

The Cost of the Culturati: Studying the Neighborhood Stability Impact of Cultural District Designations

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The decision to declare a district for a specific cause is a critical policy decision; making an area an official office park or designated cultural site means it will attract specific types of residents and businesses and require specific amenities. This paper reviews the impact of designating a cultural district as a place-based policy, specifically by developing a measure of neighborhood stability and applying a stress test of neighborhood stability in cultural districts during the Great Recession. The model underpinning the neighborhood stability measure is an optimal stopping time model which frames neighborhood rents as a Brownian motion with drift. This structure imposes minimalist assumptions and develops two reduced form parameters which describe individual preferences for how long to live in a neighborhood. This analysis is in the style of [Alvarez et al. \(2015\)](#). The parameters are then used to test neighborhood stability, with the result that neighborhoods designated specifically as cultural districts are far less likely to experience negative stability (e.g., large amounts of residential out-migration and thus shorter residency spells) with a causal effect size four times larger than the effect size of a recession itself. However, such neighborhoods are also more likely to experience an influx of newer higher income residents after designation, implying the beneficiaries of the new stability may be those who priced out the original creators of the neighborhood's cultural capital.

1 Introduction

Urban revitalization efforts have played a major role in the much-documented millennial movement back to the city. (Couture and Handbury, 2017) One of the common toolkits of the urban revitalization planner is the creation of special districts, such as the Avenue of the Arts in Philadelphia or NoDa in Charlotte. These designations are essentially place-based policies which then serve as signals to entrepreneurs and potential residents that these districts are the intended center of specific economic or social activities. Residents seeking identity-specific (such as in gayborhoods) or industry-specific amenities (the arts district) are more likely to settle in these areas due to the perceived benefits of consumption and production agglomeration, respectively. As a particular example, the Avenue of the Arts in Philadelphia was a major initiative on the arterial Broad Street in the Center City District whose motivation was entirely to condemn blighted housing in the district and replace it with creative industries to drive vitality in a new central business district. (Bounds, 2006)

Special districts are often loci for high rates of minority entrepreneurship, and the designation as a district can act as a way to send a clearer signal to new, less informed consumers about the neighborhood's business and residential communities. This formal designation is thus a critical policy measure that in a sense "brands" a neighborhood to potential consumers. A famous example — the formal designation of the South Beach, Florida Gayborhood was a landmark moment in LGBTQ+ migration into the region. While South Beach was certainly a queer space before this designation by the city, new in-migration from queer folks who were not South Beach residents remarkably increased after designation. (Kanai and Kenttamaa-Squires, 2015)

However, such designations can also attract external, higher-income residents to previously unknown neighborhoods, causing pre-designation residents to trickle out as rents and local amenity prices rise. Then, there is a classic real estate investment cycle problem, where revitalization comes at the expense of current residents. What sets this policy apart from other place-based policy design is persistence of the special district amenity. The designation of a special district is often more lasting than a passing place-based economic policy like a tax abatement. (Ratiu, 2013) As a result, while an industrial park subsidy displaces one generation of buyers, (Redfearn, 2009) cultural districting policies could drive a more continuous rate of neighborhood turnover as the wealthiest consumers within the relevant cultural group turnover the cultural district itself.

(Kubrin and Ishizawa, 2012)

Then, the question of how “stable” designated cultural districts like Gayborhoods, Chinatowns, or Arts Districts truly are is not a straightforward question. On the one hand, one can argue that the designation acts as a time-persistent amenity which anchors individuals of a specific “type” to that district. (Lee and Lin, 2017, for more on persistent amenities) On the other hand, one can argue that such districts because of their high profile after designation may tend to experience a consistently higher rate of instability as residents and entrepreneurs remain in flux with new tastes, trends, and income brackets.

This paper investigates the question of designated cultural district (DCD) stability, and evaluates whether designation as a special district comes at the cost of long-term neighborhood instability. The extent to which the long-term cost is desirable in the name of urban revitalization from a purely economic standpoint (admitting the shortcomings of such an analysis) is then discussed. I develop a reduced-form distribution to model the decision-making problem faced by residents of a special district on considering when to leave the district. The model frames leaving the district in terms of an optimal stopping time problem with the operative decision being when to leave conditioned on a stochastic process which models neighborhood rents (a Brownian motion with drift).

I thus provide the following contributions to the field: (1) I develop a direct corollary to results in unemployment dynamics to methods of neighborhood choice. (2) I discuss the creation of a measure of neighborhood stability and the challenges this poses. On this, I develop a measure which controls for individual preferences by developing a measure of the “type” of an individual from the model which gives contribution (1), allowing full identification of the impact of neighborhood features on the resident’s expected lifetime in a neighborhood. (3) I argue that designation as a cultural district contributes to robustness of a neighborhood against exogenous shocks using the Recession as a case study, extending expected resident lifetimes despite the shock by an effect size 3 times as strong as the effect of the Recession itself. However, DCDs also likely raise rents and price out previous residents, so it is an open question as to for whom the neighborhood is more stable; the original creators of the culture of the district, or new, potentially displacing forces.

This paper uses data from RentBureau, a credit bureau dedicated to the multifamily industry which collects rental histories from a network of apartment owners and managers. Individual rental terms are observed, including

collections, rental amount, and final payment dates, as a census. This dataset is available from January 1997 until June 2010.

The remainder of the paper is structured as follows. In Section 2, I provide further background on the DCD and literature which mirrors the methodological choices of this paper. The theory and structure of the model is built out in section 3, with some comments on the individual model provided in Appendix A. Brief data summaries follow in Section 4. Section 5 provides results and discusses the development of a policy model which uses the individual-level reduced form parameters to isolate the causal effect of DCDs on neighborhood stability. I also develop a picture of what “neighborhood stability” truly means in a measurement sense in this section. Section 6 summarizes our key conclusions.

2 Literature Review

New residents of a neighborhood who do not leave after the first year are more likely to stay in the neighborhood for a long period of time. (Deng et al., 2003) A marketer might suggest a loyalty effect sets in and keeps residents in their neighborhood. The sociological anchoring effects of community back up this explanation as a potentially causal story. (Temkin and Rohe, 1998) A game theorist may argue that individuals arrive in neighborhoods with imperfect information, and that those who sort out in the first year are those who discover that their information was incorrect to the point that the neighborhood was suboptimal. (Anenberg, 2016) Both likely hold some grain of truth, suggesting that the hazard rate of migration out of a neighborhood is a mix of heterogeneity and duration dependence. This paper uses the labor model of an optimal stopping time problem for hazard rates in- and out of unemployment and applies it to the resident’s optimal out-migration time problem. We develop nonparametric decompositions of heterogeneity and duration dependence in the manner of Alvarez et al. (2015). The predecessor to this paper, they frame the decision to take a job as an optimal stopping time problem. They cast wages into a Brownian motion with drift, and I intend to do the same with local neighborhood rents. Their derivation also allows decomposition of the job-finding hazard into heterogeneity and duration dependence, while developing a nonparametric estimation for a paper of latent sufficient statistics. Studies of separation into unemployment have used this structure to analyze whether recall expectations (expectation of re-employment as in the case of a temporary layoff) muddle

duration-dependent signals. (Nekoei and Weber, 2015) Generally, the nonparametric mixed hazards model has been used with time-varying covariates because it is quite easily identified. (Brinch, 2007)(Hobbs, 2015) The method across the literature generally devises a structural evolution for key individual-level parameters, popularly including individual discount rates and some stochastic or fixed formulation for reservation wages. Spinnewijn (2015) introduces biased beliefs in to the classic two-period model of unemployment, obtaining sufficient statistics from a modified Baily formula. He proves that in this setting identification of two moments of the individual utility problem is sufficient for policy design. Generally, sufficient statistics approaches estimate wage elasticity to a parameter of interest, such as uninsurance benefit rates. (Kroft and Notowidigdo, 2016)

