income and average residential rent. Our calculation of the economic policy impact includes the following steps: (a) calculating each measure's mean final value per scenario; (b) using (a) to calculate the absolute rate of change ($|t1-t0|/t0$) per scenario and performance measure in relation to the baseline scenario; (c) calculating the mean of (b) per scenario. The result is normalized using a min-max approach to ensure values are between 0 and 1. This economic policy score should not be considered a welfare optimizing measure. Rather, it is a transparent composite index of system-wide deviation from the baseline. We use absolute proportional deviation from the baseline because changes are not uniformly 'good' or 'bad' across all indicators. We apply equal weights as a neutral and transparent choice since the model does not specify a theoretical welfare function that would justify privileging one outcome over the other.

Figure 6 represents every scenario as two points, connected by a line, with one point (in blue) representing epidemic control policy and the other (green) point denoting economic policy. It is immediately apparent that a gradient of impacts appears over the economic dimension while the impact of the public health policy is binary. This is a natural outcome and underscores that one does not need to consider epidemic control outcomes when considering economic support. However, this logic does not work in the reverse direction. Economic outcomes need to be considered when making public health decisions. In fact, all of the lockdown scenarios ('+' in Figure 6) produce greater impacts than any of the non-lockdown scenarios ('-'), meaning that economic interventions policies can only mitigate but not eliminate the economic impacts of epidemic control.

This analysis also provides insights regarding the trade-off between various economic policies. First, the gradient of increasing impact from the no support ('0'), through the household/business subsidies ('H'/'B' respectively), and up to the full support ('HB') scenarios shows that the greater the intervention, the greater the impact, within the range defined by a given public health response. It also shows that business wage subsidies actually encourage greater change, with or without household cash transfers, as the B and HB impacts are clearly differentiated from the 0 and H scenarios which are clustered together.

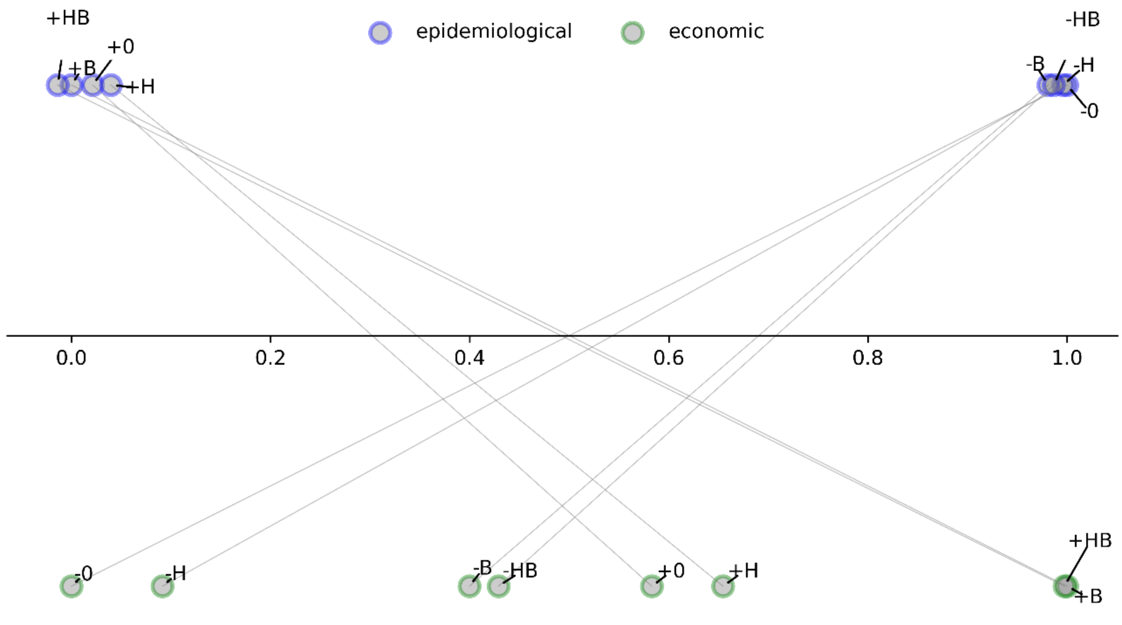

Figure 6. The trade-off between public health and economic impacts. +,- indicate lockdown and non-lockdown scenarios. 0, H, B, HB indicate no support, household cash transfer, businesses wage subsidy and both policies, respectively.

5.5 Sensitivity Analysis:

Appendix A6 presents two representative examples of sensitivity tests for key outcome variables simulated by the model, average mean wages and average residential housing prices (per sqm). In both cases the simulation runs for a period of over two years and as noted in Appendix 2, model parameters (α, β, λ and γ) are fitted heuristically. These parameters define the key wage change equation in the model (Appendix A3.6) where wages change as a function of floorspace, employment rates, and building occupancy rates. In both examples, the parameter values chosen for use in the study are represented by the pink line. As can be seen, despite differences in levels, the simulation trajectories in both examples are preserved throughout the simulation despite the changes in parameter values.

