The Developer’s Decision Calculus: An Agent-Based Model of Commercial Development

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Abstract: While considerable research has been devoted to understanding the impact local regulatory environments on housing development, few studies have examined the implications of land-use regulations for commercial development. The paucity of studies is unfortunate given that commercial development often provides municipalities with considerable economic benefits (e.g., employment) and a crucial source of tax revenue. This study presents a formal model of the commercial development process that explicitly incorporates the dynamic interaction of commercial developers and local cities. Specifically, we construct an agent-based model (ABM) of the commercial development process that represents some key features of the development process. We form several general expectations from the theoretical model and explore these expectations through a series of simulations.

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INTRODUCTION

Scholars of regional economics have devoted considerable time and effort to describing the implications of local regulatory environments for explaining variation in the level of city development. Much of the literature, however, focuses on housing development and few studies address the implications of government regulation for commercial development projects. The paucity of studies is regrettable given that commercial development projects often provide cities with noticeable economic benefits (e.g., employment), while also providing an important source of tax revenue.\(^1\) In addition, few studies examine the decision making process of private developers and even fewer studies model the dynamic interaction of cities and development companies. This study provides an initial attempt to model these dynamics, utilizing an agent-based model (ABM) design to represent the core behavioral processes of developers and local governments. While the model provides a simplified version of the development process, we hope to show that ABMs—with their emphasis on nonlinear interactions, adaptation, and emergence—provide a useful structure of constructing theories of the development process.

The primary concern of this study is to examine the relationship between local regulatory environments, the decisions of companies to develop, and the implications of these decisions have for cities and the bottom line of companies. As such, an important first step is to describe the connection of local regulations for the development process. Economists generally agree that the primary impact of land use regulations on real estate

\(^1\) For instance, retail development and the sales taxes that it generates provide a key source of revenue for many local communities. Moreover, finding alternative sources of revenue has become more important in recent decades; particularly, given the reduction in federal transfers to local governments initiated by the Reagan Administration in the mid 1980s (Fahim 2005).
developers is to raise the costs of production (Katz and Rosen 1987; Pollakowski and Wachter 1990; Malpezzi 1996). Downs (1991) classifies three different types of cost increasing effects: (1) direct restrictions on supply and restrictions on developable land, (2) direct cost increases, and (3) time delays. Each of these effects has important implications for the costs of project development; however, our primary focus is on the effects of regulatory delays and to a lesser extent on supply restrictions via zoning regulations. While the literature on residential zoning is well developed (c.f., Quigley and Rosenthal 2004 for an overview), the effects of regulatory delays has been explored less extensively in the academic literature. As Downs (1991) points out, permitting and processing procedures may take considerable time based on the type of development project. These “time-consuming procedures include fulfillment of duplicate requirements from different agencies for the same information, multiple review processes, and constant revisions in plans to satisfy various officials or citizens” (Downs 1991, pg. 1103).

Private development companies are well aware of the implications of regulatory delays for the profitability of a particular development project. For instance, a recent report released by PricewaterhouseCoopers (commissioned by the American Institute for Architects, 2005) provides an extensive account of the relationship between permitting times and development. Combining expert opinion and Bureau of Economic Analysis (BEA) data, the study finds that permitting delays significantly raise costs to builders and thus raise the costs associated with new and existing units. Moreover, the study documents cases in which the costs associated with government delays renders local development projects unprofitable. As a result, projects are either abandoned or moved to

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2 While Downs’ sole focus is on the impact of regulatory costs on affordable housing, his basic classification adequately represents the main features of regulatory costs in the context of commercial development as well.
a different locale (with considerable cost to the developer and local residents). While the
details of the report are outside of the scope of this review, the general finding is clear:
government time delays have important implications for decisions on where developers’
choose to employ their scarce resources.³

In the remainder of this study, we develop a computational model of the
commercial development process that focuses specifically on regulatory delays. This
model relies on a combination of economic theory and the local development process to
construct a representation of developer and city interactions. The model will provide
insight into various questions of commercial development, including the impact of
regulatory delays on a developer’s decision calculus, as well as the conditions under
which accounting for time delays increases the profitability of development. In addition
to examining the developer’s decision process, we explore the ways in which city’s adapt
their behavior to compete with neighboring cities. After developing the model, we form
some general expectations regarding the models behavior and explore these expectations
via a series of simulations (or controlled computational experiments). Given that ABMs
are relatively new to students of local economic development, however, we begin with a
brief introduction the ABMs and simulation as a social science method.

