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Natural Amenities, Neighbourhood Dynamics, and Persistence in the Spatial Distribution of Income

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We present theory and evidence highlighting the role of natural amenities in neighbourhood dynamics, suburbanization, and variation across cities in the persistence of the spatial distribution of income. Our model generates three predictions that we confirm using a novel database of consistent-boundary neighbourhoods in U.S. metropolitan areas, 1880–2010, and spatial data for natural features such as coastlines and hills. First, persistent natural amenities anchor neighbourhoods to high incomes over time. Secondly, naturally heterogeneous cities exhibit persistent spatial distributions of income. Thirdly, downtown neighbourhoods in coastal cities were less susceptible to the widespread decentralization of income in the mid-twentieth century and experienced an increase in income more quickly after 1980.

Key words: Suburbanization, Gentrification, Locational fundamentals, Multiple equilibria, Natural amenities.

JEL Codes: R23, N90, O18, D31

1. INTRODUCTION

Neighbourhood change is common and contentious. Two-thirds of neighbourhoods in the thirty-five U.S. metropolitan areas studied by Rosenthal (2008) transitioned from one income quartile to another between 1950 and 2000. In declining areas, homeowners fear deteriorating values even as entrants enjoy new opportunities; in gentrifying areas, rising prices cause anxiety for longtime renters. And in response to shifting neighbourhood demands, policymakers often act to preserve neighbourhood quality or quicken the pace of change.

Although changes in neighbourhood status are widespread, it is less well known that neighbourhood change varies across cities. While in some cities neighbourhoods seem immune from change—leading to overall persistence in the internal structure of the city—other cities experience quickly changing neighbourhoods and spatial patterns of income. For example, Los Angeles has long had a stable arrangement of high incomes and prices along its beaches and in its

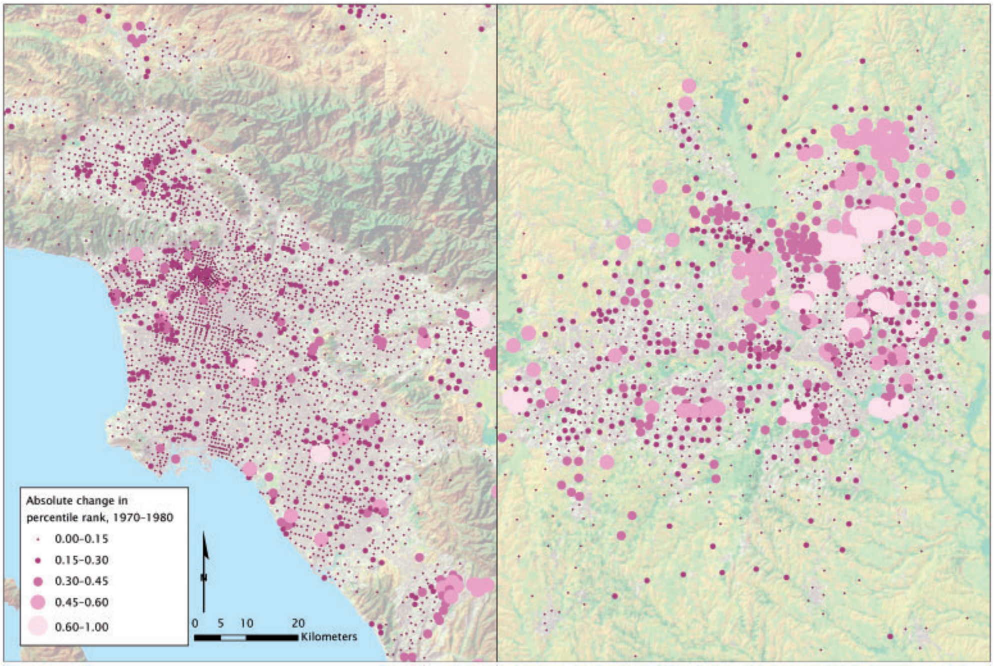

FIGURE 1

Churning and persistence in the spatial distribution of income: Los Angeles versus Dallas

Notes: These maps show 1970 neighbourhoods in the Los Angeles (left) and Dallas metropolitan areas as dots. Dots are sized and shaded according to the absolute value of the 1970–1980 change in each neighbourhood's percentile ranking (by average household income) within the metropolitan area. Map scale is 1:500,000. Base map is from U.S. Geological Survey (2013).

foothills; between 1970 and 1980, the average neighbourhood in the Los Angeles metropolitan area moved just 9 percentile points across the city's income distribution. In contrast, over the same period, the average metropolitan Dallas neighbourhood moved 21 percentile points. (Figure 1 illustrates these differences between Dallas and Los Angeles.)

In this article, we examine why the geographic distribution of income is persistent for some neighbourhoods and cities but turns over frequently elsewhere. Our explanation highlights the role of natural geographic features that have persistent amenity value—for example, oceans, mountains, and lakes. We begin with the idea that persistent natural amenities can "anchor" neighbourhoods to high incomes even as they experience various shocks over time. A key implication is that for cities as a whole, greater *natural* variation among neighbourhoods can hold back neighbourhood change, leading to overall stability in the spatial distribution of income. Thus, in naturally heterogeneous Los Angeles, the spatial distribution of income is persistent, but in flat Dallas, the spatial distribution of income churns quickly.

We present a dynamic model of household neighbourhood choice to formalize our thinking. Neighbourhoods derive amenity value from both natural features and endogenous characteristics such as safety, school quality, or shopping. High-income households outbid low-income households for neighbourhoods with greater overall amenity value. Neighbourhoods are also subject to idiosyncratic shocks to amenity value over time. We characterize conditions when these shocks can potentially reverse the historical spatial pattern of income.

We test and confirm several implications of our theory using a new database of consistent-boundary neighbourhoods in many U.S. metropolitan areas, spanning the census years from 1880 to 2010. We match these data to spatial information on the location of many persistent natural features, including shorelines, mountains, lakes, rivers, temperate climates, and floodplains. We also develop a hedonic weighting method to aggregate amenity values from many natural features into a single index.

Our first main result is that persistent natural amenities anchor neighbourhoods to high incomes over time. More precisely, conditioned on initial income, neighbourhoods with superior natural amenities are more likely to become or remain high-income neighbourhoods. In short, this result is a nuanced version of the folk wisdom among realtors that a beachfront home will better retain its value over one with a mundane view.

Our second and key result is that cities with dominant natural features (*e.g.* a coastline or mountain range) exhibit internal spatial distributions of income that are dynamically stable. In other words, neighbourhood incomes tend to fluctuate less over time in a city such as Los Angeles, with its beaches, hills, and valleys, than in a city such as Dallas, which more closely resembles a flat, featureless plain. Intuitively, a shock to a neighbourhood's amenity value—because of idiosyncratic migration, effects of policy, natural disasters, etc.—has the potential to change the historical distribution of income across neighbourhoods. But in cities in which some neighbourhoods have overwhelming natural advantages, small shocks or interventions are unlikely to undo history.

Our final main result is that the anchoring effect of superior natural amenities is stronger in a city with dominant natural features. Relying on the fact that many U.S. central cities were founded near superior natural amenities, we show that downtowns in coastal cities, compared with downtowns in interior cities, declined less in income in the early and mid-twentieth century and improved more in income after 1980. In short, coastal city downtowns have been better anchored to high incomes during periods of both nationwide suburbanization and gentrification.

This result relates to a central debate in economics about the roles of natural fundamentals versus endogenous amenities in the spatial distribution of income. In our model, as in others featuring endogenous amenities, multiple equilibria are possible.[1] If households care only about being near other households, then they might crowd together in any neighbourhood (*e.g.* downtown or in the suburbs). However, this multiplicity is limited by locational fundamentals: As emphasized by our third result, fundamentals are more likely to determine outcomes when there is greater natural heterogeneity across locations.

We address several identification issues in evaluating our evidence. One important empirical challenge is that we do not directly observe the amenity value of natural features. For example, a natural feature can be either an amenity or a disamenity: a river used for industrial purposes can detract from surrounding neighbourhoods. To address this concern, we first focus on high-value natural features, such as proximity to the ocean, for which we believe the benefits are obvious and significant relative to the value of other amenities. A second strategy is to condition natural features on other observables, such as historical incomes or place names, that are more likely in the presence of superior amenities. Intuitively, stretches of coastline that have historically attracted high-income households are probably quite amenable. We also discuss the related identification challenge of changes in the value of natural features over time. We find that neither the anchoring effect of natural amenities on neighbourhood income *ranks* nor the tendency for the highest-income households to locate near natural features has increased significantly.

Neighbourhoods in growing cities tend to experience greater fluctuations in income. Our view is that city growth acts as a shock to the relative value of extant neighbourhoods. In our empirical work, we adjust for changes in city size by examining only changes in *relative* percentile rankings

1. This feature is shared with models in which endogenous benefits come instead from agglomeration economies (*cf.* Krugman, 1991; Rauch, 1993; Arthur, 1994).

within a fixed group of neighbourhoods in each 10-year period. In addition, we show that our results are robust to controlling for city growth and the age of housing.

1.1. *Related work*

First, our work is related to a broad body of literature examining the geographic sorting of different types of households (Tiebout, 1956). Of course, the cross-sectional implications of variation in natural value are well known. Neighbourhoods near large water features or at elevation have long attracted affluent households. For example, patricians preferred ancient Rome's hills:

> Certain districts [were] favored more than others; some, because they are accessible; and others, because they are beautiful in themselves or command a fine view. The Aventine, Caelian, Palatine, even the Sacred Way and the Subura, the Carinae, the Esquiline, Quirinal, Viminal, Pincian, the Campus Martius, the Capitoline and the district beyond the Tiber—all these furnish sites for private homes. (Witherstine, 1926, p. 566)

Similarly, in New York City, "[b]efore the American Revolution, the wealthiest residents of Manhattan lived on the waterfront lanes—especially Dock Street—at the southeastern tip of the island, where they could enjoy proximity to business and the beauty of the upper bay" (Jackson, 1985, p. 18). What is less frequently observed is how natural features might restrain neighbourhood dynamics. In Brueckner *et al.*'s (1999) static monocentric city model of household location choice, there may be multiple equilibria—with the rich living in either the city centre or the suburbs—if the exogenous amenity advantage of the centre is small. Our contribution is to extend this intuition to a dynamic setting. In addition, our work departs from theirs in testing these implications empirically.[2]

Secondly, previous work has highlighted various factors in neighbourhood change: ageing homes filtering from high- to low-income households (Brueckner and Rosenthal, 2009), spillovers among neighbourhoods (Aaronson, 2001; Guerrieri *et al.*, 2013), transportation technology or infrastructure (LeRoy and Sonstelie, 1983; Baum-Snow, 2007; Glaeser *et al.*, 2008), African American migration to cities (Boustan, 2010), or a combination of factors (Kolko, 2007).[3] In contrast to much of this literature, we highlight the role of natural features and emphasize variation across cities in neighbourhood dynamics. Moreover, our results suggest that evidence for alternative theoretical channels is often stronger when considering cities in which churning is more salient (*i.e.*, cities that more closely resemble flat, featureless plains).