6. Discussion

The empirical results suggest a form of endogenous urban restructuring triggered not only by the epidemic shock itself but by the interaction of unsynchronized policy instruments. This has direct implications for urban resilience and governance (Kajdanek and Radzimski 2025). Rather than depicting resilience as a rapid return to a pre-shock equilibrium, the findings suggest a transition to a new steady state characterized by more fragmented commercial structures, weaker labor markets, and intensified housing pressure. This aligns with evolutionary perspectives on resilience, where adaptation may come at the cost of welfare deterioration (Boschma 2015). From a governance standpoint, the results highlight the limitations of silo-type interventions: public health measures such as lockdowns and economic support policies operate at different spatial and temporal logics. When they are not coordinated they generate cascading cross-market effects (Felsenstein and Grinberger 2020). The model thus reinforces the argument that resilient urban governance requires policy integration across sectors, not merely policy intensity within sectors. In this sense, resilience is less about 'bouncing back' and more about managing interdependencies across urban systems.

The findings also speak directly to recent housing and rent vulnerability debates (Jiao et al 2024, Shin et al 2025). The simulation shows that epidemic-induced restructuring leads to a contraction in effective housing supply along with rising population pressure and sustained rent increases. Importantly, this occurs even when household incomes are partially supported. This indicates that income-side interventions alone are insufficient to stabilize housing outcomes and that the mechanism is structural. The expansion of commercial uses (especially small businesses) crowds out residential uses while labor market weakening reduces household capacity to compete for increasingly scarce housing. This produces a classic affordability squeeze with higher rents combining contracting income. This result suggests that housing vulnerability is not simply a function of income shocks but of system-wide reallocation processes linking land use, labor markets, and policy design. Moreover, the fact that population continues to grow despite the decline in residential housing stock points to the development of density pressures and overcrowding. This is a key dimension of vulnerability that is often underemphasized in standard affordability metrics.

Finally, the results provide an explanation of why sector-specific support can generate cross-market distortions. Business wage subsidies stabilize firms in the short run and lower the effective cost of operating small-scale commercial activities. This creates an incentive for the proliferation of smaller, less labor-intensive firms, which displace larger establishments and reduce aggregate labor demand. The result is the paradoxical situation of more firms but fewer jobs, lower wage bills and tighter housing. Concurrently, increased commercial activity competes for space with residential uses, tightening housing supply and driving up rents. These distortions arise because the subsidy targets one margin (firm survival) while ignoring general equilibrium effects across land, labor, and housing markets. In effect, the policy introduces a relative price distortion by lowering the cost of labor retention for firms without accounting for spatial competition and demand spillovers.

7. Conclusions

In summary, this analysis underscores the conditions under which business wage subsidies and household cash transfers intensify urban reorganization and transformation in the wake of an urban epidemiological crisis. Given the limitations of the modeling framework viz. the use of quasi-agent firms, a stylized one-wave epidemic, the assumption of unconstrained land-use conversion and simplified mobility patterns, the results should be considered demonstrative rather than predictive. The simulated outcomes highlight a changing urban economic landscape with more but smaller businesses, a decline in jobs and wages, reduced residential housing stock, rising rents and business subsidies that amplify restructuring rather than stabilization of the urban system. This all points to worsening housing pressure and labor-market conditions with likely welfare deterioration.

The paper also shows how epidemic-control and economic-support interventions interact across urban submarkets. For example, support for the business sector, whether via maintaining the pre-epidemic conditions or through promoting restructuring, may be achieved via interventions in the housing market. This underscores the interdependent nature of urban markets. Furthermore, it also emphasizes the interdependent nature of policy tools. The policy implications of this are clear: trying to treat the business sector without consideration of these contingent impacts and spillovers may be inefficient and even harmful at times. Instead of attempting to provide a stand-alone solution for one specific sector, attempts should be made to provide a comprehensive solution that takes into consideration relations between urban markets.

At a broader level, this kind of insight emphasizes that sectoral policies in interconnected urban systems are never neutral. Interventions aimed at stabilizing one market can reallocate resources in ways that amplify instability elsewhere. Our results therefore make the case for a shift from sector-specific to system-specific policy design. Under this regime, evaluation criteria are not dedicated to short-term stabilization within a market but to the overall structure of urban equilibria that policies induce over time.