AGENT-BASED MODELS: AN INTRODUCTION

The origin of computational simulation as a means of conducting research
corresponds to the first uses of computers in universities in the 1960s. While early
models relied primarily on simulating and forecasting policy relevant variables using

³ Other scholarly work (mainly among scholars working in conjunction with private organizations) supports
the general findings of this study (see Carl and Kelly 2004).
differential equations and micro-simulation⁴, recent advances have been made in the use of multi-agent (or agent-based) systems. Computational models, in their simplest form, are “theories expressed as computer programs” (Taber and Timpone 1996). Specifically, the typical ABM includes a set of theoretically relevant agents that interact in a well-defined environment to achieve a set of pre-specified goals. Often agent interactions include the “exchange of information” (or bits of code that represent some variable of interest) and modify their behavior based on the behavior of other agents (Gilbert 2006).

According to Gilbert (2006), ABMs generally rely on the following assumptions:

1. **Autonomy**—Agents interact with little of no central authority
2. **Purpose**—Agents are goal oriented
3. **Social Ability**—Agents are interdependent or respond to other agents
4. **Adaptation**—Agents are adaptive and backward looking

ABMs provide many of the benefits of formal modeling (including clarity of assumptions, internal validity, etc.; see Taber and Timpone 1996), while also allowing researchers to represent complex, nonlinear processes that are not easily expressed through the use of standard equation-based approaches. Moreover, when adaptation as opposed to strict optimization is a crucial component of the theoretical process of interest, ABMs and computational simulation may be the only formal method capable of representing the underlying phenomena (Axelrod 1997). As argued in Axelrod (1997), computational modeling and simulation provide “a third way of doing science.” As with deductive methods, agent-based modelers start by making explicit assumptions; however, they do not prove theorems. Instead, they rely on inductive methods and simulation to explore a model’s behavior using a series of computational experiments. These models provide considerable advantages over other formal approaches when the complexity of a

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⁴ The “first wave” was primarily differential equations (in the 1960s). The “second wave” corresponded to the use of micro-simulation in the 1970s (see Gilbert and Troitsch 2005 for an overview).
phenomenon of interest does not permit analytic solutions via algebraic manipulation (Axelrod 1997; Taber and Timpone 1996).

A key feature of ABMs—which flows directly from their nonlinear, interactive nature—is their focus on emergence: properties arising from interactions of agents that cannot be deduced from aggregating the properties of the agents. As Durkheim explains, “The hardness of bronze lies neither in the copper, nor the tin, nor in the lead which have been used to form it, which are all soft or malleable bodies. The hardness arises from the mixing of them” (cited in Macy and Willer 2002, pg. 6). ABMs allow researchers to examine how the interactions and motivations of individual agents produce global patterns of behavior. Thus, these models work to “bridge the gap” between micro-level motivations and macro-level patterns (Macy and Willer 2002; Gilbert and Trotzsch 2005). In the context of our model of development, ABMs enable us to analyze how individual developers and cities interact to form overall regional patterns.