The sufficient statistics is also quite present in the neighborhood choice literature, to which this paper makes its contribution. The search for such sufficient statistics is in particular still a topic of discussion. Segregation levels, for example, are not able to characterize racial sorting impacts on income and education. (Bayer and McMillan, 2005) Wealth has been estimated to be a key driver for neighborhood relocation and churn (in a model, notably, which does not account for multi-period savings or consumption). (Bayer et al., 2016) I argue that generally, churn is a more apt sufficient statistic than rents alone in the place-based policy literature because such policies tend to price out existing residents and gentrify neighborhoods. (Givord et al., 2013) Indeed, rents primarily benefit city government tax budgets and those who afford to own local housing capital; gentrification imposes costs by pricing out non-owning, often low-income, households, causing loss of efficiencies from accrued local knowledge. (Shaw and Hagemans, 2015) Thus, quantifying churn is of major interest when thinking about efficiency. A persistent threat of asset loss can impose well-being effects and generally make individuals less likely to use credit, affecting their ability to make own-optimal consumption choices. (Sakizlioglu, 2014) Generally, measures of demand for skilled labor is sufficient to estimate tract demographic, population skill-levels, and housing prices. (Edlund et al., 2015) When analyzing impacts, on displacement, the sufficient statistics tend to come from rents or are indirectly derived from a rent-based measure. (Liu et al., 2017) (Furman and Orszag, 2015) This is the perspective this paper will adopt and subsequently defend. This is consistent with literature on neighborhood choice from other perspectives as well. For example, models of private provision argue that an “impatience rate” can be viewed as the source of heterogeneity in deciding to privately provide a public good. (Bhattacharya et al., 2017) Then,

the individual level decision in the literature tends to be driven (akin to in the labor literature) by two factors; a timing problem and a rent level.

The experiment in this paper is an impulse response (exogenous shock) experiment which uses changes in hazard rates during a recession to test differences across neighborhoods. A study of the Great Recession on the long-term unemployment rate uses a similar decomposition into duration dependence and heterogeneity to compare pre-Recession and post-Recession hazards. (Kroft et al., 2016) Another paper uses the exogenous shock of plant closures to determine whether there is a significant signaling effect in unemployment duration. Their model is a simply proportional hazards specification with a single-term estimator, however - not a fuller structural approach. (Becker and Jahn, 2015)

The final relevant literature is the discussion of the anchoring effect of cultural districts. Amenities can act as anchors which fix neighborhoods to certain income levels with less volatility over time when they are persistent. Empirical results on the topic are mixed. (Lee and Lin, 2017) This paper questions whether designating an area as a cultural district can act as an anchor point for higher income members of the targeted communities. Actual empirical results are mixed. An exercise in South Beach, Florida suggests that the queer community before and after the designation of the gayborhood has become more dispersed, and that queer entrepreneurs were gradually priced out by in-migrants from other cities who have taken over the strip. (Kanai and Kenttamaa-Squires, 2015) Theoretically, however, cultural districts like ethnic enclaves should promote agglomeration by overcoming language barriers and work-rule differences in immigrant populations which result in underemployment in other neighborhoods. (Kaplan, 1998) City planners have long discussed the merits and drawbacks of anchor-based development which creates anchor institutions that can help prevent fragmentation of communities after development. In the status quo, however, the location of affordable housing is not correlated with proximity to institutional and neighborhood amenities, where anchor-based revitalization is targeted. (Silverman et al., 2015) This suggests that as an experiment, there is indeed a clean treatment effect when considering specialty districts as possessing potential anchors in the status quo, as opposed to neighboring districts.

3 Theory

3.1 Individual Choice Problem

The individual i when choosing a neighborhood trades off consumption of a housing good and other consumption. Greater expenditure on rents implies lower expenditure on consumption, and with greater expenditure on rents tends to come a higher utility from amenities (because one can spend more, access is more likely to neighborhoods with tailored local amenities). This tradeoff is not absolute a low rent can still lead to a decent value of amenities, so I adopt the following relatively flexible utility function for the individual maximization problem.

$$\max_j U_{ijt} = c_{ijt} \cdot A_{jt} \quad (1)$$

$$\theta_{it} \geq c_{ijt} + R_{ijt} \quad (2)$$

$$A_{jt} \geq \underline{A}_{jt} \quad (3)$$

The last equation refers to the fact that individuals demand some world-clearing nonnegative amenity value at minimum. For the purposes of this paper, we assume that income is equivalent across neighborhoods j . This is obviously not the case, as some individuals will have specific skills that only earn wages in the vicinity of certain workplaces, but one can craft a skill-adjusted measure of amenities to adjust for such a consideration. I assume away structure due to savings so the model strictly excludes the possibility of borrowing. In such a setting, the maximized utility should correspond to:

$$\max_j U_{ijt} = (\theta_{it} - R_{ijt}) \cdot A_{jt} \quad (4)$$

Imagine now the rent-setting problem. Developers charge the individual a rent which should increase in the value of local amenities with a fixed baseline price according to the land value of the neighborhood. A hedonic component that should correlate with income also comes into play; individuals with higher income are more likely to buy homes with the extra bathroom or bedroom. So, willingness-to-pay for rent should adopt a potentially linear form that mirrors the following

$$R_{ijt} = \omega_j + \omega_A A_{jt} + \omega_\theta \theta_{it} \quad (5)$$

One can adjust for imperfect local competition by adding a markup to this rent function which varies with land supply tightness (ρ_j) or a local cost of new construction that might be connected to land use policies. This markup can be absorbed by the coefficients and components of rent in (5).

Residents will therefore choose a neighborhood based on the amount of amenity received for rent. Of course, if rents themselves are a function of amenities present, then we can obtain a marginal utility of amenities in a closed form.

$$\max_j U_{ijt} = (\theta_{it} - R_{ijt}) \cdot \frac{1}{\omega_A} (R_{ijt} - \omega_j - \omega_\theta \theta_{it}) \quad (6)$$

$$\frac{\partial U_{ijt}}{\partial R_{ijt}} = \frac{1}{\omega_A} \theta_{it} - \frac{1}{\omega_A} (2R_{ijt} - \omega_j - \omega_\theta \theta_{it}) \quad (7)$$

Then, individuals will choose to leave a neighborhood for some maximal amenity (which drives a maximal rent an individual is willing to trade off before consumption gets undercut). The notation for this value is \bar{R}_{ijt} . Now we borrow a convention from labor economics, however; individuals will not choose a neighborhood unless it meets some minimal level of amenity (and, in turn, rent), \underline{R}_{ijt} . This can correspond to some world-clearing price of a home, the amenity value of the last neighborhood the individual was in, or some other measure of an amenity floor. In labor economics, this is the benefit received during unemployment. This is weakly greater than 0.

We tackle a system with N neighborhoods. In a neighborhood with an amenity level A_{jt} , if an individual pays rent on housing of R_{ijt} , denote the present value of the neighborhood to the resident as $E(A) - E(R)$. For convenience, we will drop the subscripts in this section, where the subscripts may clutter the analysis. Then, individuals will move into the neighborhood as long as $E(A) \geq E(R)$ and $R \leq \theta$ for income θ . \underline{R} is the lowest rent at which the individual will live in a neighborhood. This rent is determined by \underline{A} , the lowest amenity value at which they will live in a neighborhood, assuming rents are increasing in amenity value. The highest rent is given by \bar{R} , corresponding to the rent at which utility from consumption will start to decrease to a suboptimal level if rent rises at a *fixed* amenity value. Structurally, each individual has an

unobservable \underline{A} and a (thus unobservable) reservation rent derived from this amenity level. They also have an unobserved ceiling rent level, \bar{R} .

3.2 Structure

An individual resident is in state $j(t)$ corresponding to which neighborhood they live in in period t . They experience a state-dependent stochastic process that drives the evolution of individual potential rents over time:

$$d\log(R_{ijt}) = \mu_{j(t)}dt + \sigma_{j(t)}dB(t) \quad (8)$$

for standard Brownian motion $B(t)$. The residential state is described by neighborhood and potential log rent. A worker can choose to enter a neighborhood at some fixed cost ψ . Workers are risk-neutral with discount rate $r > 0$.

To ensure that the problem is well behaved, apply the condition $r > \mu_{j(t)} + \sigma_{j(t)}^2/2$ for each possible state $j(t)$. If this is violated for some $j(t)$, the expected value of staying in this fixed neighborhood will be infinite. I discuss this restriction further in the appendix, and derive subsequent results as well.