Thirdly, there is a large body of literature on changes in the internal structure of cities, especially examining the widespread decentralization of U.S. cities in the early and mid-twentieth century and the more recent gentrification of many central cities (Jackson, 1985; Mieszkowski and Mills, 1993). We extend this literature by documenting income gradients for a wide section of cities as early as 1880. In addition, our article is one of the few to document and relate variation across cities to differences in natural heterogeneity. Another exception is Burchfield *et al.* (2006), who show that sprawl—the amount of undeveloped land surrounding

2. Other theoretical papers share a similar intuition about transitions between static equilibria, with Fujita and Ogawa (2013) being an early example. Krumm (1980) provides and tests a static model with endogenous amenities and location choices. Bond and Coulson (1989) note that neighbourhoods are more likely to "tip" from high- to low-income (or vice versa) when housing quality is more homogeneous across neighbourhoods.

3. Carlino and Saiz (2008) find that amenable neighbourhoods, defined as those including tourist information offices or sites on the National Register of Historic Places, experienced greater increases in incomes and prices in the 1990s. In contrast to their study, we avoid the endogeneity of neighbourhood amenities by examining only natural features. In addition, while their evidence exploits only within-city comparisons, we examine heterogeneous neighbourhood dynamics across cities.

an average dwelling—varies across cities according to the presence of available aquifers on the suburban fringe and hilly terrain. Our article differs in that we examine neighbourhood dynamics rather than land use.

Finally, our work is related to the literature in development and geography concerned with persistence in the spatial distribution of income and population. In theory, such persistence might be caused by geographic features, durable sunk factors, or amenities that are endogenous to location decisions (*cf.* Davis and Weinstein, 2002; Rappaport and Sachs, 2003; Redding *et al.*, 2011; Bleakley and Lin, 2012; Lin, 2015). Our work departs from this literature by focusing on the within-city distribution of income versus the distribution of income or population across cities or other subnational regions.[4] However, our results hint that natural variation may be an important explanation for differences in locational persistence on other spatial scales.

2. THEORY

The following stylized model highlights the role of natural amenities in neighbourhood dynamics. To clearly illustrate our key economic mechanism and its implications, we present a simple two-neighbourhood version. This model abstracts from other important theoretical channels emphasized elsewhere in the literature, but we discuss and control for these omitted channels in our empirical analysis. In Online Appendix A.3, we relax assumptions and show that our theoretical predictions are robust to settings with more than two neighbourhoods and correlated amenity shocks over time.

2.1. *Model*

Consider a city with two neighbourhoods, a beach and a desert, indexed by $j = b, d$. Each neighbourhood has one unit measure of land, owned by absentee landlords. The beach offers an exogenous, persistently superior natural amenity level, $\alpha_b > \alpha_d$.

Neighbourhoods vary in their *endogenous*, *aggregate* amenity level A, which consists of four parts:

$$A_{j,t} \equiv \alpha_j + E(\theta | j,t) + m_t + \varepsilon_{j,t}. \qquad (1)$$

First, α_j is the persistent natural amenity value offered by neighbourhood j in all periods. Secondly, $E(\theta|j,t)$ is the average income of neighbourhood j residents in period t. With this term, we intend to capture the value of endogenous amenities that tend to be correlated with neighbourhood income, such as safety, school quality, or shopping. Note that we normalize units of $A_{j,t}$ so that $E(\theta|j,t)$ has a unit coefficient in utility. Thirdly, m_t captures city-level amenity trends common to all neighbourhoods, such as citywide improvements in transportation infrastructure.[5] Fourthly, $\varepsilon_{j,t}$ captures idiosyncratic amenity shocks, such as natural disasters or unexpected changes to the quality of local governance. We assume that $\varepsilon_{j,t}$ is independent and identically distributed with a cumulative distribution function $G(-\infty, \infty)$.

The city has a two-unit measure of workers, heterogeneous in income θ. In each period t, a worker chooses a neighbourhood j, consumes one unit of land, pays rent $R_{j,t}$, spends the rest of her income on numeraire $c_{j,t}$, and receives utility $A_{j,t} \cdot c_{j,t}$. There are no moving costs or savings,

4. Some recent studies examine persistence within a single city: Villarreal (2014) finds persisting effects of historical marshes in Manhattan, and Brooks and Lutz (2014) document persistent influences of historical streetcar lines in Los Angeles. In contrast, our article compares persistence across cities.

5. Any citywide trends m_t cancel out when workers make neighbourhood choices within the city and thus do not affect our theoretical results. We include m_t in equation (1) only to account for the components of aggregate amenities that affect (or do not affect) our theoretical results.

so a worker need not solve a dynamic problem. Instead, each worker chooses the neighbourhood that provides the best utility in each period. In sum, a type θ worker solves the following problem in each period:

$$\max_j A_{j,t} \cdot c_{j,t} \text{ subject to } c_{j,t} + R_{j,t} = \theta$$
$$= \max_j A_{j,t} \cdot (\theta - R_{j,t}).$$

2.2. *Equilibria within a period*

Next, we characterize equilibria within a period. Note in the utility function $A_{j,t} \cdot c_{j,t}$ that aggregate amenities $A_{j,t}$ and numeraire consumption $c_{j,t}$ are complements. This complementarity implies that high-income workers are willing to pay more for aggregate amenities.[6] Therefore, high-income workers sort into superior aggregate amenity neighbourhoods by outbidding low-income workers, who are then priced out by equilibrium rents.

Since each neighbourhood has one unit of land and each worker consumes one unit of land, each neighbourhood accommodates one unit measure of workers in equilibrium. Therefore, the top 50% of workers by income will live in the superior aggregate amenity neighbourhood, and the bottom 50% will live in the other neighbourhood. Let Θ_H be the set of θ in the top 50% and Θ_L be the set of θ in the bottom 50%. Then, the average income of the superior aggregate amenity neighbourhood is $\bar{\theta}_H \equiv E(\theta|\theta \in \Theta_H)$ and that of the inferior neighbourhood is $\bar{\theta}_L \equiv E(\theta|\theta \in \Theta_L)$.

Lemma 1. (Sorting). *In each period, high-income Θ_H workers live in the superior aggregate amenity neighbourhood, and low-income Θ_L workers live in the inferior aggregate amenity neighbourhood.*

This perfect sorting implies that there are only two possible equilibrium states in each period: S_1 and S_2. In S_1, high-income workers live at the beach, and low-income workers live in the desert. This state is an equilibrium if and only if the aggregate amenity of the beach is greater than that of the desert:

$$S_1: A_{b,t} = \alpha_b + \bar{\theta}_H + m_t + \epsilon_{b,t} \geq A_{d,t} = \alpha_d + \bar{\theta}_L + m_t + \epsilon_{d,t}. \tag{2}$$

Analogously, in S_2, high-income workers live in the desert and low-income workers live at the beach. This state is an equilibrium if and only if the aggregate amenity of the desert is greater than that of the beach:

$$S_2: A_{b,t} = \alpha_b + \bar{\theta}_L + m_t + \epsilon_{b,t} \leq A_{d,t} = \alpha_d + \bar{\theta}_H + m_t + \epsilon_{d,t}. \tag{3}$$

Note that S_2 can be supported as an equilibrium by superior endogenous amenities, a large idiosyncratic shock, or both. Intuitively, good schools and high-income agglomerations can rationalize each other in naturally mundane locations.

These two conditions jointly imply that an equilibrium always exists; if one condition is not satisfied, the other one is always satisfied. They also imply that there can be multiple equilibria. For example, both conditions are satisfied if endogenous amenity differences $(\bar{\theta}_H - \bar{\theta}_L)$ are sufficiently large—if, say, households care a lot about school quality.

6. Formally, the single crossing property holds between aggregate amenities and rents: $\frac{\partial}{\partial\theta}(-\frac{\partial V/\partial A}{\partial V/\partial R}) > 0$, where $V \equiv A \cdot (\theta - R)$ is the utility a type θ worker receives in a neighbourhood with aggregate amenity A and rent R. Our results are robust to alternative specifications that preserve this property.

Proposition 1. (1) *There exists an equilibrium in each period.* (2) *There can be multiple equilibria in each period.*

Finally, rents are determined so that the marginal worker (*i.e.* the median worker on the Θ_H–Θ_L boundary) is indifferent between the two neighbourhoods. We set rent for the inferior aggregate amenity neighbourhood to be 0.[7]

2.3. *Equilibrium selection and history dependence*

Amenity shocks to neighbourhoods determine which one of the three possible equilibrium configurations is realized. Two possibilities are that the within-period equilibrium is unique: S_1 is the only equilibrium, or S_2 is the only equilibrium. A third possibility is that both S_1 and S_2 are equilibria in that period. When both S_1 and S_2 are equilibria, we select the state chosen in the previous period.[8] Thus, the selected equilibrium state switches back and forth over time between S_1 and S_2, and a selected equilibrium state persists until amenity shocks *rule out* the state as no longer an equilibrium. Note that with multiple equilibria and history dependence, the model can rationalize observations of persistent poverty in superior natural amenity neighbourhoods (*e.g.* an inner-city slum next to the beach).

Since the selected outcome of period t depends on that of $t-1$, the selected equilibrium path follows a Markov chain. We obtain transition probabilities between states from conditions (2) and (3). Following our equilibrium selection rule, the state changes from S_1 to S_2 if and only if S_1 is no longer an equilibrium. Thus, the transition probability is

$$\Pr(S_2|S_1)=\Pr(\varepsilon_{d,t+1}-\varepsilon_{b,t+1}>a_b-a_d+\bar{\theta}_H-\bar{\theta}_L). \quad (4)$$

Analogously, the probability of transitioning from S_2 to S_1 is

$$\Pr(S_1|S_2)=\Pr(\varepsilon_{b,t+1}-\varepsilon_{d,t+1}>a_d-a_b+\bar{\theta}_H-\bar{\theta}_L). \quad (5)$$

Note that $\Pr(S_1|S_2)$ is greater than $\Pr(S_2|S_1)$ because $\alpha_b-\alpha_d>0>\alpha_d-\alpha_b$ and both $\varepsilon_{d,t+1}-\varepsilon_{b,t+1}$ and $\varepsilon_{b,t+1}-\varepsilon_{d,t+1}$ follow the same probability distribution.

Lemma 2. $\Pr(S_1|S_2)>\Pr(S_2|S_1)$.

Intuitively, the economy tends to return to S_1, the more “natural” state in which high-income workers live in the superior natural amenity neighbourhood.

2.4. *Theoretical implications*

This section derives three implications we test in Sections 4, 5, and 6. Because our empirical analysis focuses on the relative rank of neighbourhoods within a city, we cast theoretical

7. There are multiple equilibria in rents because demand and supply of land are both perfectly inelastic. Our theoretical implications do not depend on which equilibrium rents are selected.

8. A large number of papers in economic geography use the idea that equilibrium selection might be determined by history; see, for example, Krugman (1991). A common way to motivate the role of history is to assume a myopic adjustment process, with migration frictions, from an initial endowment or equilibrium. This approach simplifies analysis of equilibrium selection, and, depending on certain parameter values, may be consistent with fully rational, forward-looking households (Ottaviano *et al*., 2002). Redding *et al*. (2011), Bleakley and Lin (2012), and Hanlon (2017) provide evidence of history dependence in the location of economic activity.

implications in terms of income percentile ranks (*i.e.*, the percentage of neighbourhoods in the same city that have the same or lower average income). In our model of two neighbourhoods, the income percentile rank r of the low-income neighbourhood is $r_{\mathrm{L}} \equiv 0.5$ and that of the high-income neighbourhood is $r_{\mathrm{H}} \equiv 1$.