THE MODEL: AGENTS AND THE ENVIRONMENT

City Decision Algorithm

Cities are represented in the model as units in a 33 x 33 square grid, which approximates the distribution of cities across a geographic space. Figure 1 provides a visual example of how the hypothetical geographic region appears in the computer program. Consistent with the literature on land use regulation and local economic development, we assign a number of characteristics to each city in the geographic space. First, the economic profitability (profits) associated with building (building is represented by the variable build) in each city is distributed across the grid following a standard normal distribution. For simplicity, profits are assumed to take on a value between 0 and
50, and the normal distribution is centered on 25. We also assume that the profits associated with a particular development project decrease at a constant rate—i.e., our model incorporates the standard economic assumption of diminishing marginal returns. Specifically, we incorporate this assumption by introducing a “discount parameter” into the program code, which reduces the profitability of subsequent projects in a city by a fixed amount. It is important to note that this parameter provides a clear “first mover advantage” for development companies. The second primary variable of interest is the time delay ($delay$) associated with each city, which is distributed randomly across the spatial grid. The $delay$ variable ranges from 1 to 10 months, which is generally consistent with survey data at the city level on time delays.\footnote{Based on a recent survey conducted by the Wharton School, variation under 10 months of delay seemed a reasonable approximation for residential housing projects (Gyourko, Saiz, and Summers 2007). Moreover, we conducted a survey of California City Managers in the summer of 2007 which suggests that this figure is generally consistent with commercial projects as well (for more information on this survey, see footnote). Though, in both cases, there are several major outliers in terms of regulatory times.} Third, the amount of land zoned for commercial use ($zone$) is distributed randomly across the geographic space. In terms of the model, this variable influences the number of commercial developments (or buildings) that are permitted in each city. We assume that the $zone$ variable remains constant throughout a simulation run—i.e., zoning changes are not allowed in this simple version of the model.

*Insert Figure 1 about here*

In our model, cities do not simply provide the geographic space for development—they react and adapt to their surrounding environment. Given the underlying characteristics discussed above, public officials are assumed to maximize the number of commercial buildings in their cities and thus maximize the tax revenue and employment opportunities associated with commercial development (or $U = U(b_i)$ for city
i, where b represents the number of buildings). We recognize that defining the city’s utility function strictly in terms of the number of buildings greatly simplifies the city decision making process and fails to incorporate a “city’s strategic vision” into the calculus (i.e., some cities simply may not want and will not permit commercial projects). Nevertheless, the zone variable discussed above could be interpreted as representing this “vision” dimension, as some cities in the model will not permit any commercial development.

Given the underlying city characteristics and the assumed utility function, how do cities adjust their behavior to attract more development? We model cities as adapting their regulatory policies to more closely represent the policies of successful neighboring cities—i.e., cities in our model follow the dual strategies of adaptation and optimization.

There is a well-developed literature on city-level cooperation and competition that suggests that cities are interested in the actions of their neighbors (c.f., Goetz and Kayser 1993; Gordon 2007). While cities are usually assumed to compete by offering incentives or subsidizing project development, regulatory delays offer another policy relevant variable that may be manipulated by local officials to facilitate development. Moreover, recent empirical work by Gyourko, Saiz, and Summers (2007) indicates that time delays may be the critical variable in explaining variations in regulatory environments across metropolitan statistical areas. Specifically, the authors’ factor analysis results suggest that approval delays explain the greatest level of variation in their aggregate “Wharton

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6 Our emphasis on development above all other objectives suggests that our model is consistent with a more general rational choice literature on city economic development and city competition (Peterson 1981; Schneider 1989). Nevertheless, the ABM framework presented here can be easily extended to represent alternative explanations (e.g., political influence models, etc.) of city-to-city interactions.

7 It is important to note that personal experience in local government and commercial development in the Southern California region suggests that delays may be the critical factor in location decisions.
Residential Land Use Index. Given the above argument, the city’s are programmed to make decisions in three general steps:

**Step 1.** Given the utility function $U = U(b_i)$, city $i$ examines the economic success of their eight surrounding neighbors with respect to buildings, organizing their building values into a 1 x 8 “neighborhood vector” $(N)$.

**Step 2.** City $i$ maximizes the neighborhood vector with respect to the number of buildings to find the most successful city in its immediate region, or $MaxN = b_{max}$.

**Step 3.** If $b_{max} > b_i$, then city $i$ adjusts its regulatory environment (which is represented as delay in our model) to more closely reflect the city with $b_{max}$ (specifically, they move the average distance between the two delays), given a pre-specified “adoption probability” equal to $a$. $a$ represents the simple fact that even if the “correct” policy for attracting commercial development is known, not all cities will be in a position to change their policy environments.