The resident will remain in a neighborhood while $j(t) = j$ and $R_{ijt} < \bar{R}$, but will churn out the first time this condition is violated. This condition is strict as long as ψ is strictly positive. This encompasses an interpretation of voluntary movement, but a reinterpretation where developers have price setting power will demonstrate the profits for the developer earns a profit $R_{ijt} - \underline{A}$ (\underline{A} is the amenity level that is used to determine the reduced-form \underline{R} , corresponding to a level of utility from out-of-neighborhood amenities) and can attract new residents for a fixed cost ψ - then, this can also capture forced eviction and developer-driven mobility.

Residents are described by discount rate r , base amenity utility \underline{A} , and the parameter space governing the stochastic process for their potential rents. In reduced form, we obtain two parameters, \underline{R} and \bar{R} . The distributions are entirely arbitrary across the population.

To determine the length of residency, note that the residency will occur once rents breach the lower threshold, \underline{R} . The log-rent will follow the set stochastic process and the residency spell continues until the log-rent breaches the upper threshold, \bar{R} . The residency spell is thus the first passage time of this Brownian motion with drift, an inverse Gaussian with d.f.

$$f(t, \alpha, \beta) = \frac{\beta}{\sqrt{2\pi}t^{3/2}} \exp\left(-\frac{(\alpha t - \beta)^2}{2t}\right) \quad (9)$$

where $\alpha = \mu_j/\sigma_j$ and $\beta = (\bar{R} - \underline{R})/\sigma_j$. The former varies over the reals, while the latter is weakly positive. For nonnegative α , the resident almost surely churns out of the neighborhood in question. But, if α is negative, they have a probability $e^{2\alpha\beta} < 1$ of leaving the neighborhood and therefore may never do so.

The shape of the inverse Gaussian is fairly flexible. There are specific characteristics that are worth noting. Hazards at move-in ($t = 0$) are always 0. It achieves a maximum value at a finite time t , then declines to a long-run limit $\alpha^2/2$. The expected duration of residency is β/α , with a variance of β/α^3 . Asymptotically, the remaining duration of residency approaches $2/\alpha^2$ (note this can be larger or smaller than the expected residency time at move-in depending on α , implying both positive and negative duration dependence on possible). The flexibility of possible behaviors associated with a longer duration of residency allows modeling a dynamic selection problem, where developers in new neighborhoods are likely to cater first to individuals with the highest reservation rents, then the next group, and so forth.

This analysis will assume that parameters are time-invariant at first. One can argue that heterogeneity in parameters across the population can be modeled through unobserved (latent) parameters, and I explore these options once I complete the discussion of testability.

3.3 Integration: From Individual Parameters to Neighborhood Distributions

As with any model of behavior, this model must be falsifiable given data. If a population is observed where each individual has some fixed structural parameters ($r, \psi, \underline{A}, \bar{R}, \mu_j, \sigma_j$) and the reduced form parameters (α, β). If each individual is only observed for a single residency in the neighborhood, the model is non-falsifiable and thus non-testable. Why? Because a single-spell data-point is perfectly explained by assuming that if d periods pass, then $\sigma_j = 0$, $\mu_j = (\bar{R} - \underline{R})/d$. This would imply $\alpha, \beta \rightarrow \infty$ and $\beta/\alpha \rightarrow d$. Unfortunately, unlike in the labor literature, where one observes repeat unemployment spells with nonzero probability the likelihood of observed two spells of residency in the same neighborhood infrequent at best. Such individuals become part of a

selection problem as they are likely to have stronger attachments to local communities or resources than those who do not repeatedly enter a community.

This is where this paper diverges from the previous labor literature that has informed the model thus far. Rather than estimating individual optimal stopping times and hazard rates out of neighborhoods, we integrate the distribution of optimal stopping times across all individuals in a neighborhood to determine what the neighborhood-level distribution of hazards looks like. We can then estimate neighborhood-level survival functions rather than individual-level hazards. Then, each neighborhood has structural parameters which are each a distribution of individual-level parameters, $(r, \psi, \underline{A}, \bar{R}, \mu_j, \sigma_j)$ and reduced-form parameters (α, β) .

3.4 Testing the Model

Now, say we have a sample of residents of size M from neighborhood j whose durations correspond to an observed vector \vec{t} of dimension M . Each has some set of structural parameters as above. Now, their reduced-form parameters are drawn from a joint neighborhood-level distribution g . Then, the density for time of residency (alternatively, the residency “spell”, to mirror the labor literature language):

$$\phi(\vec{t}) = \int \int f(\vec{t}, \vec{\alpha}, \vec{\beta}) g(\alpha, \beta) d\alpha d\beta \quad (10)$$

This differs markedly from the approach of labor economists whose work originates this model. Rather than identifying these individual-level parameters with any fineness, this approach acknowledges this is not possible with repeated renter data and pools across observations.

Allow $\phi^{(i)}$ to denote the derivative of ϕ with respect to t_i . From the functional form of the residency spell duration identified in (9), these derivatives satisfy:

$$\phi^{(i)} = \int \int \left(\frac{\beta^2}{2t_i^2} - \frac{3}{2t_i} - \frac{\alpha^2}{2} \right) f(\vec{t}, \vec{\alpha}, \vec{\beta}) g(\alpha, \beta) d\alpha d\beta \quad (11)$$

Equivalently,

$$\frac{2t_i^2 \phi^{(i)}}{\phi(\vec{t})} = E(\beta^2 | t_i) - 3t_i + E(\alpha^2 | t_i) \quad (12)$$

There is a degree of precision in the previous incarnation of this model that

is lost in the aggregation process. Rather than having the ability to estimate a distribution for α and β for the individual, this model must sacrifice the individual-level inference. This is a quirk of residential data; the estimation is unstable otherwise. However, the conditions for model testability are the same. Both expectations in (12) must be nonnegative. For a constant hazard rate of residency h , so that the density of completed spells is $\phi(\vec{t}) = h^2 e^{-h \sum_i^{I_j} t_i}$ these will be

$$E(\beta^2|t_i) = 3 \frac{\prod_i^{I_j} t_i}{\sum_i^{I_j} t_i} \text{ and } E(\alpha^2|t_i) = 2h - \frac{3}{\sum_i^{I_j} t_i} \quad (13)$$

Then, $E(\alpha^2|t_i)$ violates nonnegativity when the sum of duration times across individuals, $\sum_i^{I_j} t_i < 3/(2h)$, or one and a half times the mean duration. Then, constant hazard rates cannot be generated for just any set of residency spells.

If the constant hazard is now unfixed, with a distribution in the population G , then the density of these completed spells is $\phi(\vec{t}) = \int h^2 e^{-h \sum_i^{I_j} t_i} G(h)$. Then, $E(\alpha^2|t_i)$ is negative if the ratio of the third moment of h to the second moment is positive.

Each moment of the joint distribution of (α^2, β^2) can be obtained through the k^{th} partial derivative. I focus on this first moment of the joint distribution as the litmus test of interest for the time being.

3.5 Nonparametric Identification

Again using the aggregated densities across individuals observed in the neighborhood, I non-parametrically identify the joint distribution of (α^2, β^2) across individuals. Identification is equivalent to identification of the joint distribution of $(|\alpha|, \beta)$. The joint distribution of (α^2, β^2) can be nonparametrically identified by comparing results across multiple neighborhoods with residents who experience a fixed vector \vec{t} (with at least 2 residents being observed in each studied neighborhood). One can compute the joint distribution $\hat{g}(\alpha^2, \beta^2)$ according to

$$\psi(\alpha^2, \beta^2, \vec{t}) = \frac{f(\vec{t}, \alpha, \beta) \hat{g}(\alpha^2, \beta^2)}{\int \int f(\vec{t}, \alpha', \beta') \hat{g}(\alpha'^2, \beta'^2) d\alpha' d\beta'} \quad (14)$$

This could be inverted to solve for this joint distribution $\hat{g}(\alpha^2, \beta^2)$. This test should not depend on the sample \vec{t} used to derive the distribution $\hat{g}(\alpha^2, \beta^2)$, a fact which can be used to test sensitivity of the model.