This work provides an opportunity to understand the trade-offs inherent in using multiple policy measures in a given location. For example, while household subsidies affect household competitiveness within the local housing market, this is not a policy measure directed specifically at the housing market (in contrast for example, to direct subsidies to housing costs). Our results show that due to cross-market linkages, housing pressures emerge even when policies are not explicitly aimed at the housing market. Housing outcomes are therefore not just a residual effect but a central policy concern. Ignoring the housing dimension risks intensifying vulnerability and offsetting the intended benefits of both public health and economic support policies. This is an avenue for further development in the model. Unintended restructuring seems to be endemic to policy intervention. Future work will need to focus on identifying and channeling these forces in a normative direction.

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Appendices

A1: Entities, Characteristics and Values

Entity	Characteristic	Values
Household	Size (agents)	1-8
	Children (agents)	0-5
	Car ownership (# cars)	0, 1, 2
	Income (NIS/month)	0 to infinity
	Asset	Asset ID
Agent	Age (years)	0-99
	Age group	Child (ages 0-17), Adult (ages 18-64), Elderly (ages 65+)
	Disability	Disabled / non-disabled
	Employment status	Not participating in the workforce, unemployed, employed
	Socio-economic decile	1-10
	Income (NIS/month)	0 to infinity
	Workplace building	Building ID
	Epidemiological status	Susceptible, infected–undiagnosed, infected-diagnosed, quarantined-susceptible, quarantined-infected-undiagnosed, quarantined-infected-diagnosed, hospitalized, dead, recovered
	Household	Household ID
Assets	Building	Building ID
	Area (sq m)	0 to infinity
	Value (NIS)	0 to infinity
	Rent (NIS/month)	0 to infinity
Building	Land use	Empty, residential mixed, commercial, industrial, public, retirement home
	Statistical area	Statistical area ID
	Settlement	Settlement ID
	X,Y coordinates	0 to infinity
	Floors	1-20
	Value per sq m (NIS)	0 to infinity
	Floorspace (sq m)	0 to infinity
Job	Building	Building ID
	Occupation status	Unoccupied / occupied
	Salary (NIS)	0 to infinity

.

A2: Simulation Model Parameter Values

Parameters	Values	Source	Comments
Migration probabilities (intra-neighborhood, intra-settlement, other settlement)	Defined per SA	2008 census data on migration volumes	Migration volumes are divided by total population size at the beginning of the year and by 365 to produce daily migration probabilities
Im			Defined by the ratio between in-migration and out-migration volumes
In-commute probability	0.52	2008 census data on commuting patterns	Share of jobs occupied by non-residents
Out-commuting probability	Zone 31: 0.59 Zone 34: 0.21		Share of employed residents working outside of the city
Minimal monthly wage	4300	Social Security 2012 data	
Wtp	1/3	Author determined	A common heuristic defines that households should not spend more than a third of their income on housing
ω_d, ω_a, ω_{a1}, ω_{a2}	0.5, 1/3, 0.5, 0.5		Values set so all components have equal weights within the respective equations
Tp	12		Equivalent to 12 months, thus transforming the housing prices into monthly rents
$\bar{a}$	3		
th_{c-}, th_{r-}, th_{c+}	-20, 20, 40		Set through sensitivity tests
α, β, γ, δ	0.4, 0.6, 0.25, 0.8		
μ_w, σ_w	Varies	Calculation	Calculated at the beginning of the simulation based on agent data. μ_w changes throughout the simulation (see section 2.3)
Jobs per m^2 parameters	Industrial:0.023 Commercial:0.014 Public: 0.0011 Residential:0.0000		The total number of jobs per industries associated with each land-use, as per 2008 census data, divided by the total floorspace volume for buildings of that land-use, according to the SoI buildings geodata layer
B_0, β_1, $SE(\beta_0)$, $SE(\beta_1)$, $COV(\beta_0, \beta_1)$	1.1003, 1.1003, 0.0013, 0.0013, 0.0000		Estimation via regression analysis

A3. Equations Listing for Sub-Models

A3.1. Housing Market Demand

Equation 1: Neighborhood Score ($SR_{n,h}$): this calculates how attractive a neighborhood n is to household h. It balances the distance to work (d) with demographic preferences (Z). ω_d is the weight given to distance, and I is an indicator of whether the household has workers**.**

$$SR_{n,h} = \omega_d * I(|W_h| > 0) * \frac{\bar{d}_{n,h}}{\max\limits_{n1 \in N} d_{n,n1}} + \left(1 - \omega_d * I(|W_h| > 0)\right) \frac{P(Z_{age\_g})/P(0) + P(Z_{inc})/P(0)}{2} \quad (1)$$

where: $SR_{n,h}$ is the score of unit n for household h,
ω_d is a weight parameter,
$I(|w_h|>0)$ is a binary indicator which equals 1 if any of h's members are employed, 0 otherwise,
$\bar{d}_{n,h}$ is the average commuting distance of h's members from n to their workplaces,
$d_{n,n1}$ is the distance between two spatial units n and $n1$, where N is the set of all spatial units,
$P(x)$ is the standard normal density value for x

Equation 2: Standardized Preferences (Z_x): this standardizes the household's attributes (x_h) against the city or regional mean (μ) and standard deviation (σ) to determine how "typical" or "atypical" a household is compared to its neighbors

$$Z_x = \frac{x_h - \mu_{x,r}}{\sigma_{x,r}} \quad (2)$$

where: x_h is the value of characteristic x of household h (average age group when $x=age\_g$, total income when $x=inc$), Z_{age}, Z_{inc} are the standardized values (see eq. 2) for age and income, respectively,
$\mu_{x,r}$ is the mean value of x within city/region r,
$\sigma_{x,r}$ is the standard deviation value of x within city/region r.