Our first implication is at the neighbourhood level: conditioned on initial income, the beach tends to increase more (or decrease less) in future income versus the desert. In other words, superior natural amenities "anchor" neighbourhoods to high incomes over time. To illustrate this implication, we separately calculate the expected change in income percentile rank for the beach and the desert when they are inhabited by low-income workers.

First, consider the beach inhabited by low-income workers. This happens when the city is in S_2. If the city remains in S_2 in the next period, the income percentile rank of the neighbourhood does not change. If the city changes to S_1, its income percentile rank rises from r_{L} to r_{H}. Thus,

$$E(\Delta r|j=b, r=r_{\mathrm{L}}) = (r_{\mathrm{H}} - r_{\mathrm{L}}) \cdot Pr(S_1|S_2). \tag{6}$$

Next, consider the desert inhabited by low-income workers. This happens when the city is in S_1. As above, we compute the expected change in rank as

$$E(\Delta r|j=d, r=r_{\mathrm{L}}) = (r_{\mathrm{H}} - r_{\mathrm{L}}) \cdot Pr(S_2|S_1). \tag{7}$$

These two equations and Lemma 2 jointly imply

$$E(\Delta r|j=b, r=r_{\mathrm{L}}) > E(\Delta r|j=d, r=r_{\mathrm{L}}).$$

In other words, conditioned on initially containing low-income households, the beach tends to increase in income more than the desert. Similarly, we can also show that, conditioned on initially containing high-income households, the beach tends to decrease in income less than the desert. Combining the two cases, we obtain Proposition 2.

Proposition 2. (Natural amenities anchor neighbourhoods to high income). *Conditioned on initial income percentile rank, a superior natural amenity neighbourhood tends to increase more in income than an inferior natural amenity neighbourhood.*

Our next implication is at the city level: cities that feature greater heterogeneity in natural amenities tend to have spatial distributions of income that are more stable over time. Notice that $(\alpha_b - \alpha_d)$ captures heterogeneity in natural amenities across neighbourhoods. We use the expected over-time variance of neighbourhood income for the city $E[Var(r_{j,t}|j)]$ to capture *instability* in the city's spatial distribution of income.

Proposition 3. (Naturally heterogeneous cities have persistent spatial distributions of income). *The expected over-time variance of neighbourhood income percentile rank, $E\left[Var(r_{j,t}|j)\right]$, decreases with across-neighbourhood heterogeneity in natural amenity, $\alpha_b - \alpha_d$.*

Proof. See Online Appendix A.1. ||

Proposition 3 is our key theoretical result. To view the intuition, suppose that the two neighbourhoods are *ex ante* identical: $\alpha_b = \alpha_d$. Over time, each neighbourhood's income will be r_{H} or r_{L} with equal probability. This maximizes the over-time variance in income rank and churning at the city level. Now suppose that natural heterogeneity $\alpha_b - \alpha_d$ is larger. With greater natural heterogeneity, more periods will be observed when the beach is the high-income neighbourhood and the desert is the low-income neighourhood. This will reduce the over-time variance of neighbourhood income. In the limiting case, if the difference in natural value $\alpha_b - \alpha_d$ is extremely large, then the beach will be the high-income neighbourhood almost all the time. This implies an over-time variance in income for both beach and desert close to zero.

Our final implication combines elements from the previous two propositions. As in Proposition 2, we compare how superior and inferior natural amenity neighbourhoods change, and, as in Proposition 3, we compare cities with varying internal natural heterogeneity.

Proposition 4. (Natural amenities are stronger anchors in naturally heterogeneous cities). *The difference between superior and inferior natural amenity neighbourhoods, in expected income changes conditioned on initial income, increases with across-neighbourhood heterogeneity in natural amenities, $\alpha_b - \alpha_d$.*

Proof. See Online Appendix A.2 ||

In other words, the anchoring effect of natural amenities increases with natural heterogeneity at the city level. In Section 6, we test this implication and extend this test to the context of central city neighbourhood dynamics.

2.5. *Discussion*

2.5.1. Relaxing simplifying assumptions. Our stylized model makes several simplifying assumptions and uses specific functional forms to clearly illustrate the role of natural amenities without unnecessarily complicating our analysis. For example, households' perfectly inelastic demand for a unit measure of land ensures that the income cutoff for sorting between neighbourhoods is constant at the median, thus avoiding cutoff changes over time.

However, our key propositions hold for other specifications that preserve the following core elements. First, workers' preferences are such that there is perfect sorting by income on aggregate amenities. Secondly, aggregate amenities increase with natural amenities, average income, and amenity shocks. Together, these assumptions ensure that there are three possible equilibrium configurations in each period: S_1 only, S_2 only, or both S_1 and S_2. Combined with a history-based equilibrium selection rule, our three main results follow.

2.5.2. Housing demand. A natural concern about simplifying assumptions is whether they are innocuous. In fact, Proposition 2 might be reversed if the income elasticity of demand for land is sufficiently high: high-income households would choose inferior aggregate amenity neighbourhoods in exchange for more space. This would violate the core structure described previously. Then, conditioned on initial income, superior natural amenity neighbourhoods would tend to *decline* in income.

Fortunately, these contrasting predictions allow us to test whether the income elasticity of demand for land is large enough to reverse our theoretical prediction. Our empirical results consistent with Proposition 2 suggest instead that our simplifying assumption of inelastic demand is indeed innocuous, at least in this context.

2.5.3. More than two neighbourhoods and correlated amenity shocks. Other simplifying assumptions in the model are that the city consists of two neighbourhoods and that the idiosyncratic shocks are uncorrelated over time. Online Appendix A.3 presents an extended model that relaxes these assumptions and shows that our theoretical implications are robust.

Instead of two neighbourhoods, the city has $J \in \mathbb{N}$ neighbourhoods, and the aggregate amenity shock $\epsilon_{j,t}$ follows the AR(1) process $\epsilon_{j,t+1} = \rho\epsilon_{j,t} + \nu_t$, where ν_t is independent and identically distributed. We also extend the equilibrium selection rule in Section 2.3: When multiple equilibria are possible, we choose the one that is closest to the selected equilibrium in the previous period in terms of Euclidean distance between neighbourhood income vectors.

With the extended model, we analytically prove Lemma 1 and Proposition 1. We use numerical methods to demonstrate that Propositions 2, 3, and 4 hold widely when the aggregate amenity shock follows a stationary process (*i.e.* $\rho < 1$). Note that the stationarity condition is not very restrictive, since overall trends in amenities are captured by m_t in equation (1).

3. DATA

3.1. *Census data and geographic normalizations*

We confirm several testable implications of our theory using a novel database of consistent-boundary neighbourhoods spanning many U.S. metropolitan areas from 1880 to 2010. We use census tracts as neighbourhoods because tracts are relatively small geographic units and data are available at the tract level over our sample period, even in historical census years. For each census tract, we collect information about household income, population, and housing from decennial censuses between 1880 and 2000 and the American Community Survey (ACS) between 2006 and 2010.[9]

Since boundaries change from one decade to the next, we normalize historical data to 2010 census tract boundaries. For example, we calculate average household income in 1940 for each 2010 tract by weighting the average household incomes reported for overlapping 1940 census tracts, where the weights are determined by overlapping land area.[10]

Our panel is unbalanced. Growing cities that add neighbourhoods and expanding census coverage both contribute to increases in the number of tracts over time. In addition, our ability to match households to neighbourhoods is limited by the availability of maps showing the spatial location of historical census tracts or enumeration districts. Table 1 shows the number of metropolitan areas and consistent-boundary neighbourhoods available in each year. Overall, we observe over 60,000 neighbourhoods across 308 metropolitan areas and 12 census years from 1880 to 2010. However, the number of observations used in our empirical analysis varies across tests with data availability.[11] The data are most complete for later census years, especially after 1960, and we do not have any data for census years 1890 and 1900.

We assign each neighbourhood to a single metropolitan area, using the Office of Management and Budget's definitions of core-based statistical areas (CBSAs) from December 2009. We refer to each metropolitan area as a "city". (We address changes in metropolitan area boundaries over time by dropping non-urbanized areas in each period, as described in Online Appendix B.3. Thus, neighbourhoods do not appear in our panel until they are urbanized and part of the metropolitan economy.) When relevant, we aggregate CBSAs to consolidated statistical areas. For example, we

9. Because of small annual sample sizes and privacy concerns, the ACS data represent 5-year averages of residents and houses located in each tract. For convenience, we refer to these data as coming from the year 2010, although they actually represent an average from 2006 to 2010.

10. For census data from 1970 and later, we use the population of overlapping census blocks as weights, instead of overlapping land area. Online Appendix B.2 describes the census data and geographic normalization in detail. Online Appendix Table B1 reports summary statistics.

11. Small boundary normalization errors account for the small number of tracts in 2000 that do not appear in 2010, but these tract fragments are ultimately dropped in our regressions.

TABLE 1
Number of consistent-boundary neighbourhoods by census year

Year	Metros	Neighbourhoods
2010	308	60,757
2000	308	60,766
1990	308	60,299
1980	277	56,176
1970	229	49,888
1960	135	38,669
1950	51	17,679
1940	43	11,527
1930	10	1,962
1920	2	2,505
1910	1	1,748
1880	29	3,071

combine the Los Angeles-Long Beach-Santa Ana CBSA with the Oxnard-Thousand Oaks-Ventura and Riverside-San Bernardino-Ontario CBSAs.

Finally, we spatially match neighbourhoods to a variety of persistent natural features. We collect information on a large number of highly visible and important physical attributes. For each neighbourhood, we separately calculate the distance from the tract centroid to (1) the nearest coastline (*i.e.* the Atlantic or Pacific Ocean, the Gulf of Mexico, or a Great Lake), (2) the nearest (non-Great) lake, and (3) the nearest major river. We also calculate (4) the average slope, (5) the flood-hazard risk, (6) the average 1971–2000 annual precipitation, (7) July maximum temperature, and (8) January minimum temperature. In addition, we match neighbourhoods to other factors, including distances to the nearest seaport and the city centre or central business district (CBD). Online Appendices B.4 and B.5 describe these data.

3.2. *Neighbourhood percentile ranks*

Because we are interested in neighbourhood income relative to other neighbourhoods within the same city, we rank tracts within each metropolitan area and census year. We use neighbourhoods' percentile rank $r_{i,t}$, a variable bounded by 0 and 1. For example, in 2010, Malibu (within the Los Angeles metropolitan area) and the Upper East Side (within the New York metropolitan area) have $r_{i,2010} = 0.979$ and 0.990, respectively. By using ranks, we also control for differences in wage levels across cities and years, and we accommodate alternative measures of neighbourhood status in historical years when income measures are unavailable.

We use average household income to rank tracts within each metropolitan area, except in historical census years 1880–1940 when income data are not available. For 1930 and 1940, we use average housing rents to rank tracts. In 1880–1920, lacking data on both income and prices, we use an imputed occupational income score or the literacy rate. The assumption behind these substitutions is that the ordering of average income among neighbourhoods is the same as that of housing rent, occupational income score, or the literacy rate. We have verified empirically that our results are robust to using these alternative measures when they are available. For example, a regression of neighbourhood ranks by average rent on ranks by average income for the 3 census years in which both measures are available yields an estimated coefficient of 0.927 (cluster-robust SE = 0.002) and an R^2 of 0.857, suggesting that these measures are very closely related.