**Developer’s Decision Algorithm**

On the developer side, our model maintains the standard assumptions describing economic agents—i.e., they are rational, utility (or profit) maximizers. We define two “classes” of developer agents: the first agent maximizes profit alone ($U = U(p_j)$ for developer $j$, where $p$ represents profits), while the second agent maximizes with respect to both profit and the expected delay associated with a particular development project ($U = U(p_j, d)$). In order to simplify the discussion below, we refer to the first class of developers as “naïve” maximizers (n-maxes) and the second class as “sophisticated” maximizers (s-maxes). N-maxes provide a baseline of developer behavior to compare with the more sophisticated s-maxes and thus allow us to assess the importance of delay times in the developer’s decision calculus. Both classes of agents’ posses the market information ($info$), which determines their ability to examine surrounding cities and

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8 To be sure, their data does not suggest that regulatory delays are the only source of variation. Other factors such as local political pressure also matter (see Gyourko, Saiz, and Summers (2007)).
gauge the profitability of development projects. In terms of the actual program, Info determines the length of the radius used to buffer the geographic area around the developer’s current location. Moreover, to simplify the analysis, we assume that developers only participate in one project at a time. Given these behavioral assumptions, the developer’s are programmed to make decisions in three steps:

**Step 1.** Developer j surveys their surrounding cities based on a pre-specified level of “market information” (info) in order to gauge profitability and development opportunities.

**Step 2.** Developer j organizes the information on profit from step 1 into a profit vector \((P)\) and maximizes the vector using the developer’s specified utility function (e.g., if \(U = U(p_j)\), then \(\max_{p} P = p_{\text{max}}\)). The length of the profit vector is determined by the variable info.

**Step 3.** If \(p_{\text{max}} > p_j\), then developer j moves to the city where profits are the highest \((\text{profit} = p_{\text{max}})\), builds, and the city’s profitability is adjusted to represent the discount parameter. If the city’s delay \(> 0\), developer j is held at the city for the number of months equal to delay and forgoes other investment opportunities during this period.

**Model Expectations**

We have described a model where rational developers move to different cities, build commercial projects, and are held at a given city based on the city’s underlying regulatory structure. Moreover, cities adapt their regulatory environments to match successful neighbors in order to attract future development projects. Given the above specification and assumptions, we form several expectations regarding the model’s behavior. First, we expect developers maximizing on both profits and delays (i.e., s-maxes) to perform better in terms of profits than agents maximizing on profits alone. This expectation flows directly from the opportunity cost to developers of delayed project approval. Second, we expect to observe clusters in regulatory environments across the spatial grid. The process of adaptation should drive similarities in delay times between
neighbors in our hypothetical geographic space. The extent of the clustering activity will be meditated by the adoption probability \((a)\) and thus we will explore the sensitivity of modifying this parameter. We explore these expectations using a series of computational experiments in which we systematically vary model parameters and observe the model’s behavior through simulated data. While the above expectations are quite general, they highlight the types of analyses that researchers may perform using ABMs, as well as some of the potential benefits of using simulation to explore highly nonlinear, interactive environments.

MODEL BEHAVIOR: COMPUTATIONAL EXPERIMENTS

We begin by exploring a “Base Model,” which describes a “typical” simulation run under a set of pre-specified parameters. Specifically, the assumed initial conditions under the Base Model include:

- Number of s-maxes = 10
- Number of n-maxes = 10
- Market Knowledge = 20
- Discount Rate on Profitability = .8 (note: this rate represents the diminishing marginal utility assumptions specified above)
- Adoption Probability \((a) = .5\)

We let each simulation “run” for 120 ticks (or time units), which approximates 10 years given that the assumed unit of time is months. Moreover, zoning is “loose” in the sense that many cities in the base model are assumed to have sufficient land zoned for commercial purposes. 9 Figure 2 provides a snapshot of the “dashboard” used to conduct the computational experiments, which provides the tools to adjust the models underlying parameters and variables.