A3.2. Housing Market Supply

Equation 3: Neighborhood Housing Value ($V_{n,t}$):this updates neighborhood value based on the growth of households (h), the ratio of residential units (r), and the level of services (s).

$$V_{n,t} = V_{n,t-1} * \left(1 + ln\left(\frac{|H_{n,t}|/|h_{n,t-1}| + |r_{n,t-1}|/|r_{n,t}| + |s_{n,t}|/|s_{n,t-1}|}{3}\right)\right) \quad (3)$$

where: a, b, and n represent asset a located within building b which belongs to neighborhood n,
$V_{n,t}$ is average housing value in neighborhood n at time t,
$|h_{n,t}|$, $|r_{n,t}|$, and $|s_{n,t}|$ are respectively the number of households, residential assets, and service (commercial and public) buildings in neighborhood n at time t,
$V_{b,t}$ is the total value of building b at time t

Equation 4: Building Value ($V_{b,t}$): this translates neighborhood value to a specific building b by multiplying the building's floor space (fs_b) by the neighborhood value (V_n), adjusted by service changes

$$V_{b,t} = fs_b * V_{n,t} * \frac{|s_{r,t}|}{|s_{r,t-1}|} \quad (4)$$

where: fs_b, fs_a are respectively the floorspace volumes of building *b* and asset *a*,
r is the set of buildings within a given radius from building *b*,

Equation 5: Monthly Rent ($R_{a,t}$): this sets the rent for unit *a*, through which households identify affordable assets. It is based on household income (*inc*), willingness to pay (*wtp*), and how the building's value compares to the city average.

$$R_{a,t} = \widetilde{inc} * wtp * \left(1 + \frac{V_{b,t} * {}^{fs_a}/_{fs_b} - \mu_V}{\sigma_V * tp}\right) \quad (5)$$

where: $\widetilde{inc}$ is the median income across all households,
wtp is the willingness to pay for housing parameter,
μ_V, σ_V are the mean asset value and the standard deviation of asset values, respectively,
tp is a time normalizing parameter.

A3.3. Business Sector Demand

Equation 6: Activity Count (A_i): this determines the daily trips made by agent i. It subtracts points for disabilities (dis) or being very young/old, and adds points for car ownership.

$$A_i = \left\lfloor 2 * j * \left(\bar{a} - \frac{I(w_i)}{2}\right) * \left(1 + \omega_a * \left(I(car_i) - I(age\_g_i \in [1,3]) - I(dis_i)\right) + I(wi_i)\right)\right\rfloor$$
(6)

where: A_i is the number of activities for agent *i*,
j is a random number between 0 and 1,
$\bar{a}$ is a model parameter representing the average length of a routine,
ω_a is a weight parameter for individual attributes,
$I(w_i)$, $I(car_i)$, $I(age\_g_i \in [1,3])$, $I(dis_i)$, $I(wi_i)$, $I(age\_g_i=2)$, $I(age\_g_i=3)$ are indicator functions.

$I_{()}$=1when respectively the agent is employed,,the agent household owns a car, the agent is from age groups 1 or 3 (children or elderly), the agent has a disability, agent workplace is within the simulation world (i.e. does not commute from outside), agent is from the adult age group and agent is from the elderly age group; otherwise $I_{()}$=0.

Equations 7 and 8: Selection Scores (SA_n, SA_b): these formulae determine which neighborhood (*n*) and building (*b*) an agent chooses to visit based on distance and building floor space (*fs*).

$$SA_n = \left(1 - \frac{d_{n,i}}{\max_{n1 \in N} d_{n,n1}}\right) * \left(I(car_i) + I(age\_g_i = 2) - I(age\_g_i = 3) - I(dis_i)\right) * \omega_a + \max_{b \in n} SA_b \quad (7)$$

$$SA_b = \omega_{a1} * \left(I(u_b > 1) * \frac{fs_b}{\max_{b1 \in n, u_{b1} > 1} fs_{b1}} + I(u_b = 1) * \frac{|H_b|}{\max_{b1 \in n, u_{b1} = 1} |H_{b1}|}\right) + \omega_{a2} * \left(1 - \frac{|E_r|}{|B_r|}\right)$$
(8)

where: $d_{x,y}$ is the distance between two locations (agent *i* and neighborhood *n*, or two neighborhoods *n, n1*),
b is a building within neighborhood *n,*
ω_{a1}, ω_{a2} are weight parameters,

u_b, $I(u_b>1)$, $I(u_b=1)$ are, respectively, the land use of building b and indicator functions returning 1 if u_b is non-residential and non-empty (land use code > 1) or if u_b is residential (land use code =1); 0 otherwise,
fs_b is the floorspace volume for building b,
$|H_b|$ is the number of households residing in building b,
$|E_r|$, $|B_r|$ are, respectively, the number of empty buildings and the number of all buildings within a distance r of building b.