4. NATURAL AMENITIES AS NEIGHBOURHOOD ANCHORS

In this section, we evaluate Proposition 2's prediction that *conditioned on initial income*, neighbourhoods with superior natural amenities tend to increase in income more than other neighbourhoods. This proposition suggests the following neighbourhood-level regression:

$$\Delta r_{i,t} = \beta_0 + \beta_1 \mathbf{1}(a_i) + \beta_2 r_{i,t} + \delta_{m,t} + \epsilon_{i,t}, \tag{8}$$

where $\Delta r_{i,t}$ is the forward change in neighbourhood i's income percentile rank within metropolitan area m between t and $t+1$, $\mathbf{1}(a_i)$ is an indicator for superior natural amenities, $r_{i,t}$ is its initial percentile rank in t, and $\delta_{m,t}$ is a metropolitan area–year fixed effect.[12] We cluster errors $\epsilon_{i,t}$ at the metropolitan area–year level.

Proposition 2 predicts that $\beta_1 > 0$. Including the initial rank $r_{i,t}$ follows from the conditioning statement of the proposition. The metropolitan area–year fixed effect $\delta_{m,t}$ ensures that identification of β_1 comes from variation in natural amenities *within*, not across, metropolitan area–years. As noted previously, we use various persistent features to measure superior neighbourhood natural amenities: first separately and then combined into a single index using predicted values from a housing-price regression.

4.1. *Coastal proximity*

We begin with coastal proximity as a measure of natural amenity. In our baseline regressions, we assign $\mathbf{1}(a_i) = 1$ for a neighbourhood i if its centroid is within 500 m of an ocean, the Gulf of Mexico, or a Great Lake.[13] Table 2, column (1) reports estimation results for the starkest specification suggested by the model, including only coastal proximity, initial rank, and metropolitan area–year effects. Conditioned on initial income, the estimated effect of coastal proximity is slightly negative, although it is indistinguishable from zero.

At first view, this result appears to challenge our theory. But omitted variables in this parsimonious specification, which abstracts from several important neighbourhood factors, bias the result in column (1) downward. In particular, since many U.S. cities and their downtowns were founded near significant natural features such as harbours, there is a strong correlation among neighbourhood proximity to coastlines, downtowns, and seaports.[14] Because these factors may also affect subsequent neighbourhood change—Brueckner and Rosenthal (2009) show that neighbourhoods with older homes tend to decline—estimation of equation (8) without them may lead to a downward omitted-variable bias. In columns (2) through (4), we attempt to correct this bias by including the following control variables: (1) distance to the nearest seaport (interacted with metropolitan coastal status), (2) distance to the CBD, (3) initial population density, and (4) the average age of the initial stock of houses in the neighbourhood.[15] By including these regressors, either singly or together, we hope to control for the historical structure of the city.

12. Note that we compute the change in percentile rank $\Delta r_{i,t}$ for each neighbourhood by subtracting its initial rank $r_{i,t}$ from next period's rank $r_{i,t+1}$. Since this change can only be calculated for neighbourhoods that exist in both the initial period and the subsequent period, neighbourhoods that are added to the metropolitan area are *not* included in this calculation. This is one way in which our empirical analysis abstracts from differences in city growth rates. The included metropolitan area–year effect also controls for city growth common to all neighbourhoods in each metro–year. In addition, using 10-year changes restricts our baseline sample to observations between 1910 and 2010, although later robustness checks with varying time horizons and start years use our 1880 data.

13. We use an indicator variable to allow for nonlinear effects of proximity. Our results are robust to alternative distance thresholds; see Online Appendix B.8. Our results are also robust to considering oceans and Great Lakes separately.

14. In our sample of coastal cities, the correlation coefficients between distance to the coast and distances to the city centre or the nearest seaport are 0.77 and 0.51, respectively.

15. Note that data availability constraints narrow the sample sizes in columns (3) through (6).

TABLE 2
Coastal proximity anchors neighbourhoods to high incomes

	μ $[\sigma]$	(1)	(2)	(3)	(4)	(5) $r_{i,t}>0.9$	(6) Names
1(Coast)^{a,b,c}	0.05	−0.004	0.013***	0.007*	0.014***	0.045***	0.031***
	[0.22]	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)
Initial Percentile rank	0.50	−0.161***	−0.169***	−0.184***	−0.202***	−0.204***	−0.203***
by income ($r_{i,t}$)	[0.29]	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Log distance to	5.02		0.028***		−0.004	−0.004*	−0.004*
nearest seaport^{d}	[4.83]		(0.004)		(0.002)	(0.002)	(0.002)
Log distance to	7.51			0.035***	−0.008***	−0.008***	−0.008***
city centre	[1.95]			(0.003)	(0.002)	(0.002)	(0.002)
Log population	9.74				−0.036***	−0.036***	−0.036***
density	[1.04]				(0.001)	(0.001)	(0.001)
Log average	3.00				−0.019***	−0.019***	−0.019***
house age	[0.53]				(0.004)	(0.004)	(0.004)
Metro–year f.e.		✓	✓	✓	✓	✓	✓
R^2		0.081	0.090	0.116	0.202	0.202	0.202
Neighbourhoods		298,776	298,776	297,518	281,321	281,321	281,321
Metro–years		1,357	1,357	1,313	1,263	1,263	1,263

Notes: Each numbered column displays estimates from a separate regression. Column titled "μ $[\sigma]$" shows sample means and standard deviations. Regressions use pooled observations of 60,872 consistent-boundary neighbourhoods over 10 census years, 1910–2000. Dependent variable is 10-year forward change in percentile rank by income ($\Delta r_{i,t}$); mean, 0, standard deviation, 0.16. All regressions include metropolitan area–year effects. Standard errors, clustered on metropolitan area–year, in parentheses; $^{*}p<0.10$, $^{***}p<0.01$. [a]Neighbourhood centroid is within 500 m of an ocean, the Gulf of Mexico, or a Great Lake. [b]Explanatory variable in column (5) is neighbourhood centroid is within 500 m of an ocean, the Gulf of Mexico, or a Great Lake, *and* neighbourhood initial rank is in top income decile. [c]Explanatory variable in column (6) is neighbourhood centroid is within 500 m of an ocean, the Gulf of Mexico, or a Great Lake *and* neighbourhood name includes "beach", "coast", "bay", "cove", "lagoon", "ocean", or "shore." [d]Log distance to nearest seaport times metropolitan indicator for coastal proximity.

When controlling for historical factors, the estimated effect of coastal proximity is now positive and precisely estimated, consistent with Proposition 2. The estimate in column (4) suggests that, conditioned on initial income, coastal neighbourhoods tend to increase 1.4 percentile points more than interior neighbourhoods every 10 years. The comparison of the estimates across columns (2) through (4) confirms that these variables control for omitted factors in similar ways.

A second source of downward bias is measurement error. We do not observe the true natural amenity value of neighbourhoods: some beaches may be extraordinary, while others might be continually socked in by fog or even polluted. To address this downward bias, we condition natural features on other observables that tend to increase with natural value. One, we examine natural features near historically high-income neighbourhoods. Because households can observe whether a particular natural feature is an amenity, natural features near top-ranked neighbourhoods in an initial year are more likely to be positive amenities. For example, the beach near historically high-income Malibu is likely to be a superior amenity.[16] We assign $\mathbf{1}(a_i)=1$ if and only if the neighbourhood is proximate to a natural feature *and* the neighbourhood was initially in the top decile of neighbourhoods by average income. (We verify that this strategy mitigates the effects of this type of measurement error and reduces the downward bias of our estimates using Monte

16. While this strategy is consistent with our theory, unobservable factors that favour neighbourhoods with both superior natural amenities and high resident income could also generate the same empirical pattern. For example, land use policy might favour coastal high-income neighbourhoods compared with interior high-income neighbourhoods but not similarly favour coastal low-income neighbourhoods compared with interior low-income neighbourhoods. We discuss the role of historical housing and land use regulation, two possible factors fitting this description, in Section 4.3.

Carlo simulations in Online Appendix C.) Column (5) shows the estimated conditional effect of coastal proximity on neighbourhood change increases to 4.5 percentile points.

Secondly, we examine neighbourhoods with names suggesting superior natural amenities. If a neighbourhood next to a polluted beach is relatively unlikely to call itself a "beach", we can reduce measurement error by assigning $\mathbf{1}(a_i)=1$ if and only if the neighbourhood is proximate to a natural feature and its name contains words connoting desirable natural amenities. We match neighbourhoods to place names from the Geographic Names Information System (GNIS).[17] Column (6) of Table 2 shows that the estimated conditional effect of coastal proximity on neighbourhood change increases to 3.1 percentile points when conditioning on amenable names. (Conditioning coastal neighbourhoods on names including "beach", "coast", "bay", "cove", "lagoon", "ocean", or "shore" increases the average income of coastal neighbourhoods from 0.47 to 0.57. This is one way to see that conditioning on names increases the likelihood that a geographic feature is indeed an amenity.)

A third source of downward bias is unobserved time-invariant neighbourhood factors. Suppose that in equation (8), $\epsilon_{i,t}=u_i+v_{i,t}$, where u_i captures unobserved factors.

$$\Delta r_{i,t}=\beta_0+\beta_1\mathbf{1}(a_i)+\beta_2 r_{i,t}+\delta_{m,t}+u_i+v_{i,t}. \tag{9}$$

The correlation between $\mathbf{1}(a_i)$ and u_i, conditioned on initial income $r_{i,t}$, is negative, leading to downward bias in $\hat{\beta}_1$.[18] This bias makes our estimate of $\hat{\beta}_1$ a lower bound for the true effect of superior natural amenities (see Online Appendix C). To see why, consider the two neighbourhoods i and j with varying *measured* natural amenities $\mathbf{1}(a_i)<\mathbf{1}(a_j)$ but the same initial income $r_{i,t}=r_{j,t}$ in period t. That they have the same initial income suggests that the neighbourhood with inferior measured natural amenities is likely to have other unobserved fixed characteristics that are amenable (*i.e.* $u_i>u_j$). Unfortunately, the common solution to eliminate unobserved fixed factors u_i by time-differencing equation (9) precludes identification of β_1 since time-invariant natural features drop out. Further, few instrumental variables would seem to satisfy the exclusion restriction since any variable related to coastal proximity is likely to be correlated with income change.[19]

It is well known that central-city neighbourhoods declined in the mid-twentieth century: in our data, neighbourhoods within 5 km of CBDs experienced a relative decline of 2.9 percentile points every 10 years between 1950 and 1980. Interestingly, our estimates of the anchoring effect of coastal proximity are similar in magnitude to the absolute average rate of decline of downtown neighbourhoods during this period. Further, the additional downward bias from unobserved fixed factors suggests these estimates are a lower bound.

17. The GNIS maintains uniform usage of geographic names in the federal government. We use named populated places, which range from rural clustered buildings to metropolitan areas and include housing subdivisions, trailer parks, and neighbourhoods. These named populated places exclude natural features. See Online Appendix B.5.