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9 The number of commercial projects allowed in each city is distributed based on a uniform random distribution with a maximum building number of 20 projects.
Under the Base Model, we find that s-maxes consistently score higher in terms of profits when compared to n-maxes. To refresh, the profitability of a given project ranges from 0 to 50, with higher numbers representing greater profitability. After 100 simulations, the mean value of the summation of profits across s-maxes was 11,116, while the equivalent value for n-maxes was 9,971. Using a standard difference of means test, the difference is statistically significant at the 1% error level (p=.0004). This finding confirms our general expectation that the level of regulatory delay influences the profitability of firms and thus it “pays” to be mindful of a city’s regulatory process. However, this is not the whole story. Systematically varying the models parameters enables us to analyze the conditions under which time delays “matter” and why the model is producing these results.

First, the initial findings are robust to varying levels of market information. Holding the s-maxes’ info constant and changing the n-maxes’ info to represent perfect information, we find that significant differences persist (s-mean = 10,409, n-mean = 9,672; p = .0000), though the absolute difference in the means decreases. The results are considerably different, however, when examining the effects of the discount parameter. To refresh, the discount parameter represents the rate at which projects become less profitable after an initial development and thus incorporates the assumption of diminishing returns. Moving the discount parameter from .8 to .5, the mean value for the s-maxes equals 8,973, while the mean value for the n-maxes equals 9,646 (p = .0000). This finding suggests that the importance of taking time into account is greatly reduced (and potentially eliminated) when the number of profitable projects is scarce.
It is critical to remember that developers’ are not maximizing profits in a vacuum: cities are adapting based on the actions of developers, as well as the policies of neighboring cities. Based on the model, cities are moving closer to their more successful neighbors in terms of their approval times and this movement is conditioned on an exogenous probability of adoption. From the evidence presented on the general success of s-maxes, it is reasonable to expect that the dynamic evolution of cities will be to reduce the overall level of delays. Indeed, this expectation is confirmed based on the simulations analysis. Figure 3 presents the average distribution of cites organized by the level of regulatory delays. As shown in the figure, the model indicates that the distribution is clustered toward the origin: more specifically, the distribution is single peaked at 3 months and skewed toward the origin. This finding is consistent with the limited data we have on commercial development delays. Figure 4 presents the distribution of commercial development delays across 98 cities in California, as reported in a recent survey of California City Managers.\textsuperscript{10} As shown in the figure, California delays are single peaked on 3 to 6 months; however, the distribution tends to be skewed away from the origin. While we cannot make any strong conclusions from such a limited dataset and only rough correspondence, general similarities are encouraging.

\textit{Insert Figure 3 and Figure 4 about here}

The adaptive behavior of cities in our model highlights the process of emergence in agent-based theoretical designs. Figure 5 and Figure 6 provide snapshots of this adaptive process using our spatial grid and different values of the parameter $a$. In the each

\textsuperscript{10} We conducted an internet survey of California City Managers and Planning Officials in the summer of 2007. The survey consisted of a series of questions regarding local regulatory measures, including specific questions on housing, mixed-use development, and commercial projects. The surveys response rate was 36%. 
of the figures, darker squares represent cities with longer regulatory delays and vice versa. As shown in Figure 4 (which represents the Base Model), the model generates a considerable amount of spatial clustering, with pockets of low, medium, and high delay areas. Even more interesting, however, is that the spatial clustering continues at very low probabilities of adoption. As shown in Figure 5, while regulatory environments are more dispersed at lower values of $a$, considerable clustering remains at a probability as low as .1. This finding suggests that even if cities adapt their behavior at low probabilities, we should find clustering in regulatory activity when analyzing actual data on city regulatory behavior. The identification of clustering illustrates the ways in which ABMs—with their focus on emergence—can generate new hypotheses linking micro and macro behavior.