A3.4. Housing Market Supply

Equation 9: Potential Profitability (PP_b): the difference between the percentile of visits (P_V) the building receives and the percentile of wages (P_W) it pays. If visits are high and wages are low, profitability is high.

$$PP_b = P_W(w_b) - P_V(\bar{v}_b) \tag{9}$$

where: PP_b is the potential profitability for building b,
$P_X(x)$ is the percentile value of x over set of values X,
w_b, W are the sum of (potential) wages paid in b and the set of total wages over all buildings, respectively,
v_b, V are the mean number of visits over the last 30 iterations sum in b and the set of mean visits over all buildings, respectively

A3.5. Labor Market Demand

Equation 10: Occupied Jobs Ratio (OJ_t): this represents the simple ratio of occupied jobs (J_o) to total available jobs (J).

$$OJ_t = \frac{|J_o|}{|J|} \tag{10}$$

where: OJ_t is the ratio of occupied jobs,
$|J_o|$ is the number of occupied jobs,
$|J|$ is the total number of jobs

Equation 11 Wage Change Ratio (WCR_t): this adjusts wages based on the change in job occupancy. If occupancy rises, wages trend upward.

$$\gamma WCR_t = \left(\frac{(OJ_t/OJ_{t-1})^{1-\beta}}{\left(\sum_{b\in B_t} fs_b / \sum_{b\in B_{t-1}} fs_b\right)^{\alpha}}\right)^{1/\gamma} \tag{11}$$

where: WCR_t is the wage change ratio at time t,
fs_b is floorspace volume for building b,
B_t is the set of all non-empty buildings at time t,
α, β, and γ are model parameters.

A3.6. Labor Market Supply

Equation 12: Job Score ($JS_{i,k}$): this represents how agent i ranks job k. It weights the commute distance (d) against how close the offered salary is to their expected income (inc_i).

$$JS_{i,k} = \omega_d * \left(1 - \frac{d_{ik}}{\max_{k1\in K} d_{ik1}}\right) + (1-\omega_d) * \left(1 - \frac{inc_i - \min_{k1\in K} inc_{k1}}{\max_{k1\in K} inc_{k1} - \min_{k1\in K} inc_{k1}}\right) \tag{12}$$

where: $JS_{i,k}$ is the score assigned to job k by agent i,

ω_d is a weight parameter,
d_{ik} is the distance between agent *i*'s home and *k*'s location,
inc_i is agent *i*'s income,
K is the set of all available jobs.

Equation 13: Drop-out Probability ($P_{i,t}$): this expresses the probability that an agent stops looking for work. This grows as the time spent in unemployment (*t*) increases.

$$P_{i,t} = 1 - e^{-t/30} \tag{13}$$

A3.7. Epidemiology and Policy

Equation 14: Contagion Probability ($P_{j\to k}$): expresses the probability of agent j infecting agent k. This considers the age of the victim (P_c), the duration of the infecter's illness (f_D), and a general transmission constant (η).

$$P_{j\to k} = P_c(age_k) * f_D(dur_j|\nu,\theta) * P_{j\leftrightarrow k} * \eta \tag{14}$$

where: $p_{j\to k}$ is the probability of infected agent *j* infecting susceptible agent *k*,
$p_c(age_k)$ is the agent-contingent contagion probability for agent *k*,
$f_D(dur_j|\nu,\theta)$ is the probability density function of the Gamma distribution evaluated at the agent's *j* duration of infection (dur_j), with ν and θ being the shape and scale parameters, respectively.
$p_{j\leftrightarrow k}$ is the probability of agents *j* and *k* interacting,
η is a normalizing factor,

Equation 15: Interaction Probability ($P_{j\leftrightarrow k}$): the likelihood of two people actually interacting given the similarity between them in terms of age, income, and home locations.

$$P_{j\leftrightarrow k} = 1 - \frac{|\Delta age_{jk}|/100 + |\Delta inc_{jk}|/\max_{l\in A}\Delta inc_{lk} + d_{jk}/\max_{l\in A} d_{lk}}{3} \tag{15}$$

where: Δx_{jk} is the difference in the value of attribute *x* (age, income) between agents *j* and *k*,
d_{jk} is the Euclidean distance between *j*'s and *k*'s places of residence,
$\max_{l\in A} x_{lk}$ is the maximum value of *x* (income difference, distance) between any agent in the set of agents *A* and agent *k*.