18. This issue is related to dynamic panel bias in the cross-country growth convergence literature (*cf.* Caselli *et al*. 1996). However, it differs in that our interest is in the effect of time-invariant natural factors, while that literature has traditionally focused on consistently estimating the mean reversion parameter β_2. A further issue raised by Caselli et al. is that control variables $\mathbf{X}_{i,t}$ are endogenous. The direction of bias is not clear since we do not model these control variables explicitly. However, the conditions for an endogenous control variable to *overestimate* β_1 are not easy to satisfy. In short, both the unobserved effect and the measured natural amenity must increase neighbourhood income, but their correlations with the endogenous control variable must have opposite signs.

19. Under certain conditions that appear to be satisfied in our data, it may be that an imperfect instrument can provide a lower bound on the true value of β_1 (Nevo and Rosen, 2012). In our experiments, using place names or an alternative measure of coastal proximity as instruments yields estimates of the anchoring effect of coastal proximity between 4.5 and 10.7 percentile points, respectively.

Finally, consistent with mean reversion in neighbourhood status, the coefficient on initial rank is negative and precisely estimated. In Online Appendix B.7, we note that this mean reversion is (1) robust to using nonlinear techniques; (2) driven by the middle of the income distribution, not by censored changes at extreme incomes (as might be expected if mean reversion were purely mechanical); and (3) apparent even in nominal incomes, showing that this pattern is not exclusively driven by our use of percentile ranks. Mean reversion in neighbourhood status is also consistent with long-run results for Philadelphia neighbourhoods reported by Rosenthal (2008).

4.2. *Other natural features and an aggregate natural amenity index*

Table 3 shows that our results are robust to other amenity measures. Column (1) reproduces estimated effects of coastal proximity from Table 2. Columns (2) through (6) use indicators for different natural features: lakes, rivers, hills, temperate climates, and low flood risk.[20] Panel A uses the specification from Table 2, column (1), controlling only for initial income and metro–year fixed effects. Panel B adds controls for historical factors, as in column (4). Panel C corrects for measurement error by conditioning natural features on their initial proximity to top-decile neighbourhoods, as in column (5). Finally, Panel D corrects for measurement error by conditioning natural features on neighbourhood names, as in column (6).

In general, the estimated effect of natural features is positive. This is universally true when we correct for measurement error in Panel C. But it is also true for most of our natural amenity measures in Panel A. This contrasts with the dependence of a positive result for coastal proximity on the inclusion of controls for historical factors, and it highlights the unique effect of the historical development of U.S. cities on our coastal proximity results. As noted previously, within coastal metropolitan areas, neighbourhood distance to an ocean or a Great Lake is strongly correlated with distances to the nearest seaport 0.50, −0.31, and −0.23, respectively). In contrast, neighbourhood distance to a non-Great lake is only weakly related to these factors (the absolute correlation coefficients are all <0.06).[21] Thus, it is unsurprising that estimates of the conditional effect of lakes and hills on neighbourhood change in Panel A are positive and precisely estimated despite omitted controls for historical factors.[22]

We combine these features together into an index of aggregate *natural* value by predicting rent from our various observed natural features. We regress the logarithm of neighbourhood median housing rent, reported in censuses from 1930 to 2010, against a complete vector of dummy variables indicating proximity to all of our natural features (at many thresholds), log population density, log distance to the CBD, log number of housing units, average housing age, log distance to the nearest seaport, and metropolitan area–year effects. Then, we predict values for housing rents based on just the estimated natural feature coefficients.[23]

20. The table notes describe how our indicator variables are defined and which sets of words are used to condition on names in Panel D.

21. Hills are negatively correlated with historical factors, explaining the attenuation of their estimated effect from Panel A to B.

22. Note that the regressor of interest in column (5) is an indicator for moderate temperatures and little precipitation. Nearly all of the within-metro variation in this variable comes from coastal California metropolitan areas. Thus, this indicator is closely related to coastal proximity. Similarly, the indicator for low flood risk in column (6) is also strongly correlated with coastal proximity. These correlations with coastal proximity explain why the estimates in Panel A are negative.

23. This hedonic regression omits endogenous factors such as school quality. However, the resulting predicted values may be unbiased estimates of the *natural* amenity value of neighbourhoods if omitted factors are related to the observed factors in the same way. For example, if school quality is related to coastal proximity but not hills, then the estimated coefficients on coastal proximity and hilliness will be biased, relative to each other. However, if school quality

TABLE 3
Anchoring: other measures of natural amenity

(1) Coast	(2) Lakes	(3) Rivers	(4) Hills	(5) Temp. & dry	(6) Pr(flood) < 1%	(7) Nat'l val. > p(95)
A. Indicator for natural feature						
−0.004	0.044**	0.004**	0.050**	−0.033**	−0.025**	0.013*
(0.004)	(0.006)	(0.002)	(0.004)	(0.013)	(0.003)	(0.005)
B. With controls for historical factors						
0.014**	0.031**	−0.003*	0.008*	0.015	−0.001	0.028**
(0.003)	(0.005)	(0.001)	(0.003)	(0.010)	(0.002)	(0.004)
C. Indicator for natural feature and $r_{i,t}>0.9$[a]						
0.045***	0.057***	0.026***	0.034***	0.031***	0.042***	0.040***
(0.005)	(0.014)	(0.005)	(0.004)	(0.009)	(0.003)	(0.005)
D. Place names[b]						
0.031***	0.030**	−0.004	−0.005	0.025***	0.005*	0.019**
(0.005)	(0.007)	(0.003)	(0.003)	(0.007)	(0.002)	(0.005)
E. Sample means of natural amenity indicator, 1910–2000						
0.053	0.006	0.093	0.063	0.073	0.640	0.053

Notes: Each cell in Panels A–D displays estimates from a separate regression. Dependent variable is the forward 10-year change in percentile rank by income ($\Delta r_{i,t}$); mean, 0, standard deviation, 0.16. All regressions include metropolitan area–year effects. Panel E shows the sample means of natural feature indicators noted in column headings. Standard errors, clustered on metropolitan area, in parentheses; $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. Explanatory variable is an indicator for proximity within 500 m in columns (1)–(3), average slope greater than 15° in column (4), mean January minimum temperature between 0 and 18 °C and mean July maximum temperature between 10 and 30 °C and mean annual precipitation less than 800 mm in column (5), mean annual flood probability of less than 1% in column (6), and top 5% in natural value estimated using hedonic weights as described in the text in column (7). Regressions use 298,776 observations of 60,872 consistent-boundary neighbourhoods in 308 metros, 1910–2010, except column (6), which uses 103,442 observations of 27,133 neighbourhoods in 177 metros with valid floodplain data for more than 95% of neighbourhoods. [a]Explanatory variable in Panel C is an indicator for natural amenity *and* neighbourhood initial rank is in top income decile. [b]Explanatory variable in Panel D, column (1) is an indicator for natural amenity *and* the neighbourhood name includes "bay", "beach", "cape", "coast", "cove", "gulf", "lagoon", "ocean", "sea", or "shore". Column (2): "lake", "pond", or "island". Column (3): "brook", "creek", "fall", "rapid", "river", "spring", or "stream". Column (4): "bluff", "butte", "canyon", "cliff", "height", "hill", "knoll", "mount", "ridge", "summit", "terrace", "view," or "vista". Column (5): same as column (1). Column (6): "stream" or "river". Column (7): all of the above.

Table 3, column (7) shows that our results are robust to using this hedonic index to measure aggregate natural value. The estimated effect of aggregate natural value is similar in magnitude to that of coastal proximity. In our preferred estimates controlling for historical factors and correcting for measurement error, the top 5% of neighbourhoods by natural value tend to increase 1.3 – 4 percentile points more in rank than other neighbourhoods over 10 years. This is about one-half of the sample standard deviation of 0.16 in 10-year changes in neighbourhood rank. Again, due to unobserved neighbourhood fixed factors, we consider these estimates to be a lower bound on the anchoring effect of natural amenities.

The previous results estimate the average effect of natural amenities on neighbourhood income growth across different initial income ranks. As a robustness check, we estimate heterogeneous effects using a non-parametric approach. Figure 2 plots kernel-weighted local polynomial smooths of sample changes in neighbourhood income percentile rank, $\Delta r_{i,t}$ versus initial ranks $r_{i,t}$

is related to the overall natural advantage of neighbourhoods, then the estimated coefficients on coastal proximity and hilliness will be biased in the same way, but the relative weights will be unbiased. In this case, predicted rents may be a good indicator for the aggregate natural value of neighbourhoods.

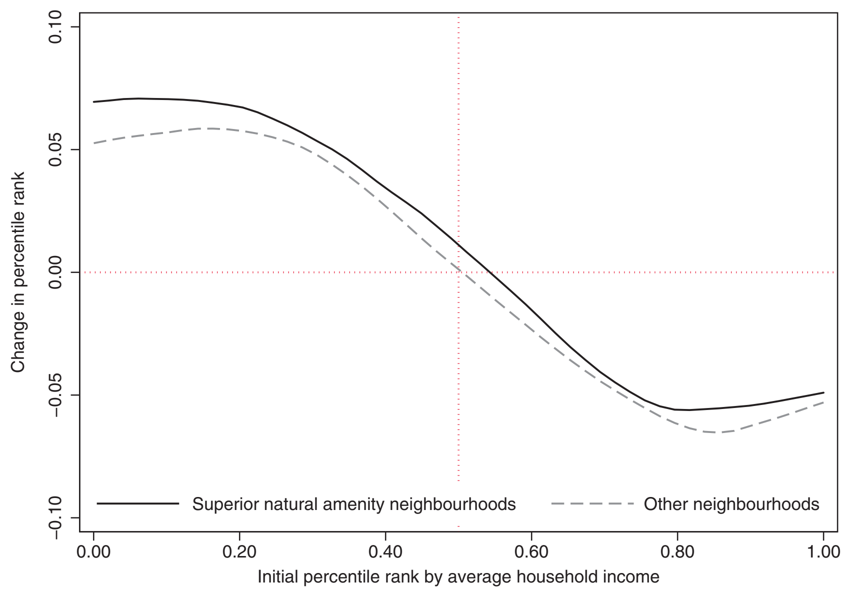

FIGURE 2

Conditioned on initial income, superior natural amenity neighbourhoods increase in income

Notes: This plot shows kernel-weighted local polynomial smooths using the Epanechnikov kernel and rule-of-thumb bandwidth. Superior natural amenity neighbourhoods are the top 5% of neighbourhoods by our aggregate natural value index.

separately for neighbourhoods in the top 5% and bottom 95% in aggregate natural value. Note that for a given initial rank, superior natural amenity neighbourhoods tend to improve more in income versus other neighbourhoods. The average vertical distance between the two lines corresponds to the estimate in Table 3, Panel A, column (7).[24]

4.3. *Discussion*

Next we discuss various factors that may be correlated with natural features. As noted earlier, endogenous factors excluded from both our stylized model and equation (8) may be important channels driving the anchoring of superior natural amenity neighbourhoods to high incomes. We also discuss the alternative explanation that our anchoring results may be driven by an increasing valuation of natural amenities.

4.3.1. Historical housing and land use regulation. Historical buildings may attract high-income workers, as emphasized by Brueckner *et al*. (1999), and we have just seen that they tend to be correlated with coastal proximity. Similarly, coastal areas may attract households that care about certain amenities and act to preserve them through restrictive land use zoning (Kahn and Walsh, 2015). Ideally, these factors might be controls in our anchoring regression, except for poor data availability in historical census years. Instead, here we perform cross-sectional regressions of changes in income from 2000 to 2010 on coastal proximity, including

24. Figure 2 may give the mistaken impression that unconditional changes in rank $E(\Delta r)$ are greater for superior natural amenity neighbourhoods. This is not necessarily the case since superior natural amenity neighbourhoods tend to be of high initial rank.