Alternatively, in a more applicable estimation process which mirrors a New-

tonian procedure, one can assume a starting distribution of types $g(\alpha, \beta)$. For each of these types, the model provides a density $f(\vec{t}, \alpha, \beta)$ which produces the density of actual durations $\phi(\vec{t})$. In a setting with finitely many types $N = \text{card}\{(\alpha, \beta)\}$ and sets of durations $T = \text{card}\{\vec{t}\}$, this is the linear system $\phi = F \cdot g$ for likelihood matrix $F : F \in \mathbb{M}^{T \times N}$ and $g \in \mathbb{R}^N$ a vector which indicates the share of each type in the population. This gives ϕ , the vector of share of each duration in the population. As long as F is invertible, the model is identified. If we assume momentarily $N = T$ (as the other cases will yield many or no solutions), identification is a matter of the rows of the likelihood matrix being linearly independent. As the density of realized durations for one neighborhood is not a linear combination of the density of realized durations for others, the model is identified. In other words, it is unlikely that direct linear dependence is to arise in a highly randomized setting with a large variety of duration types.

3.6 Decomposition of Changes in the Hazard Rate

Define $F(t, \alpha, \beta) = \int_t^\infty f(t', \alpha, \beta) dt'$ as the fraction of type (α, β) residents with spells longer than t periods. Then, the distribution of types among those same workers is

$$\tilde{g}(\alpha, \beta|t) = \frac{(1 - F(t, \alpha, \beta))g(\alpha, \beta)}{\int \int (1 - F(t, \alpha', \beta'))g(\alpha', \beta') d\alpha' d\beta'} \quad (15)$$

The density of residual move-out durations for a given type conditional on the unemployment spell lasting at least t periods,

$$\tilde{f}(\tau, \alpha, \beta|t) = \frac{f(t + \tau, \alpha, \beta|t)}{1 - F(t, \alpha, \beta)} \quad (16)$$

Finally, then, the density of residual residency duration lasting at least t periods is

$$f^r(\tau|t) = \int \int \tilde{f}(\tau, \alpha, \beta|t) \tilde{g}(\alpha, \beta|t) d\alpha d\beta \quad (17)$$

The expectation of this density will be denoted $D^r(t)$. This can be computed directly once the joint distribution of the reduced form (α, β) are identified. Now, if we want to decompose the change in expected durations into the effects of heterogeneity and duration dependence. The contributions of heterogeneity and duration dependence are then:

$$\begin{aligned}
 D^r(t) - D^r(0) &= \int \int \int_0^\infty \frac{d}{ds} (\tilde{f}(\tau, \alpha, \beta|t) \tilde{g}(\alpha, \beta|t)) ds d\alpha d\beta \\
 &= \int \int \int_0^\infty \frac{d}{ds} \tilde{f}(\tau, \alpha, \beta|t) \tilde{g}(\alpha, \beta|t) + \tilde{f}(\tau, \alpha, \beta|t) \frac{d}{ds} \tilde{g}(\alpha, \beta|t) ds d\alpha d\beta \\
 &=: D^h(t) + D^s(t)
 \end{aligned}$$

A similar decomposition can also be constructed on the hazard rates. The hazard rate $h(t) = \int \int h(t, \alpha, \beta) \tilde{g}(\alpha, \beta|t) d\alpha d\beta$. This decomposition gives a term for structural duration dependence and a term for heterogeneity, respectively, as:

$$h^s(t) = \int \int \int_0^t \frac{d}{ds} h(s, \alpha, \beta) \tilde{g}(\alpha, \beta|s) d\alpha d\beta \quad (18)$$

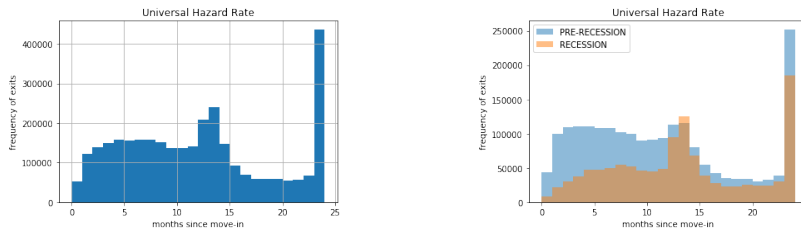
$$h^h(t) = \int \int \int_0^t h(s, \alpha, \beta) \frac{d}{ds} \tilde{g}(\alpha, \beta|s) d\alpha d\beta \quad (19)$$

4 Data

Tenureship data is obtained from the RentBureau dataset. This Experian-produced project contains payment and residency records for 13 years (1997-2010) for an apartment company's residents across many zip codes. The data includes rent amounts (which allows cleaner tests of a priori assumptions about the stochastic process) and records of when a resident enters and exits their apartment. The data also presents a detailed account of payment, non-payment, and collections by month through the lease.

I provide a dataset-level histogram of survivals in the Figure (1a). Note that survivals are censored at the two-year mark (24 months on the x-axis), so we must develop a right-censoring correction. The histogram suggests that a large number of individuals churn out at the two-year mark, but the truth is that part of this large bar contains entries which have resided in their apartments for *at least* two years, not exactly two years.

The second subplot compares survivals in the period of the Great Recession, defined to begin in September 2008, to those which occurred beforehand. Offhand, we generally see the shapes as relatively similar, simply with fewer observations during the recession. I also report the overall joint distribution of pairs of tenures across neighborhoods in a surface plot in (2). Some key ob-



(a) Histogram describing the universe-level hazard function. (b) Histogram comparing observations which moved out before the recession to those which moved out during the recession.

Figure 1: Descriptive histograms for resident move-out times in the entire universe of the dataset.

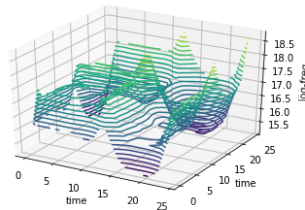
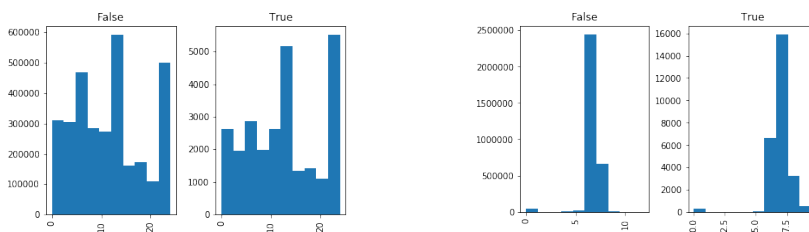


Figure 2: Joint distribution of pairs of tenure lengths (length of residency) within zip codes.

servations: first, note the joint distribution is generally convex, which reflects the declining hazard rate (likelihood to move out) at longer durations (ignoring the peak at 24 due to right-censoring). Second, the joint density is noisy. This does not appear to be primarily due to sampling variation. Rather, there is clear persistence of a yearly tenureship dropoff as this is the likely duration of the average rental lease. The extremely high joint frequencies of multiples of 12 suggests that this is being replicated in the data. This is very much an artifact of the data, and it can be dealt with in two ways. The first; it can be smoothed out using a spectral analysis technique. The second; it can be allowed to remain as is and the model will simply be judged on the surface plot shown for measures of likelihood. Both methods are discussed in the calibration section.

The dataset’s breadth includes several DCD zip codes which are used in this study:

1. Atlanta: Gayborhood, 30318 and Chinatown 30341



(a) Histogram comparing the length of stay in zip codes marked as treatment areas (TRUE) due to designation as cultural districts to other (control, FALSE) districts. (b) Histogram comparing log-rents in zip codes marked as treatment areas (TRUE) due to designation as cultural districts to other (control, FALSE) districts.

Figure 3: Comparisons of tenure and log-rent distributions by allocated control and treatment groups.

2. San Diego: Gayborhood 92103 and Chinatown 92104
3. Los Angeles: Gayborhood 90012 and Koreatown 90005 and 90006
4. New Orleans: The Garden District 70119
5. San Francisco: The Castro, 94114
6. New York City: Riverside District, 10069
7. Tampa: River Arts District, 33602

We use these cities as experimental areas, with the DCDs as treated zip codes. There are 2391 zip codes in the total dataset, from which we extract 123 zip codes. Of these, the zips listed above and any zip codes within a 2-mile catchment (to catch proximity effects) are assigned as treatment. Each zip code has an average of 1340 different residency records. To summarize, I present a simple comparison of log rents and tenure distributions across treatment and control groups in Figure (3).