Equation 16: Effective Reproduction Rate (R_e): this calculates the current "strength" of the epidemic by dividing new cases (I_t) by the weighted sum of previous cases that are currently in their infectious window.

$$R_e = \frac{I_t}{\sum_{s=0}^{t} I_{t-s} * f_D(s|\nu,\theta)} \tag{16}$$

where: I_t is the number of newly diagnosed agents at day *t*,
$f_D(s|\nu,\theta)$ is the probability density function, representing the generation interval distribution, i.e. the proportion of new cases for which individuals infected in day *s* are responsible.

A3.8. Simulation Initialization

Household preferences are drawn randomly from a normal distribution $r\sim N(\mu,\sigma)$ whose parameters are derived from the results of a log-log regression of travel distance to the city center on travel time , i.e. $log(td_j)=\beta_0+ \beta_1*log(tt_j)+\epsilon$ where td_j and tt_j are travel distance and travel time, accordingly, from asset j to the city center[3]. The regression model coefficients are calculated for each unique city or neighborhood within the simulation world. The matching step selects the asset that best fits the household's characteristics, i.e. the asset whose utility shows the minimal difference from the household's randomly drawn preferences.

$$u_{ij} = \frac{tt_j * fs_j}{inc_i * wtp - 22 * \overline{inc} * tt_j} * \frac{(p_{j,s-1} - p_j) + 22 * \overline{inc} * (tt_{j,s-1} - tt_j)}{tt_{j,s-1} - tt_j} \quad (17)$$

$$\mu = \beta_0 + \frac{\beta_1}{n} * \sum_{j=1}^{n} \frac{tt_j}{p_j} \quad (18)$$

$$\sigma^2 = \mathrm{SE}(\beta_0)^2 + \mathrm{SE}(\beta_1)^2 + 2 * \mathrm{COV}(\beta_0, \beta_1) * \mathrm{SE}(\beta_0) * \mathrm{SE}(\beta_1) \quad (19)$$

where:
u_{ij} is the utility household i derives from residence in asset j,
tt, p, fs represent travel time to the city center, monthly rent per meter, and floorspace, respectively.
inc_j is household j's monthly income assuming 22 working days per month,
$p_{j,s-1}$-p_j denotes the price difference between asset (dwelling j and a comparison asset used to estimate the local housing price gradient with respect to travel time.

wtp is the willingness to pay for housing parameter,
$\overline{inc}$ is the average hourly household income, i.e. *inc/144*, assuming 144 working hours per week,
$x_{j,s-1}$ relates to the mean value of x in assets nearby to asset j,
$SE(\beta_0)$, $SE(\beta_1)$ are the standard errors of the regression coefficients,
$COV(\beta_0, \beta_1)$ is the covariance between the coefficients

[3] These definitions are derived from the classic Alonso bid-rent theory and assume a Cobb-Douglas utility function $U=fs^{\alpha}*tt^{\beta}*V(Z)^{\gamma}$, Z being a vector of the goods consumed. A necessary condition for utility maximization under these assumptions is that the marginal rate of substitution between location and the amount of land at that location, is the ratio between the marginal cost of all land purchased plus the marginal cost of commuting to the price of land at a given location. The general result of the Cobb-Douglas utility function that the constant ratio of trade off between land area and spatial proximity dictated by parameters α, β allows formulating a new utility condition $\frac{\alpha}{\beta} = \frac{tt}{p(j)} \cdot \left(\frac{\partial p}{\partial tt} + \frac{\partial k}{\partial tt}\right)$, where k is the commuting cost represented in eq. 1 by $22 * \overline{inc} * tt_j$. We use the difference between the mean value across nearby locations and the value at j instead of the local derivatives, as these cannot be directly computed.