TABLE 4
Anchoring: endogenous factors, 2000–2010

	μ [σ]	(1)	(2)	(2)	(3)	(4)	(5)
1(Coast)	0.05	0.007**	0.010***	0.011***	0.010**	0.014***	0.015***
	[0.21]	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Initial percentile rank	0.50	−0.097***	−0.124***	−0.129***	−0.125***	−0.119***	−0.120***
by income ($r_{i,t}$)	[0.29]	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Log distance	4.68		−0.006***	−0.006***	−0.004**	−0.001	−0.002
to seaport	[4.88]		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Log distance	9.87		−0.010***	−0.011***	−0.009***	−0.011***	−0.010***
to city centre	[1.04]		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log population	7.53		−0.022***	−0.022***	−0.022***	−0.024***	−0.024***
density	[1.79]		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Log average	3.37			−0.008***	−0.020***	−0.017***	−0.016***
house age	[0.48]			(0.003)	(0.003)	(0.005)	(0.005)
Share houses	0.15				0.070***	0.092***	0.092***
built before 1940	[0.19]				(0.010)	(0.010)	(0.010)
Wharton residential	0.13						0.004**
land use reg. index	[0.98]						(0.002)
R^2		0.049	0.095	0.095	0.100	0.113	0.113
Neighbourhoods		60,073	60,073	60,073	60,073	22,591	22,591
Metro areas		293	293	293	293	247	247

Notes: Each numbered column displays estimates from a separate regression. Column titled "μ [σ]" shows sample means and standard deviations. Regressions use cross-section of consistent-boundary neighbourhoods, 2000–2010. Dependent variable is change in percentile rank by income ($\Delta r_{i,t}$); mean 0, standard deviation 0.13. All regressions include metropolitan area fixed effects. Standard errors, clustered on metropolitan area, in parentheses; $^{**}p<0.05$, $^{***}p<0.01$.

controls for the pre-1940 housing stock in 2000 (as a proxy for historical buildings) and the Wharton Residential Land Use Regulation Index (Gyourko *et al*., 2008). Other details of the estimation are identical to equation (8). Conditioned on the metropolitan area fixed effects, identification comes from variation across neighbourhoods (or municipalities, in the case of the Wharton index) within metropolitan areas.

Table 4 shows the result. Columns (1) and (2) show that the cross-sectional results are similar to the pooled results in Table 2.[25] In column (2), the estimated effect of house age on neighbourhood change is negative, suggesting that old homes are a disamenity. However, when we add a control for the share of houses built before 1940 in column (3), its estimated effect becomes more negative, while the estimated effect of pre-1940 homes is positive and precisely estimated. This is consistent with pre-1940 homes being an amenity, especially if they have been positively selected for survival.[26] Notably, there is hardly any attenuation of coastal proximity effect from column (2) to (3).

Estimates controlling for the Wharton index show similar results. For comparison, column (4) restricts our sample to metropolitan areas where the Wharton index is available. Notably, controlling for land use regulation in column (5) has little effect on the main estimated effect of

25. One exception is that the unconditional estimate in column (1) is positive and precisely estimated, even without controls for historical factors. Although on average over our sample period coastal neighbourhoods have tended to decline, the recent gentrification of central cities shows up here as a positive estimated coefficient.

26. One caution is that these are not causal estimates of housing age since preservation is an endogenous decision that may depend on expectations of future neighbourhood quality. We have experimented with instrumental variables estimates using neighbourhood age, historical lags of the stock of housing, and National Register sites as excluded instruments. The results are similar to the OLS estimates reported here. Neighbourhood age may be conditionally independent of neighbourhood change once distance to the city centre is controlled for. Since National Register buildings are self-nominated, they are not great candidates for an instrument. Instead, we use a separate list of National Register sites noted for their historical, as opposed to aesthetic, significance.

coastal proximity. Stricter regulation appears to act as an amenity, as seen by the positive estimated coefficient on the Wharton index. But the insensitivity of the estimate on coastal proximity again suggests that the anchoring of incomes is not significantly reinforced by stricter regulations.

4.3.2. Other factors. There may be other factors correlated with natural amenities. For example, higher-quality houses might be built in coastal neighbourhoods, further reinforcing the persistence of income there. Or there may be substantial moving frictions in superior natural amenity neighbourhoods. However, a feature shared by many of these factors is that they diminish or depreciate over time. If these frictions or other endogenous factors are responsible for generating our anchoring result over 10-year horizons, then we would expect the estimated effects of natural amenities to decline as these frictions dissipate over many decades or even a century.[27]

Instead, we find the opposite. Figure 3 shows the conditional effects of natural amenities on changes in neighbourhood income over the (very) long run. Each point is an estimated effect from a separate regression that varies the base year t and the time horizon Δt. The dependent variable is the change in percentile rank from t, the beginning year of its corresponding line segment, to $t+\Delta t$, the year corresponding to the horizontal coordinate of the point. For example, in Panel A, the point at the coordinate (1930, -0.009) indicates that the estimated conditional effect of coastal proximity on the 50-year change (1880–1930) in neighbourhood percentile rank is -0.009 ($p=0.916$).[28] (Estimates significant at $p<0.10$ are circled.) Following the dashed line to the right, the point at the coordinate (2010, 0.089) indicates that the estimated conditional effect of coastal proximity on the 130-year change (1880–2010) in neighbourhood percentile rank is 0.089 ($p=0.064$). This figure shows that, across starting years and natural amenities considered, the estimated conditional effects tend to be larger as the time horizon lengthens. We view this evidence as inconsistent with the hypothesis that the anchoring effect is driven by other historical factors, endogenous to natural amenities, that exist in the initial year t of our 10-year regressions.

4.3.3. Increasing valuation of natural amenities. A final concern related to the estimation of equation (8) is that the value of natural features may change over time. For example, the valuation of natural features may have increased because of growing income, particularly in the right tail of the income distribution. One way that this hypothesis might be tested is by estimating the conditional effect of natural amenities on 10-year changes in neighbourhood percentile rank. These estimates can also be seen in Figure 3: a thick shaded line connects estimates of the 10-year effect of natural amenities ending in each labelled census year.

According to Figure 3, there is little evidence that the conditional effect of natural amenities has increased over time, at least for changes in the percentile ranking (as opposed to changes in nominal prices or incomes) of neighbourhoods. Instead, the conditional effect of natural amenities looks stable, or even declining, over time. One potential explanation for these results is that our theory implies that increases in the valuation of aggregate amenities do not affect the relative ranking of neighbourhoods. Since we focus on the relative ranking of neighbourhoods, the effects

27. One may wonder about endogenous factors caused by natural amenity differences between years t and $t+1$. Since these natural amenity differences are predetermined, these factors are part of the overall causal effect of natural amenity differences in the initial year and thus should not be controlled for. See Angrist and Pischke (2009, pp. 64–68) on bad control variables.

28. In all regressions, we include controls for log neighbourhood distance to the nearest port (interacted with metropolitan coastal status), log neighbourhood population density, and log neighbourhood distance to the CBD. We omit the control for log neighbourhood average house age because of inconsistent data availability.

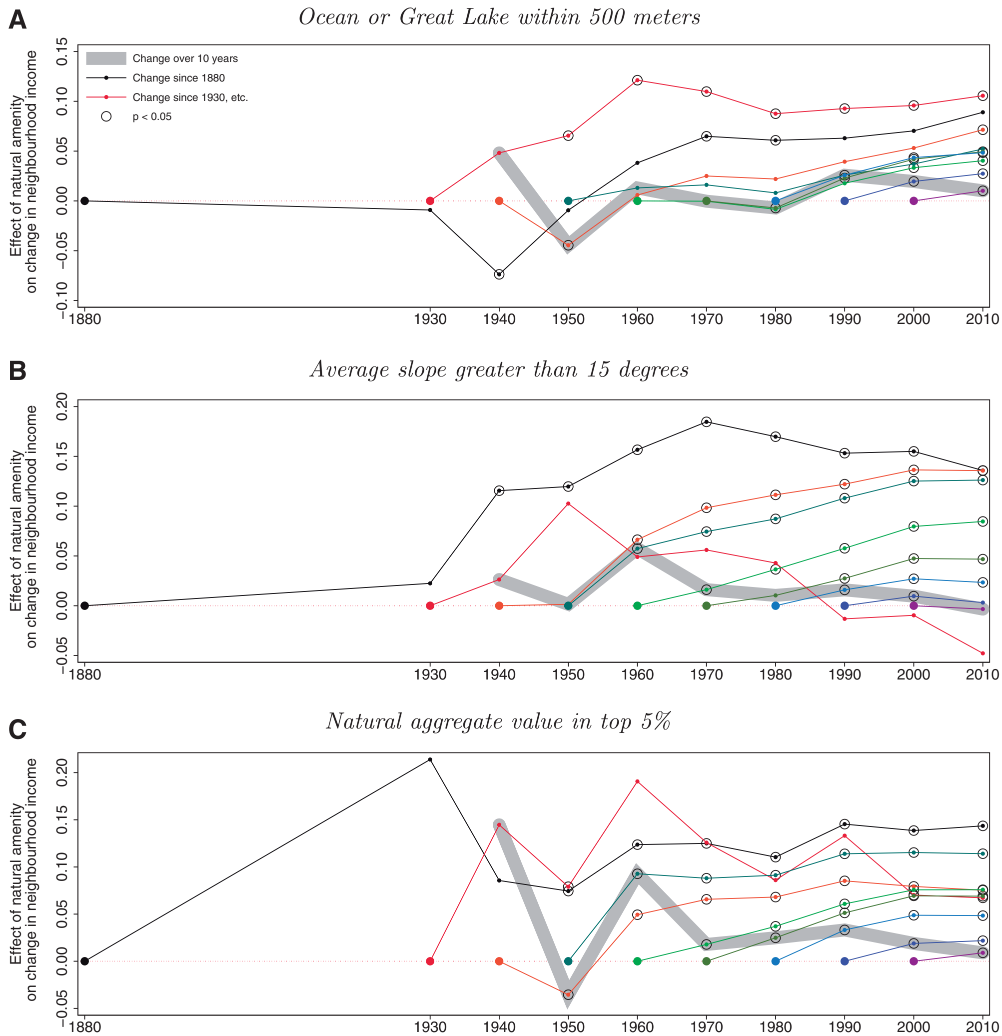

FIGURE 3

Anchoring: Changes over time in 10-year effects and long-run effects.

Notes: Each point in these three plots shows results from a separate regression that varies the base year t and the time horizon Δt. The vertical axis measures the estimated conditional effect of the indicator for the natural amenity noted in the panel title. The dependent variable is the change in neighbourhood percentile rank from t (the beginning year of its corresponding connected line) to $t+\Delta t$ (the year corresponding to the horizontal coordinate of the point). Additional control variables are log distance to the nearest seaport, log population density, and log distance to the CBD. Ten-year effects are connected by the thick shaded line. Circled points are significant at $p<0.05$.

of national increases in income or income inequality are obscured. Instead, such income effects will show up in housing or land prices in high-amenity areas, consistent with the results of Gyourko *et al*. (2013) and Diamond (2016).