Generally, there are some initially visible differences across designations in both the tenureship distribution and the rent price distribution. Rent prices appear to be less skewed slightly, in treated districts. The tenure time of a resident appears to follow a similar decrease in skewness. Note that this runs countervailing to an a priori presumption of decreased heterogeneity in treated districts due to cultural similarity. In particular, a homogeneous district is likely to have more unimodal, concentrated distributions. This is clearly not the case. Further exploration and calibration may help to elucidate why this might be happening. With the data in mind, we move to calibrating the model.

5 Calibration

5.1 Testing Compliance

To look at whether the model is able to be fit onto the data, and further whether it is rejected by the data for lack of falsifiability, I conduct a two-stage compliance procedure. I first run two possible smoothing algorithms on the data and discuss why I end up rejecting both methods. Then, I conduct the tests described in 3.4 to obtain a complete picture of what subsets of the data can be fit with the stochastic model.

High-Pass Filter I proposed using a filter in the frequency domain (essentially a high-pass filter around the annual frequency to penalize excessive changes in slope) to target one of the specific causes of the noisiness of the empirical data. The second proposal comes from [Alvarez et al. \(2015\)](#), which is the use of a Hodrick-Prescott filter.

I start with the Fourier analysis approach. Taking the Fourier transform and removing the annual component of the data results in the transformation shown in Figure (4). Recall the original histogram shown in (3a) for a comparison. The filtering operation essentially wipes out most of the noise corresponding to the peaks at 12 months and 24 months (minus the right-censoring effect at 24 months), though the semi-annual peaks are still present (as we do not filter out in six-month increments). The data captures the essential patterns of the original histogram without being too noisy. However, cutting out some of the frequencies in the upper range has also left some of the other information out of the final analysis; the histogram is less granular and I believe the filtering leaves too simplified a model in place. In fact, the slope after the first year shows why this filtering operation cannot stand; it is far too steep a dropoff and far too deep of one as well. The time domain has lost too much information in the process. Raising the high-pass filter barrier does not fix this problem.

Hodrick-Prescott Filtering The second option, the Hodrick-Prescott filter, was used in the study which precedes this paper. It has come under immense scrutiny for similar reasons behind the rejection of the high-pass filtering exercise above; it simply cleans up the data too much to the point that trends which may be spurious become emphasized. From (5), this seems to be exactly what results. In particular, the filter essentially creates a clean sine wave out of the

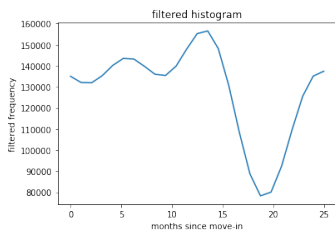


Figure 4: High-pass filtered histogram of frequency of moves.

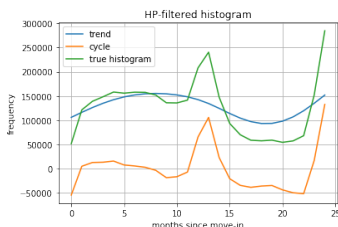


Figure 5: Hodrick-Prescott filtered histogram of frequency of moves.

data. This clean functional result is interesting in its own right, but may lead to an easy overfitting by most models and makes the censoring corrections less easy to conduct. The filter embeds this information directly into the trendline, so using the trend seems disingenuous.

I rejected both of these procedures before conducting the analysis, and the following two sections discuss alternate ways of ensuring the data is workable while making fewer assumptions about the validity of parts of the data or where the information in the data exists. A *carte blanche* filtering operation is likely too liberal given that the structural model already places an assumed stochastic structure on the model, but it was important to discuss given preceding literature.

5.2 Optimization Procedure

As is by now clear, the data is not clean enough for a simple pass through an off-the-shelf convex optimization procedure. I detail the process of finding a minimum-distance estimator here. First, argue that for a neighborhood with unspecified numbers of residency records, we can obtain a robust estimator of the aggregate density function of α_j and β_j , g , by estimating \hat{g} on a subset of the possible residency data-points. Rather than using all of the data-points in each

neighborhood then, we sample 30 timings from each neighborhood (the cutoff from the common rule derived from the central limit theorem) and estimate \hat{g} in this space. Note that the density at this point should be relatively stable, and that we should expect to estimate the same density save some sampling variation for various subsets of 30 residency spells. Then, this mirrors the practice of truncating variable-timespell panel data before analysis to a common timespell, but with a sample size across observation areas.

The data exists as some distribution $\phi(\vec{t}) \in \mathcal{D}(\mathbb{R}_+^{30})$. The distribution of our parameters, $g \in \mathcal{D}(\mathbb{R}_+^{30})$ can be constructed as:

$$\phi(\vec{t}) = \int \int \prod_{i=1}^{30} f(t_i, \alpha, \beta) g(\alpha, \beta) d\alpha d\beta \quad (20)$$

for every such $\vec{t} \in \mathbb{R}_+^{30}$. This is an inner product, so $\phi = Fg$ for positive, linear F . This is a likelihood function; it is essentially an $M \times N$ positive matrix whose columns add to 1. Each entry, $F_{i,j}$ is the probability $Pr\{t_1 \in (t_1(i), t_1(i) + dt], t_2 \in (t_2(i), t_2(i) + dt] | (\alpha, \beta) = (\alpha(j), \beta(j))\}$.

Then, the objective function of the quadratic optimization problem which falls out of the procedure is

$$\min_{g \in \Delta^N} \|Fg - \phi\| \quad (21)$$

where Δ^N is the distribution of possible types (α, β) . To compute g consider the following pre-processing measures.

1. Symmetrize the likelihood so that $\phi(t_1, t_2)$ is the average of the density of (t_1, t_2) and (t_2, t_1) .
2. The grid for α is entirely positive as we can only identify the absolute value of α .
3. Calculate the likelihood at the final bin as the right-censored likelihood; the likelihood of a residency time greater than or equal to 24 periods.
4. Relax the problem so that we do not require g to have only positive elements and the constraint that the elements sum to one. Scale positive elements of g and have them sum to 1 so that the Karush-Kuhn-Tucker conditions will be satisfied after an iteration.
5. Throw away pairs of (α, β) with density below 1 basis point.

We do not require some of the other algorithmic constraints in [Alvarez et al. \(2015\)](#) because of the right-censoring of the data (25 is a relatively low dimensionality for number of periods). The above, particularly symmetrization, are required to avoid some of the pitfalls of the noisiness of data.

6 Results and Discussion

6.1 Summary of Model

I compile the overall results in (1), aggregating datapoints regardless of treatment, including those assigned neither control nor treatment. The table is replicated for control and treatment groups. At first glance, the three estimates do not appear to differ heavily. I briefly discuss these statistics, though comparison of the overall statistics masks local dynamics and local comparisons. Generally, there is not excessive heterogeneity; the standard error of α and β is not particularly high compared to the mean in any of the groups. However, there is a great deal of heterogeneity in the mean stay itself; standard errors are generally twice the mean. Note that the mean stay in the treated areas is about half a year longer in raw value.

The cross-sectional variance of the mean duration is also not strongly variable in aggregate; it is around 40 in each group, with the standard error being around 16 (18 amongst the treatment group). The proportion of the variation in realized durations due to individual variation is then around 40 percent (43 percent in the treatment group). The asymptotic duration of a residency spell is about 7.5 months in control areas and 8.2 months in the treated areas. Then, if the individual has lived in an area for a significant amount of time already, there is a negative duration dependence (e.g., they are expected to stay longer the longer they have already stayed). This timeframe is one-third of the total timeframe observed for each record, suggesting the duration dependence effect is quite strong in our data.

I show the fit of the mean type across all neighborhoods on the durations histogram for all observations in New Orleans in Figure (6). The fit is not the

$E(\alpha)$	$E(\beta)$	$E(\beta/\alpha)$	$Std(\beta/\alpha)$
0.726	5.91	8.768	16.392
$E(2/\alpha^2)$	$E(\beta/\alpha^3)$	$Std(\alpha)$	$Std(\beta)$
7.723	41.145	0.326	2.053

Table 1: Means of several key statistics across all neighborhoods, across all time periods.