A4. Synthetic Population Validity Tests

Variable	Correlation	MAE	RMSE
residents	0.598	987.867	1351.797
households_est	0.555	369.93	479.068
mean_hh_size	0.93	0.082	0.176
hh_with_children_pct	0.757	42.951	43.694
hh_with_elderly_pct	0.734	17.269	18.664
car_1plus_pct	0.997	0.976	1.338
car_2plus_pct	0.959	2.149	2.784
hh_size1_pct	0.999	0.402	0.541
hh_size2_pct	0.998	0.401	0.478
hh_size3_pct	0.999	0.295	0.359
hh_size4_pct	0.999	0.331	0.405
hh_size5_pct	0.98	0.605	1.071
hh_size6_pct	0.757	0.66	1.868
hh_size7plus_pct	0.859	1.462	1.75
child_age_proxy_pct	0.3	29.217	30.1
adult_age_proxy_pct	0.35	17.244	18.742
age65plus_pct	0.676	11.4	11.949
disability_hear_pct	0.999	0.093	0.149
disability_see_pct	0.999	0.014	0.018
disability_remember_pct	1	0.044	0.065
disability_dress_pct	0.999	0.122	0.191
disability_walk_pct	0.999	0.366	0.5
labor_force_pct	0.99	22.94	22.994
working_pct	0.353	47.06	47.772
income_q1_pct	0.859	1.193	1.372
income_q2_pct	0.946	0.844	1.117
income_q3_pct	0.73	1.086	1.317
income_q4_pct	0.798	0.824	1.009
income_q5_pct	0.769	1.102	1.407
income_q6_pct	0.851	0.697	0.965
income_q7_pct	0.864	0.732	0.917
income_q8_pct	0.902	0.723	0.885
income_q9_pct	0.957	0.658	0.812
income_q10_pct	0.977	0.718	0.822

A5. Epidemiological Parameters- Plausibility Values

Process	Parameter	Description	Value	Source
Allocation of workplace and other activities	jpm	Jobs per m sq by land use	Unoccupied: 0, Residential: 0.0005, Commercial: 0.0315 Public: 0.0479	Computation based on data from the Israeli Central Bureau of Statistics (ICBS) and Survey of Israel (SoI)
	$\boldsymbol{\mu}_{w}$	Average monthly wage	7,177.493 NIS	ICBS
	$\boldsymbol{\sigma}_{w}$	Wage standard deviation	1,625.297 NIS	ICBS
Epidemiological variables	$\boldsymbol{\mu}_{i,a},\boldsymbol{\sigma}_{i,a}$	Parameters for infection probability distribution for age group *a*	a=0-17: $\boldsymbol{\mu}$=0.074, $\boldsymbol{\sigma}$=0.02 a=18-65: $\boldsymbol{\mu}$=0.148, $\boldsymbol{\sigma}$=0.04 a=85+: $\boldsymbol{\mu}$=0.074, $\boldsymbol{\sigma}$=0.04	$\boldsymbol{\mu}$ values were derived by computing probabilities for a baseline age group found in the literature (Roimi et al., 2021). Probabilities for other groups were computed based on estimations from the CDC (Center for Disease Control and Prevention, 2021). $\boldsymbol{\sigma}$ values were determined arbitrarily.
	$\boldsymbol{\mu}_{h,a},\boldsymbol{\sigma}_{h,a}$	Parameters for hospitalization probability distribution for age group *a*	a=0-29: $\boldsymbol{\mu}$=0.012, $\boldsymbol{\sigma}$=0.02 a=30-49: $\boldsymbol{\mu}$=0.024, $\boldsymbol{\sigma}$=0.02 a=50-59: $\boldsymbol{\mu}$=0.049, $\boldsymbol{\sigma}$=0.02 a=60-69: $\boldsymbol{\mu}$=0.073, $\boldsymbol{\sigma}$=0.02 a=70-79: $\boldsymbol{\mu}$=0.109, $\boldsymbol{\sigma}$=0.02 a=80+: $\boldsymbol{\mu}$=0.182, $\boldsymbol{\sigma}$=0.02	
	$\boldsymbol{\mu}_{d,a},\boldsymbol{\sigma}_{d,a}$	Parameters for mortality probability distribution for age group *a*	a=0-39: $\boldsymbol{\mu}$=0.00002, $\boldsymbol{\sigma}$=0 a=40-49: $\boldsymbol{\mu}$=0.00260, $\boldsymbol{\sigma}$=0.001 a=50-59: $\boldsymbol{\mu}$=0.00088, $\boldsymbol{\sigma}$=0.005 a=60-69: $\boldsymbol{\mu}$=0.02602, $\boldsymbol{\sigma}$=0.015 a=70-79: $\boldsymbol{\mu}$=0.06402, $\boldsymbol{\sigma}$=0.03 a=80+: $\boldsymbol{\mu}$=0.17410, $\boldsymbol{\sigma}$=0.100	
Creation of socio-spatial network	$\boldsymbol{\beta}$	Distance friction coefficient for gravity model	2	Determined based on common conventions
	W_1,W_2,W_3	Weight parameters for agent-agent interaction probabilities	1, 1, 1	Determined endogenously
	P_b	Minimal probability for edge existing between buildings	0.00161	Determined endogenously based on the distribution of edges per entity
	P_a	Minimal probability for edge existing between agents	0.95	