A second source of changes in the valuation of natural features is shifts in preferences among amenities. Conditioned on tastes for aggregate neighbourhood amenities, perhaps high-income households place greater weight today on natural amenities compared with endogenous amenities such as schools, shopping, or safety. One prediction of such a shift in preferences is that natural amenities will better predict high-income neighbourhoods today compared with the past.

FIGURE 4
Relative likelihood that a high-income neighbourhood is coastal

Note: This plot shows, for each census year, the relative likelihood that a high-income neighbourhood (compared with all neighbourhoods) is within 500 m of an ocean, the Gulf of Mexico, or a Great Lake.

However, we find little evidence in support of this hypothesis. Figure 4 shows that the relative likelihood that a high-income neighbourhood is coastal has remained roughly constant over 130 years.

5. PERSISTENCE IN THE SPATIAL DISTRIBUTION OF INCOME

Next, we test Proposition 3's prediction that naturally heterogeneous cities have more persistent spatial distributions of income. We begin with the following hierarchical linear model:

$$\sigma(r_{i(m)}) = \psi_m + \varepsilon_i$$
$$\hat{\psi}_m = \gamma_0 + \gamma_1 \Gamma_m + \mathbf{Z}'_m \gamma_3 + \mu_m \tag{10}$$

Here, $\sigma(r_i)$ is the *over-time* standard deviation of neighbourhood i's percentile ranking within city m between some base year t and 2010, and ψ_m is the city mean of $\sigma(r_i)$ estimated in the first level and used as the dependent variable in the second level. Γ_m is a city-level measure of variation in natural value among neighbourhoods within city m. Thus, γ_1 is identified by cross-sectional variation across cities in base year t in (within-city) natural heterogeneity. Proposition 3 predicts that $\gamma_1 < 0$. Following Wooldridge (2003), the minimum distance estimator is equivalent to estimating the second step using weighted least squares, where the weights are $1/\widehat{Avar}(\hat{\psi}_m)$. First-stage errors ε_i are clustered at the city level.

Using 1960 as our base year, we compute $\sigma(r_i)$ using the six observations from 1960 to 2010.[29] Earlier historical years have fewer neighbourhood and city observations, as seen in Table 1. Later census years have fewer periods over which to compute the over-time volatility in neighbourhood income. We show later that our results are robust to the choice of base year. For all choices of base year, we fully balance our panel; thus, for a base year of 1960, our regressions and computations

29. Our results are robust to using the variance $Var(r_i) = [\sigma(r_i)]^2$, but our linear model using the standard deviation results in a better fit, as measured by R^2.

of ranks over time exclude any neighbourhoods or cities that do not appear in our sample in any census year between 1960 and 2010.

To measure Γ_m, we take two approaches. First, we use a metropolitan indicator for coastal status. We expect coastal cities to have a higher internal variance in natural amenities than non-coastal cities because the ocean is such a dominant natural amenity. Secondly, we use the within-city standard deviation in log neighbourhood distance to the coast. This continuous measure is larger in cities where some neighbourhoods are coastal and others are not, and the curvature of the logarithm function ensures that this measure is small in interior cities where all neighbourhoods have equally poor access to the coast.[30]

Finally, to control for factors excluded from the model, we add other city-level covariates related to over-time volatility in neighbourhood income in $\mathbf{Z}_m$. For example, we control for the within-metro standard deviation of neighbourhood income to account for variation in nominal income dispersion across cities. In some specifications, we control for the within-metro standard deviation of neighbourhood house age, since neighbourhoods in cities with greater heterogeneity in endogenous factors such as housing may be more resistant to turnover.

Table 5 displays results using 1960 as our base year. Each column shows a separate regression. We multiply the dependent variable by 100 for presentation purposes, so the units are percentile points. Column 1 shows that, on average, neighbourhoods in coastal metropolitan areas experience smaller fluctuations in income over time. The coefficient on a metropolitan indicator for proximity to the ocean is negative and precisely estimated. The magnitude of the effect is approximately 23% of 1 SD in volatility across neighbourhoods and almost two-thirds of 1 SD across cities; coastal status alone explains about 12% of the variation in neighbourhood volatility across cities.

An alternative explanation of our result in column (1) is that heterogeneous cities are also land-supply constrained. This view suggests that, in flat cities, the supply of housing is more elastic, and therefore the causal link between geography and neighbourhood stability is mediated by city growth, not the value of natural amenities (*cf.* Saiz, 2010). To address this concern, we control for log metropolitan area growth in population and area. Column 2 shows the result. The estimates do suggest that growing cities are less stable, consistent with the alternative view. However, even conditioned on city growth, coastal cities are more stable. Thus, we do not view our results as being spuriously caused by differences in land-supply elasticity across cities.

Note that city population growth is associated with greater volatility in neighbourhood incomes. This is consistent with the idea that shocks to extant neighbourhoods are greater in such cities. Holding land area fixed, neighbourhoods in cities experiencing more rapid population growth seem likely to have experienced more rapid infrastructure investment, greater subdivision of older homes, greater influx of immigrants, and so on, that might correspond to larger shocks in our model. But conditioned on population growth, spreading these shocks over a larger area means more modest shocks at the neighbourhood level, and, hence, the negative estimated coefficient on metro change in land area. Figure 5 further illustrates this relationship between metropolitan population and area growth and neighbourhood volatility.

In column (3), the coefficient on within-city income inequality is negative, too, but it is less precisely estimated. This result suggests that cities with greater income dispersion across neighbourhoods are more stable. The coefficient on dispersion in house ages is imprecisely estimated. This regression also includes additional controls for the top and bottom deciles of initial income in the first level of the estimation. One concern is that because we are using percentile ranks to measure income, the over-time volatility in neighbourhood income may be

30. Results are virtually identical when we interact this measure with a metropolitan coastal indicator, which mechanically sets the internal variation of interior cities to zero.

TABLE 5
Persistence in metros with variation in coastal proximity, 1960–2010

		(1)	(2)	(3)	(4)	(5)
	$\mathbf{\Gamma}_m \equiv$		$1(Coast_m)$[a]		$\sigma(C_{i\|m})$[b]	$\sigma(\hat{a}_{i\|m})$[c]
	μ		0.29		0.42	0.07
	$[\sigma]$		[0.45]		[0.57]	[0.03]
Metro natural heterogeneity ($\mathbf{\Gamma}_m$)		−1.840** (0.742)	−1.500*** (0.523)	−1.362** (0.529)	−1.487*** (0.417)	−36.242*** (5.149)
Metro log change in population, 1960–2010	0.94 [0.78]		4.231*** (0.633)	4.213*** (0.658)	4.083*** (0.629)	5.353*** (0.564)
Metro log change in land area, 1960–2010	1.61 [1.15]		−1.606*** (0.363)	−1.572*** (0.356)	−1.817*** (0.378)	−2.457*** (0.296)
Within-metro SD in neighbourhood income (thous.)	1.91 [0.43]			−0.902* (0.504)	−0.746 (0.563)	−0.744* (0.441)
Within-metro SD in neighbourhood avg. house age	3.69 [0.78]			0.191 (0.372)	0.138 (0.340)	0.726** (0.335)
First level						
Initial rank decile				✓	✓	✓
R^2		0.117	0.555	0.572	0.602	0.695
Metropolitan areas		135	135	135	135	135

Notes: Each column displays estimates from the second level of separate two-level regressions. Row and column titled "μ [σ]" show sample means and standard deviations (SD) for dependent and explanatory variables, respectively. First-level OLS regressions (unreported) use neighbourhood observations in census year 1960 to estimate 135 metropolitan area means and cluster-robust standard errors. Dependent variable is over-time SD in percentile rank ×100, 1960–2010; mean, 12.9, SD, 7.9 in balanced panel of 38,293 neighbourhoods over 6 census years. Second-level weighted least squares (WLS) regressions use 135 metropolitan areas. Dependent variable is estimated metropolitan area means from first level, and weights are inverse estimated variance from first level; mean, 13.1, SD, 2.8. Robust standard errors in parentheses; *p<0.10, **p<0.05, ***p<0.01. [a]Measure of metropolitan natural heterogeneity Γ_m in columns (1)–(3) is a metropolitan indicator for coastal proximity. [b]Measure of Γ_m in column (4) is the within-metropolitan area SD in log neighbourhood distance to an ocean or Great Lake. [c]Measure of Γ_m in column (5) is the within-metropolitan area SD in estimated aggregate natural value.

censored for those neighbourhoods at the very top or very bottom of the income distribution. (Note, however, that such censoring is likely to affect all cities equally. In addition, because Proposition 3 is derived using percentile ranks, it already accounts for such censoring.) The insensitivity of the estimated effect of natural variation to these first-level controls suggests that our results are robust to possible censoring issues in the tails of the income distribution.

In columns (4) and (5), we use alternative measures of within-city natural heterogeneity Γ_m. Column (4) uses the within-city standard deviation in the logarithm of neighbourhood distance to an ocean or Great Lake. Column (5) uses the within-city standard deviation in our aggregate natural value index described earlier. In both regressions, the estimated coefficients are negative and precisely estimated. Standardizing the effect sizes implies similar magnitudes across measures.

Table 6 shows that these results are robust when we vary base years. Each cell reports the estimated coefficient on the within-metropolitan area standard deviation in natural value from a separate regression, with a specification identical to Table 5, column (2). Thus, that estimate is repeated in the first row, column (5) of Table 6.

Each panel shows results where the measure of within-city natural heterogeneity is noted by the panel title. Each column displays results for regressions using the base year indicated. For example, in column (1), we rely on cross-sectional variation in 1880 across twenty-nine cities, and we use the 7 census years available for a balanced panel (1880, 1960, 1970, ..., 2010) to compute the over-time volatility in income.

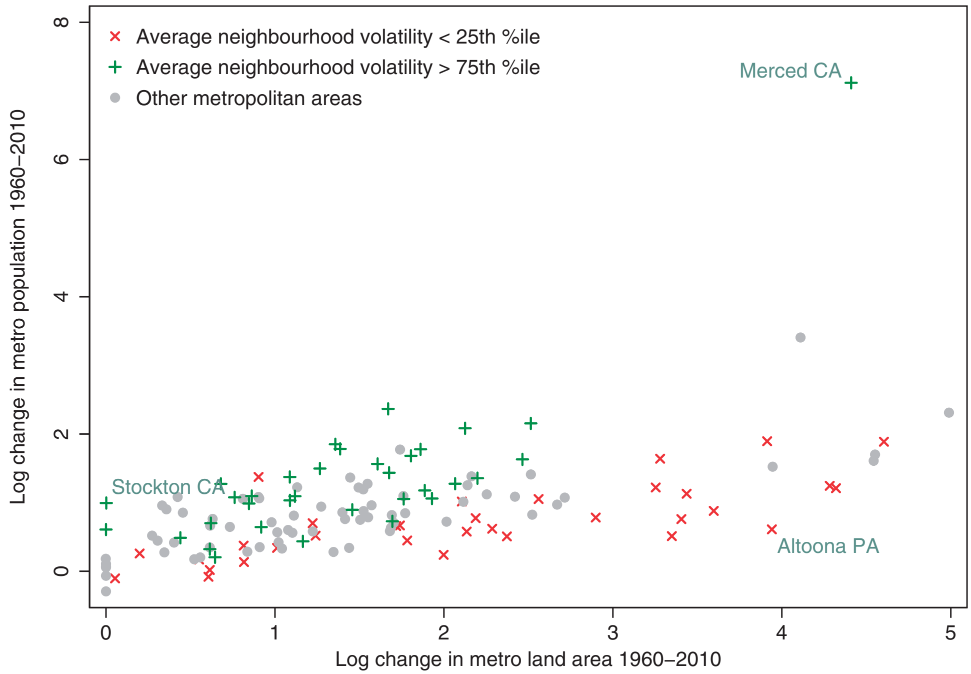

FIGURE 5

Persistence: neighbourhood volatility and metropolitan growth

Notes: This plot shows 50-year changes in population and area for 135 metropolitan areas, 1960–2010. Each point represents a metropolitan area. Metropolitan areas with an average over-time variance in neighbourhood rank at or above the 75th percentile across metros are indicated by "+" markers. Metros with an average over-time variance in neighbourhood rank below the 25th percentile are indicated by "x" markers.