$E(\alpha)$	$E(\beta)$	$E(\beta/\alpha)$	$Std(\beta/\alpha)$
0.738	5.832	8.531	16.161
$E(2/\alpha^2)$	$E(\beta/\alpha^3)$	$Std(\alpha)$	$Std(\beta)$
7.566	39.664	0.3412	2.153

Table 2: Means of several key statistics across control regions, across all time periods.

best here (nor should it necessarily be), but notice that the symmetrization has caused the mode to ignore some of the nonstationary behavior around the 12th month of residency. Then, the convex optimization procedure has produced a principled, not overfit, model.

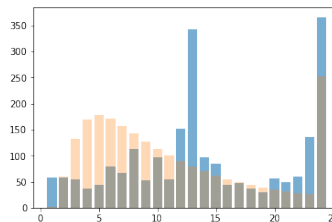


Figure 6: Fit of mean probability distribution (orange) on the New Orleans aggregated data (blue).

A sample likelihood surface is shown in (7). Clearly, the likelihoods for individual values has a fairly regular shape after the pre-processing above is conducted. This suggests the calibration is comfortable.

In an assessment of the goodness of fit, the city-level fits had an average chi-square p-value of 0.403, implying we can comfortably accept the model as a good fit. The variance on this statistic across neighborhoods is 0.199, suggesting that we are generally comfortably within model acceptance standards across the

$E(\alpha)$	$E(\beta)$	$E(\beta/\alpha)$	$Std(\beta/\alpha)$
0.672	5.921	9.004	18.392
$E(2/\alpha^2)$	$E(\beta/\alpha^3)$	$Std(\alpha)$	$Std(\beta)$
8.173	44.108	0.343	2.180

Table 3: Means of several key statistics across treatment areas, across all time periods.

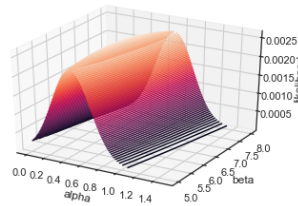


Figure 7: Surface plot of a sample likelihood.

data.

The asymptotic duration shows differential responses to rent across assignment as well. Designated cultural districts tend to have a higher estimated asymptotic duration in wealthier neighborhoods as compared to control groups, suggesting in particular that treatment groups are likely to be income-sensitive. This suggests one of two things is occurring: (1) areas which are of a higher income before designation are more likely to be designated or (2) designated cultural districts are more likely to attract high income residents upon treatment. While we do not have data on this, the inclusion of immigrant communities like Chinatowns and Koreatowns and a Little Puerto Rico seems to suggest that (2) is the more likely explanation, as such communities are generally more likely to have settled with a lower income. Higher-rent treatment areas also generally demonstrate lower proclivity to have heterogeneity, suggesting areas homogenize as these new arrivals enter the neighborhood.

Variance Decomposition I now conduct the exercise described in the theory section which decomposes residual duration of residency into a component explained by the heterogeneity in residents and one explained by duration dependence (negative in this case). Again, I start by comparing these in the overall dataset for all periods. Figure (9) compares these. Generally, heterogeneity ap-

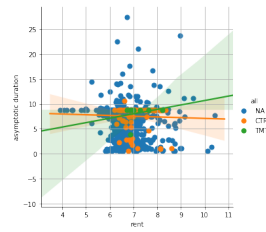


Figure 8: Comparison of effect of increasing rents on the projected asymptotic duration of a neighborhood .

pears to explain a larger component of the asymptotic variance of residency across neighborhoods.

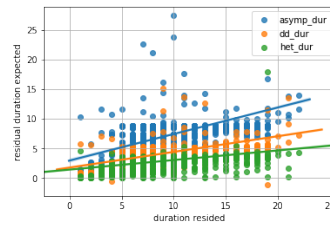


Figure 9: Comparison of durations explained by heterogeneity and duration dependence across the entire dataset.

I map the differences across treatment and control groups by comparing the proportion of variance explained by duration dependence as asymptotic duration dependence increases. These are simple linear estimators. See that the treatment groups tend to have a larger positive duration dependence after the first year, implying that once the first year has passed, the neighborhood is estimated to extract significant more loyalty effects from residents. This also implies that most of the heterogeneity “shakes out” during the first year - as this is when the proportion of variance attributed to heterogeneity is at its highest point - suggesting a compositional sorting of unlike types out of the neighborhood after the first year.

Yearly Cohorts In the next section, I discuss isolating comparisons to same-year and same-city treatment-control groups, whereas the statistics reported in this section are all pooled. This was done because the results in this section are able to share statistical strength across experimental groups, which overcomes the smaller sample size of the treatment group relative to the controls. The next

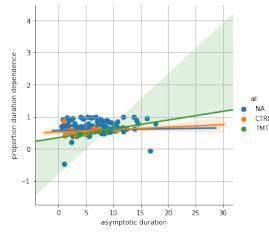


Figure 10: Increase in variation attributed to duration dependence with increasing estimated asymptotic duration in treatment and control groups

section is certainly more sample-dependent, so I use bootstrapped variances and standard errors while reporting.

I report the summary statistics of these yearly city-level cohorts in a style mimicking the tables above here in table (4).

$E(\alpha)$	$E(\beta)$	$E(\beta/\alpha)$	$Std(\beta/\alpha)$
0.7827	5.805	8.280	12.152
$E(2/\alpha^2)$	$E(\beta/\alpha^3)$	$Std(\alpha)$	$Std(\beta)$
7.017	36.508	0.312	1.902

Table 4: Means when calculated in year and city-specific pools.

The estimated values of the raw pools are fairly similar, indicating our pooled analysis was likely a decent approximation of the true underlying patterns. In particular, proportion of variance attributed to heterogeneity remains around 40% and the standard errors are similar on most counts.

6.2 Neighborhood Stability: Causality

Thus far, much of this paper has been a replication of the previous work of Alvarez, Borovickova, and Shimer. The novel contribution of the previous sections was simply a matter of building a context for the application of their model within the experiment of residency spells and neighborhood choice. I now contribute the second novel piece of this paper, the application to measuring the effect of a designated cultural district’s anchoring amenity on the hazard rate out of a neighborhood. I will use this to test whether cultural districts have a

significant impact on out-migration during an overall period of increased out-migration, the Great Recession. While the previous sections present enough nuance to develop some conclusions about potential impact of DCDs on neighborhood stability, a more causal argument is possible given the Recession as an evenly applied exogenous shock (though perhaps not evenly deep across its application, as some cities and zips were hit harder than others - more on this momentarily).

Defining “Neighborhood Stability.” The distribution $g(\alpha, \beta)$ encapsulates and expresses in reduced form the distributions of neighborhood-aggregated individual parameters, $(r, \psi, \underline{A}, \bar{R}, \mu_j, \sigma_j)$. The model for the anchoring effects are simple. Then, we can use measures from our reduced form analysis as individual-level terms. In particular, we can define a notion of neighborhood stability if a neighborhood tends to attract individuals for a longer period of time (conditioned on them staying for some mean duration - this is the definition of the asymptotic duration quantity reported in this paper). Note that by using this definition of asymptotic duration, we can be flexible on a cutoff by neighborhood; if a neighborhood has a lower baseline mean duration, it can still have a high asymptotic duration for individuals who survive that mean duration. This is a good measure of stability because it emphasizes two points: (1) local tunability, and (2) robust estimation of heterogeneity across individuals. However, it faces a critical flaw; there is no estimator for people who wish to leave a neighborhood but cannot due to the fixed costs associated with moving. Put more succinctly, it does not capture financial entrapment.

We can use the asymptotic duration as a measure of neighborhood stability with an important caveat. Asymptotic duration of a residency spell may be significantly determined by wealth of an individual, as wealthier residents are less likely to be priced out. This poses a problem as to whether the neighborhood’s amenities are a causal force for the outcome of stability or whether the individuals they attract are; attracting more stable individuals might be less attractive as an indicator of neighborhood stability as it is more subjective to time-varying tastes. Then, it is difficult from our data alone to identify the source of stable neighborhoods as a demand-side or supply-side push, but we can identify stability itself with some degree of comfort.