Routine state variable	K	Maximal number of anchor activities	3	Determined endogenously
	k	Maximal number of auxiliary activities between a pair of anchor activities	2	
	d_a	Maximal network distance between agent and building in *a_nodes* set	1	
	d_b	Maximal distance between buildings in the *i_nodes* and *c_nodes* sets	6	
Submodel 1: *Change of epidemiological status*	a_{min},a_{max}	The range of days since infection within which an agent can become hospitalized	3,15	
	m_{min}	The earliest day since infection in which the agent can die	2	
	t_d,t_r,t_{hr}	Days from infection to diagnosis/ recovery/ hospital recovery	7, 21, 28	
	t_q	Number of days until end of quarantine	7	
Submodel 2: *Identification of newly infected agents*	$w_s(t)$	The generation interval distribution - a function determining the contagion level of an agent by duration of infection	Gamma probability density function with mean of 4.5 days and std of 3.5 days	Based on estimations from the Corona National Information and Knowledge Center (CNIKC, 2021)
	n	Normalizing factor for infection	0.08	Determined endogenously via face validation
Submodel 3: *Policy activation*	R_1,R_2	R coefficient threshold for activating lockdowns	1,2	Determined endogenously

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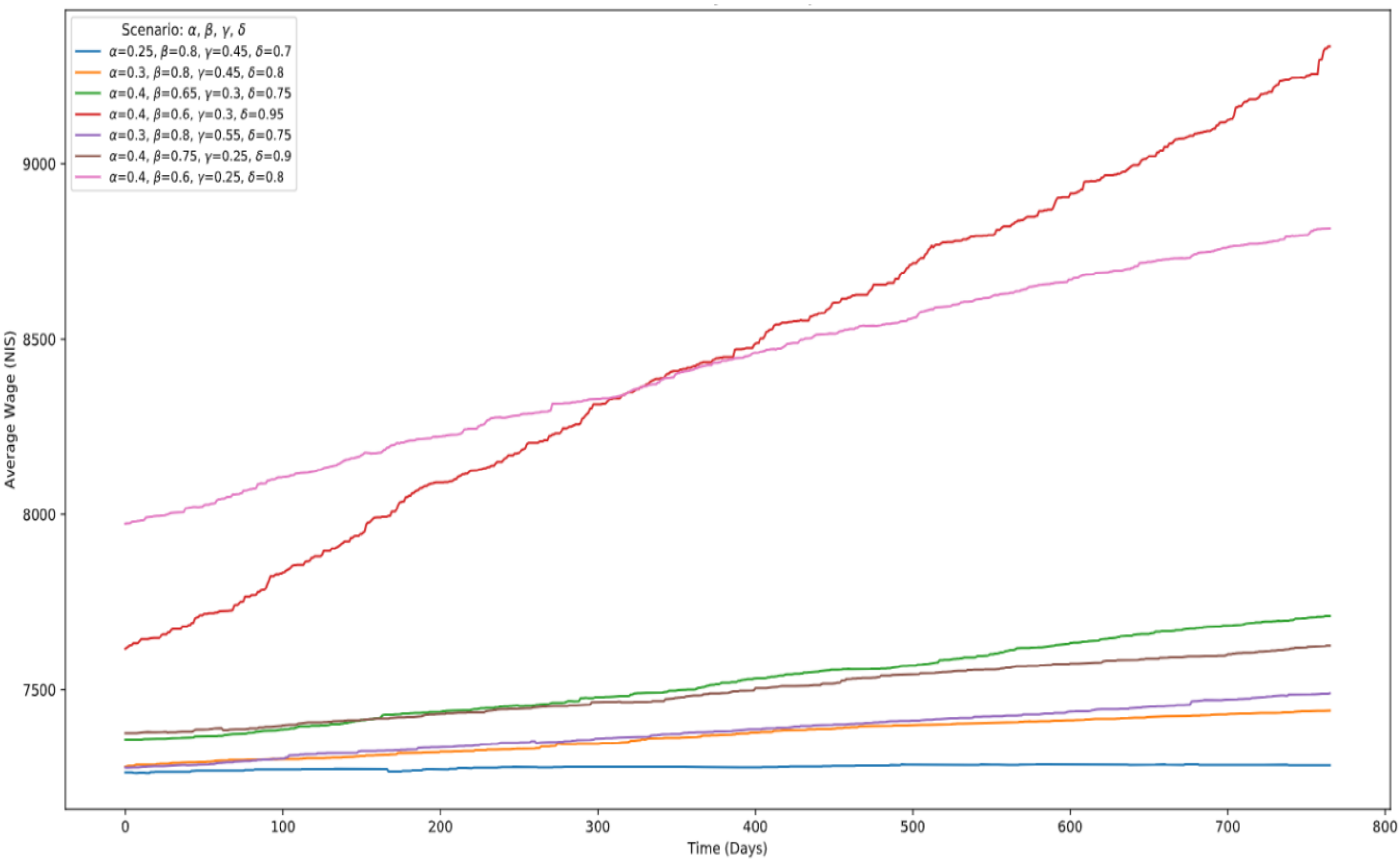
A6. Sensitivity Tests

(a) Average wage



(b) Average House Price per sq m