*Insert Figure 5 and Figure 6 about here*

With a general overview of developer and city behavior in hand, it is useful to highlight some of the dynamic interactions suggested by the model. We have already suggested that developers’ profit motivations have fundamental implications for city behavior. Specifically, developers maximizing with respect to profits and regulatory delays tend to drive adaptive cities toward lower overall time delays. Nevertheless, actions of cities have important dynamic feedback effects for developers. For instance, earlier simulation runs suggested that lower discount rates on profitability tend to eliminate the benefits of taking into account regulatory delays. However, on closer inspection, the model suggests that this result is largely a function of the tendency of cities to adapt to more efficient regulatory environments. If we adjust the adoption probability to represent a lower level—and perhaps a more realistic level given the numerous constraints on cities—of adaptation, the results move back in the direction of
the Base Model. With an adoption probability of .1, the mean profit level of s-maxes equals 9,705, while the mean level for n-maxes equals 8,998 (p = .0000).

CONCLUSIONS AND FUTURE RESEARCH

Our model suggests several testable propositions regarding commercial development, regulatory delays, and city behavior. First, based on the results of the simulation analysis, we expect cities with lower regulatory delays to have higher levels of commercial development. This proposition is based on the dynamic interaction of developers and cities, as well as the finding that “sophisticated” maximizers tend to perform better in terms of profitability. Specifically, in an environment where regulatory delays exist, developers maximize profits by accounting for delays and produce in cities with lower overall delay times. In our simplified model, developers are directly impacted by the opportunity costs of being “held up” by the regulatory environment, which restricts movement and the ability to invest resources in alternative cities. It is not difficult to imagine real world market situations in which an emphasis on opportunity costs of delays would be a crucial factor for profitability. In fact, our model highlights one such instance: when many market opportunities exist and cities have very different regulatory environments. We hope to explore this proposition empirically in future research and are currently gathering data regarding commercial developments and survey evidence on regulatory delays.

The model also produced interesting findings with regards to clustering in regulatory environments across cities. The simulation evidence suggests that if cities are in competition with one another and have the ability to adjust project delay times, we are likely to see spatial clustering in regulatory environments and dynamic movement toward
reduced delays. Moreover, the clustering activity persisted at low adoption probabilities—i.e., the probabilities one would expect given the multiple factors constraining policy change at the city level. The model is, however, a simplification of reality and other factors may impact the extent to which researchers find evidence of clustering in actual data. For instance, cities often compete with only a handful of other cities—often with similar demographic and economic characteristics—and thus the impact of clustering may be attenuated (Goetz and Kayser 1993). Nevertheless, the general tendency of clustering should remain. We hope to analyze this proposition in future research using survey data, geographic information systems (GIS), and geospatial regression techniques.

This short study on the dynamic interactions of commercial developers and cities provides only a preliminary introduction to the types of analyses scholars are able to conduct using agent-based modeling designs. Even in this quite simple model, interesting behavior emerged from the highly nonlinear interactions of city and developer agents. ABMs provide an important new tool for researchers of local policy studies and economic development, as they more fully capture the complexity of current theoretical structures, while also providing a platform for combining multiple theories into a single analytical framework. We are confident that future researchers will see the value of incorporating computational methods into the qualitative, quantitative, and mathematical methods that currently dominate the field.
WORK CITED


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FIGURES

Figure 1: Spatial Grid of Cities

Figure 2: Model “Dashboard”
**Figure 3:** Distribution in Regulatory Delays across Cities (Base Model)

![Bar chart showing distribution of regulatory delays across cities.](image)

**Question Wording:** In cases where proper zoning is already in place, what is the typical amount of time between application for approval and the issuance of a building permit for the following types of development? Commercial development between 50,000 and 100,000 square feet.

**Figure 4:** Distribution in Regulatory Delays across California Cities (Survey Data)

![Bar chart showing distribution of regulatory delays across California cities.](image)
**Figure 5**: Base Model \((a = .5)\)

![Base Model Image]

**Figure 6**: Low Probability of Adoption \((a = .1)\)

![Low Probability of Adoption Image]