Arriving at a Causal Model. Design a simple model of difference-in-differences which assesses how well treated (DCD) neighborhoods weather the impulse

shock of the Great Recession

$$\frac{2}{\alpha_{jk}^3} = c(j) + \tau_k + \delta_0 DCD_j + \delta_1 R_k + \delta_2 R_k DCD_j + \gamma P_j + \epsilon \quad (22)$$

where $c(j)$ is a city-level fixed effect that captures spatial differences in tenureship patterns, and τ_k are differences caused by time dynamics which do not get captured in evolving individual traits. R is the variable representing the onset of the recession. k is a cohort-level subscript, to account for changing distributions over time. Cohorts are defined as individuals who move into a zip code in the same year for the time being. I capture expectation of local amenities and local conditions through the logarithmic mean of rent prices, P_j for the time being; though it is an imperfect measure far and away, it is highly correlated with most local amenities. (Lee and Lin, 2017) In this way, it forms a natural fixed effect measure for zip-code level variation. Then, δ_2 serves as a fully identified difference-in-differences measure after local fixed effects are taken into account. I argue this differencing is necessary primarily due to the use of rent alone as the controlling covariate. I report the coefficients in table 5, as well as some associated measures of the model's appropriateness and goodness of fit. The difference-in-differences estimator is not significant in this regression; the treatment with designation does not significantly protect individuals from the effects of the recession on their asymptotic duration. Interestingly, the recession is also not particularly significant in this regression. However, the coefficient on the treatment effect is significant at the 10% level. This is interesting in the sense that it reinforces the significance of the treatment, but it does not tell us that the treatment itself is a causal response in the face of a recession.

I try two more models which are somewhat nested by this model. The first removes the time dummies to test whether they are too redundant given inclusion of the recession variable. The condition number of the covariance matrix for the first model is particularly high, suggesting the time dummies (largely insignificant, admittedly) are too collinear with the recession variable given the sample size. The second variation on the model also eschews time dummies. This version further relaxes the assumptions of parallel slopes (already partially satisfied by the inclusion of a rent-correlated fixed effect). Heterogeneity in the neighborhood might be an important source of information as neighborhoods which are less uniform in their responses to shocks will have different outcomes post-recession.

Looking at the model reports in Appendix B suggests the most viable model from a log-likelihood perspective is that without time controls but with a control for heterogeneity. This model suggests that in fact, the DD estimator and the estimator for the treatment area both amount to an insignificant effect. The heterogeneity, however, dominates this regression. This suggests that an unconditional analysis of the asymptotic residency duration relies primarily on the heterogeneity of the locality.

I present one final causal analysis, in which I conduct a two-stage procedure. In stage 1, I regress the asymptotic duration on the estimated mean $E(\beta/\alpha)$ of residency spell types in the zip code within cohort k :

$$E(2/\alpha^2) = \zeta E(\beta/\alpha) + \kappa \quad (23)$$

In this case, we know the slope of this regression, but variation κ can be entirely attributed to non-individual effects on the asymptotic duration. In other words, conditional on the type of the individual, I extract the component of asymptotic duration whose variance is not explained by any measure of individual preferences for neighborhood features. This measure κ I now regress against the same second-stage linear model as performed best in the previous analysis:

$$\kappa = c(j) + \delta_0 DCD_j + \delta_1 R_k + \delta_2 R_k DCD_j + \gamma_1 P_j + \gamma_2 h_j^h + \epsilon \quad (24)$$

By this, I suggest that these uncorrelated components of the asymptotic duration are determined by zip-level added “loyalties” derived from homogeneity, local affluence, local culture, and the city itself. This model is not comparable off of log-likelihood to previous models as it is not nested. However, notice that here the recession now has a direction that intuitively makes sense - it decreased the de-individualized component of asymptotic duration by 0.25 months on average, significant at 10%. The DD estimator is now nearly significant at 10%, with an increased expected asymptotic duration of 0.81 months. This suggests that the effect of a designated cultural district must be de-individualized. In particular, the component of variation corresponding to an individual’s type when conditioned strengthens the linear model overall, including significance of local fixed effects.

The interpretation of this final model is that individuals have some baseline taste for amenities and rents, α which determines their individual type as in our

original model. To isolate how a local neighborhood affects individual decision-making on the margin, we must control for their individual tastes for that neighborhood in the first place, represented by this calculated type, and look at how the residual varies with observables.

7 Conclusion

Cultural districts when designated may significantly increase the lifespan of a neighborhood in the face of a recession, if only marginally in effect size. The cultivation of this type of loyalty can have significant effects on city budgets in moments of crisis by increasing the likelihood of having a stable tax base, and can further drive longer-lasting city growth. This analysis suggests a complexity to the narrative of the designated cultural district. DCDs make neighborhoods more robust to productivity shocks, in a manner which is masked when they are considered in aggregate. The income dynamics of designation are yet unexplored, however. It is clear that designated cultural districts upon designation tend to drive up rents and attract potentially wealthier individuals, which in turn helps drive increased asymptotic duration in such localities. However, it is unclear whether displacement from DCDs after designation may actually drive out the highest-loyalty residents; the counterfactual result on neighborhood stability around designation is unclear. A future analysis comparing designation and non-designation in addition to the DCD versus the average city district may resolve some of this causal tension.

A Expanding on the Individual-Level Problem

With the given stochastic process for rents, the present value of rents will satisfy the Bellman-Jacobi-Hamilton equations:

$$rE_j(R) = \exp(R) + \mu_j E'_j(R) + \frac{\sigma_j^2}{2} E''_j(R) \quad \forall R \quad (25)$$

The solution of this set of parallel equations across all neighborhoods, r ,

$$rE_j(R) = \frac{\exp(R)}{r - \mu_j - \sigma_j^2/2} + \sum_{k=1}^N u_k \exp(\lambda_{jk} R) \quad (26)$$

where the poles have opposite sign and are the roots of the N -dimensional equation $r = \lambda_j(\mu_j + \lambda_j \sigma_j^2/2)$. A solution to this equation should also satisfy the equations:

$$\underline{R}_{ijt} < \bar{R}_{ijt} \quad (27)$$

$$E_j(\underline{R}) = E_k(\underline{R}) \quad \forall k \neq j \quad (28)$$

$$E_j(\underline{R}) = E_k(\underline{R}) + \psi \quad \forall k \neq j \quad (29)$$

$$E'_j(\underline{R}) = E'_k(\underline{R}) \quad \forall k \neq j \quad (30)$$

$$E'_j(\bar{R}) = E'_k(\bar{R}) \quad \forall k \neq j \quad (31)$$

$$(32)$$

The conditions require value functions to be continuous and differentiable at the boundaries. Finally, we have two conditions which ensure no bubble around employment or unemployment:

$$\lim_{R \rightarrow -\infty} E_k(R) = \frac{R}{r} \quad (33)$$

$$\lim_{R \rightarrow +\infty} \frac{E(R)}{\exp(R)} = \frac{1}{r - \mu_j - \sigma_j^2/2} \quad (34)$$

These equations ensure that for an arbitrarily low rent, the value functions all converge to the value of moving to another neighborhood and if the rent increases without bound then the value function converges to the value of living in neighborhood j .

The no-bubble conditions (33) imply that all $k : k \neq j$ in (26), $u_k = 0$. Other-

wise, the expected value of neighborhood j will diverge relative to other neighborhoods as rent grows asymptotically large positively or negatively. Then, the value functions will be, abusing notation slightly:

$$rE_{j(t)}(R) = \frac{\exp(R)}{r - \mu_{j(t)} - \sigma_{j(t)}^2/2} + u \exp(\lambda_j R) \tag{35}$$

with

$$\lambda_j = \frac{-\mu_j - \sqrt{\mu_j^2 + 2r\sigma_j^2}}{\sigma_j^2} \tag{36}$$

Then, we end up with $4N - 4$ equations in the unknowns $(u_j, \underline{R}, \bar{R}), \forall j \in \{1, \dots, N\}$ from the conditions in (27). The values u_j must be positive since it is feasible to stay in one neighborhood forever or never arrive in that neighborhood for all time.

These arguments collectively demonstrate that there exists a unique fixed cost which optimizes the width of inaction $\bar{R} - \underline{R}$. This section merely extended the initial argument of the base paper to an N -dimensional setting with total equivalence across possible classes, rather than having an employment-unemployment asymmetric value function. See Alvarez for more information on this.

B Regression Summary Tables

B.1 Base Model

Dep. Variable:	asymptotic duration	R-squared:	0.138
Model:	OLS	Adj. R-squared:	0.110
Method:	Least Squares	F-statistic:	4.978
Date:	Wed, 27 Mar 2019	Prob (F-statistic):	1.89e-12
Time:	17:16:49	Log-Likelihood:	-1776.3
No. Observations:	706	AIC:	3599.
Df Residuals:	684	BIC:	3703.
Df Model:	21		

	coef	std err	t	P> t	[0.025	0.975]
C(city)[Atlanta]	0.9908	2.048	0.484	0.629	-3.030	5.012
C(city)[College]	2.2074	2.151	1.026	0.305	-2.016	6.431
C(city)[Los Ang]	-0.9419	2.148	-0.439	0.661	-5.159	3.275
C(city)[New Or]	-5.8997	3.047	-1.936	0.053	-11.883	0.083
C(city)[New Yor]	-2.0203	2.357	-0.857	0.392	-6.647	2.607
C(city)[Tampa]	0.1777	2.053	0.087	0.931	-3.853	4.208
C(year)[T.1998]	-0.5781	1.335	-0.433	0.665	-3.200	2.044
C(year)[T.1999]	-0.7332	1.353	-0.542	0.588	-3.390	1.923
C(year)[T.2000]	-1.4647	1.269	-1.155	0.249	-3.955	1.026
C(year)[T.2001]	-3.4705	1.246	-2.784	0.006	-5.918	-1.023
C(year)[T.2002]	-1.9115	1.216	-1.572	0.116	-4.299	0.476
C(year)[T.2003]	-2.6072	1.172	-2.225	0.026	-4.908	-0.306
C(year)[T.2004]	-2.1911	1.152	-1.902	0.058	-4.453	0.071
C(year)[T.2005]	-2.0074	1.140	-1.760	0.079	-4.247	0.232
C(year)[T.2006]	-1.2788	1.137	-1.124	0.261	-3.512	0.954
C(year)[T.2007]	-0.6642	1.142	-0.582	0.561	-2.907	1.578
C(year)[T.2008]	-0.1897	0.390	-0.486	0.627	-0.955	0.576
C(year)[T.2009]	-0.2031	0.388	-0.524	0.600	-0.964	0.558
C(year)[T.2010]	-0.2920	0.386	-0.756	0.450	-1.050	0.466
C(treatment)	0.8125	0.472	1.721	0.086	-0.114	1.739
C(recession)	-0.6848	0.832	-0.823	0.411	-2.318	0.949
DD	0.6184	0.837	0.738	0.461	-1.026	2.263
lrent	1.1841	0.272	4.346	0.000	0.649	1.719

Table 5: Table of coefficients for the model in (22). The basic difference-in-difference estimator is denoted, “DD.”

Omnibus:	101.625	Durbin-Watson:	1.257
Prob(Omnibus):	0.000	Jarque-Bera (JB):	563.989
Skew:	0.496	Prob(JB):	3.40e-123
Kurtosis:	7.265		

B.2 Model without Time Coefficients

	coef	std err	t	P> t	[0.025	0.975]
C(city)[Atlanta]	-1.8984	1.743	-1.089	0.277	-5.322	1.525
C(city)[College]	-0.6772	1.854	-0.365	0.715	-4.317	2.963
C(city)[Los Ang]	-3.7848	1.867	-2.027	0.043	-7.451	-0.118
C(city)[New Orl]	-8.7279	2.877	-3.034	0.003	-14.376	-3.080
C(city)[New Yor]	-4.9805	2.106	-2.365	0.018	-9.115	-0.846
C(city)[Tampa]	-2.6470	1.761	-1.503	0.133	-6.104	0.810
C(treatment)	0.7074	0.476	1.485	0.138	-0.228	1.643
C(recession)	0.6736	0.264	2.550	0.011	0.155	1.192
DD	0.6999	0.847	0.826	0.409	-0.964	2.364
lrent	1.3635	0.261	5.228	0.000	0.851	1.876

Table 6: Table of coefficients for the model in (22) without time coefficients. The basic difference-in-difference estimator is denoted, “DD.”

Dep. Variable:	asymptotic duration	R-squared:	0.100
Model:	OLS	Adj. R-squared:	0.087
Method:	Least Squares	F-statistic:	7.705
Date:	Wed, 27 Mar 2019	Prob (F-statistic):	9.37e-12
Time:	17:59:37	Log-Likelihood:	-1791.7
No. Observations:	706	AIC:	3605.
Df Residuals:	696	BIC:	3656.
Df Model:	9		
Omnibus:	128.755	Durbin-Watson:	1.274
Prob(Omnibus):	0.000	Jarque-Bera (JB):	809.435
Skew:	0.646	Prob(JB):	1.71e-176
Kurtosis:	8.084	Cond. No.	296.

B.3 Model with Heterogeneity Controls

Dep. Variable:	asymptotic duration	R-squared:	0.119
Model:	OLS	Adj. R-squared:	0.104
Method:	Least Squares	F-statistic:	7.994
Date:	Wed, 27 Mar 2019	Prob (F-statistic):	3.78e-13
Time:	18:01:03	Log-Likelihood:	-1612.5
No. Observations:	664	AIC:	3249.
Df Residuals:	653	BIC:	3303.
Df Model:	10		

	coef	std err	t	P> t	[0.025	0.975]
C(city)[Atlanta]	-0.0440	1.656	-0.027	0.979	-3.297	3.209
C(city)[College]	1.0109	1.743	0.580	0.562	-2.411	4.433
C(city)[Los Ang]	-1.7796	1.778	-1.001	0.317	-5.272	1.713
C(city)[New Orl]	-6.4528	2.654	-2.431	0.015	-11.664	-1.242
C(city)[New Yor]	-3.0860	1.972	-1.565	0.118	-6.959	0.787
C(city)[Tampa]	-0.9030	1.665	-0.542	0.588	-4.173	2.367
C(treatment)	0.5707	0.471	1.211	0.226	-0.355	1.496
C(recession)	0.4780	0.242	1.979	0.048	0.004	0.952
DD	0.7748	0.786	0.985	0.325	-0.769	2.319
lrent	1.3453	0.242	5.563	0.000	0.871	1.820
propvar	-3.8544	1.005	-3.835	0.000	-5.828	-1.881

Table 7: Table of coefficients for the model in (22) without time coefficients and an added term controlling for heterogeneity in neighborhoods. The basic difference-in-difference estimator is denoted, “DD.”

Omnibus:	56.970	Durbin-Watson:	1.202
Prob(Omnibus):	0.000	Jarque-Bera (JB):	302.572
Skew:	-0.026	Prob(JB):	1.98e-66
Kurtosis:	6.307	Cond. No.	303.

B.4 Two Stage Model

Dep. Variable:	κ	R-squared:	0.115
Model:	OLS	Adj. R-squared:	0.100
Method:	Least Squares	F-statistic:	7.669
Date:	Wed, 27 Mar 2019	Prob (F-statistic):	1.56e-12
Time:	18:33:07	Log-Likelihood:	-1309.7
No. Observations:	664	AIC:	2643.
Df Residuals:	653	BIC:	2697.
Df Model:	10		

	coef	std err	t	P> t	[0.025	0.975]
C(city)[Atlanta]	-2.4593	1.050	-2.342	0.019	-4.521	-0.398
C(city)[College]	-1.8884	1.105	-1.710	0.088	-4.057	0.281
C(city)[Los Ang]	-3.1059	1.127	-2.755	0.006	-5.319	-0.892
C(city)[New Or]	-5.2551	1.682	-3.124	0.002	-8.558	-1.952
C(city)[New Yor]	-4.3181	1.250	-3.454	0.001	-6.773	-1.863
C(city)[Tampa]	-3.2019	1.056	-3.033	0.003	-5.274	-1.129
C(treatment)	0.0091	0.299	0.030	0.976	-0.577	0.596
C(recession)	-0.2566	0.153	-1.676	0.094	-0.557	0.044
DD	0.8137	0.498	1.633	0.103	-0.165	1.792
lrent	0.3439	0.153	2.244	0.025	0.043	0.645
propvar	1.7055	0.637	2.677	0.008	0.454	2.957
Omnibus:	171.883	Durbin-Watson:	1.748			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1023.804			
Skew:	1.012	Prob(JB):	4.83e-223			
Kurtosis:	8.736	Cond. No.	303.			

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