Neighbourhoods in coastal cities (Panels A and B) or naturally heterogeneous cities (Panel C) tended to experience smaller fluctuations in income over 1960–2010, echoing results in Table 5. These estimates are negative and precisely estimated. Overall, all of the estimated effects in 1940 or later are negative, and the results are especially strong and precisely estimated when considering base years from 1950 to 2000.

Some of the earlier estimates for 1930 are positive and precisely estimated. In part, we find that this is due to an unrepresentative sample of cities. The ten metropolitan areas used in the 1930 regression are all in the Northeast or Midwest regions.[31] Estimates from regressions in later base years that are restricted to these cities tend to feature reduced magnitudes and precision, suggesting that differences in the sample composition of cities may play a role in these historical estimates.

Finally, Figure 6 illustrates our main result that neighbourhoods in naturally heterogeneous cities tended to experience smaller over-time fluctuations in income over 1960–2010. Each point represents a metropolitan area. The vertical axis measures the metropolitan-level residual from a regression of mean variance in percentile rank over time on controls as in Table 5, column (4). The horizontal axis measures the within-city standard deviation in our predicted rent index; Los Angeles and the San Francisco Bay Area (labelled San Jose) are the two most naturally

31. In 1930, our metropolitan areas are Boston, Buffalo, Chicago, Cleveland, Columbus, Indianapolis, Nashville, Pittsburgh, St. Louis, and Syracuse.

TABLE 6

Persistence: robustness to other years and measures of within-metro natural heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Base year:	1880	1930	1940	1950	1960	1970	1980	1990	2000
μ	19.4	17.5	13.8	13.8	12.1	10.2	9.06	8.90	7.37
[σ]	[6.92]	[9.05]	[8.44]	[8.16]	[8.29]	[7.29]	[6.53]	[6.63]	[7.25]
A. $\Gamma_m = 1(Coast_m)$ (Metro indicator for coastal status)									
0.22	0.013	3.490*	−0.071	−0.210	−1.500***	−1.004**	−0.372	−0.255	−0.089
[0.42]	(0.388)	(1.772)	(0.531)	(0.518)	(0.523)	(0.398)	(0.300)	(0.229)	(0.176)
B. $\Gamma_m = \sigma(Coast_{i\|m})$ (Within-metro SD in log distance to coast)									
0.42	0.357	3.859*	−0.236	−0.280	−1.605***	−0.952***	−0.479***	−0.354**	−0.183
[0.62]	(0.746)	(1.681)	(0.642)	(0.551)	(0.389)	(0.227)	(0.164)	(0.143)	(0.120)
C. $\Gamma_m = \sigma(\hat{a}_{i\|m})$ (Within-metro SD in aggregate natural value)									
0.08	19.701	81.591**	−4.199	−27.573***	−34.661***	−24.080***	−12.212***	−7.346***	−3.837***
[0.03]	(12.217)	(29.894)	(7.598)	(9.574)	(5.085)	(3.411)	(2.435)	(2.820)	(2.220)
Years[a]	7	9	8	7	6	5	4	3	2
Metros	29	10	38	51	135	227	277	308	308
First level *Neighbourhoods*	3,002	1,935	11,167	17,420	38,293	49,660	55,911	60,063	60,545

Notes: Each cell displays estimates from the second level of separate two-level regressions. Column and row titled "μ [σ]" show sample means and standard deviations (SDs) for explanatory variables (in 2010) and dependent variables, respectively. Regression specifications are same as Table 5, column (2). First-level OLS regressions (unreported) use neighbourhood observations in the base year to estimate metropolitan area means and robust standard errors. Dependent variable is over-time SD in percentile rank ×100, between base year and 2010; metropolitan-level means and SDs in the first row. Second-level WLS regressions use metropolitan areas. Dependent variable is the estimated metropolitan area means from first level, and weights are inverse estimated variance from first level. Robust standard errors in parentheses; *p<0.10, **p<0.05, ***p<0.01. [a]—For each base year, we balance our neighbourhood panel to calculate over-time variances.

heterogeneous metropolitan areas by this index. The slope of the fitted line corresponds to the estimate reported in Table 6, panel C, column (5).[32] Thus, naturally heterogeneous cities exhibit more persistent spatial distributions of income over time.

6. DECENTRALIZATION AND GENTRIFICATION IN COASTAL AND INTERIOR CITIES

In this section, we test Proposition 4's prediction that natural amenities are stronger anchors in naturally heterogeneous cities. Intriguingly, this prediction also has implications for variation across cities in the widespread decentralization of income in the early and mid-twentieth century and the regentrification of downtowns since 1980. We show that coastal city downtowns, compared with downtowns in river or interior cities, have been better anchored to high incomes during both periods of nationwide suburbanization and gentrification.

First, we test Proposition 4 by adding to equation (8) an interaction between a neighbourhood indicator for superior natural amenities $\mathbf{1}(a_i)$ and metropolitan natural heterogeneity Γ_m:

$$\Delta r_{i,t} = \beta_0 + \beta_2 r_{i,t} + \beta_1 \mathbf{1}(a_i) + \beta_3 \mathbf{1}(a_i) \times \Gamma_{m,t} + \delta_{m,t} + \epsilon_{i,t}. \tag{11}$$

Proposition 4 predicts that $\beta_3 > 0$. In Section 4, we introduced various measures for superior natural amenities $\mathbf{1}(a_i)$, and, in Section 5, we introduced various measures for metropolitan natural heterogeneity $\Gamma_{m,t}$. With $\mathbf{1}(a_i)$ defined as an aggregate natural index value in the top 5%, $\Gamma_{m,t}$ measured with the (initial) within-city deviation in aggregate natural value, and controls

32. Note that two outliers, Las Vegas and Tucson, are desert cities that have low volatility but also low measured natural heterogeneity. Intriguingly, there may be unmeasured natural amenities (such as access to aquifers) in these cities that lead us to underestimate the true degree of natural heterogeneity.

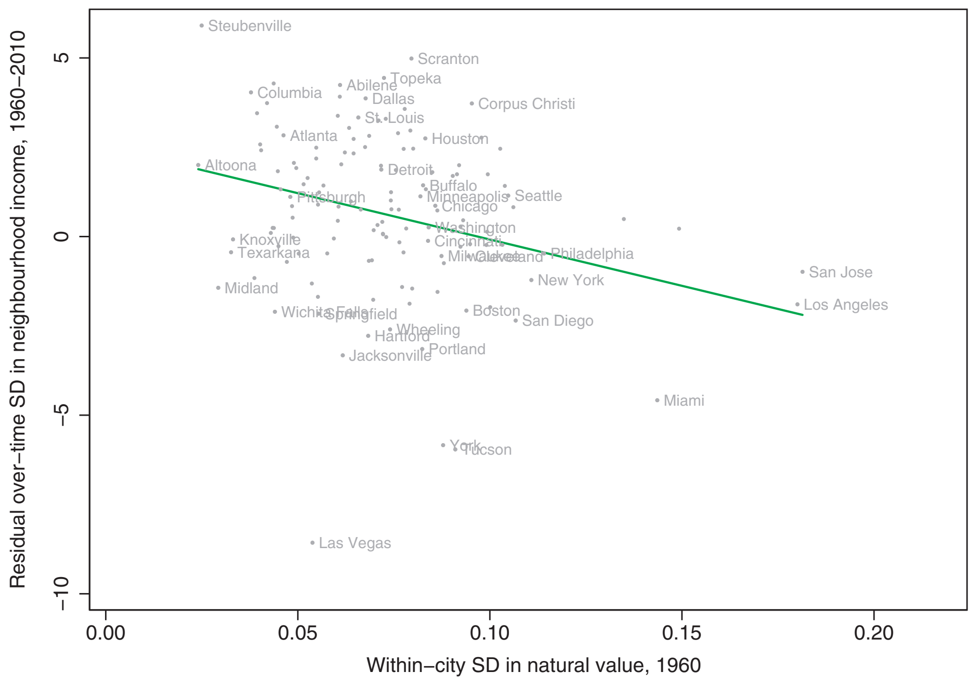

FIGURE 6

Persistence: neighbourhoods in naturally heterogeneous cities experience smaller over-time fluctuations in income

Notes: This plot shows time-series variation in neighbourhood percentile rank and cross-sectional variation in neighbourhood natural amenities. The vertical axis measures the metropolitan-level residual from a regression of mean neighbourhood 1960–2010 standard deviation (SD) in percentile rank by income ($\times 100$) on within-metropolitan SD in neighbourhood income and log changes in metropolitan population and land area over the same period. The horizontal axis measures the within-metropolitan SD in aggregate natural value using estimated hedonic weights as described in the text. The slope of the fitted line corresponds to the estimate in Table 6, Panel C, column (5).

following Table 2, column (4), we find that superior natural amenity neighbourhoods increase in income $\hat{\beta}_1 = 1.9$ percentile points cluster-robust standard error (c.r.s.e.$=$0.6) in the average metropolitan area by natural heterogeneity, and this effect increases $\hat{\beta}_3 = 3.3$ percentile points (c.r.s.e=0.6) for every 1 SD increase in metropolitan natural heterogeneity. This result is robust to other measures of $\mathbf{1}(a_i)$ and $\Gamma_{m,t}$.

Proposition 4 also has implications for variation across cities in the nationwide decentralization of income in the early and mid-twentieth century and the regentrification of downtowns since 1980. Owing to historical development patterns, many cities have their central business districts near superior natural amenities; coastal cities tended to develop from harbours and beaches, and interior cities grew from rivers. Thus, intriguingly, since coastal cities are more naturally heterogeneous than interior cities, Proposition 4 predicts that coastal city downtowns will have been better anchored to high incomes compared with interior city downtowns during both the period of widespread suburbanization and the more recent period of downtown gentrification. To test this prediction, we replace $\mathbf{1}(a_i)$ with $\mathbf{1}(CBD_i)$ in equation (11).

$$\Delta r_{i,t} = \beta_0 + \beta_2 r_{i,t} + \beta_1 \mathbf{1}(CBD_i) + \beta_3 \mathbf{1}(CBD_i) \times \Gamma_{m,t} + \delta_{m,t} + \epsilon_{i,t}. \tag{12}$$

The regression results reported in Table 7 confirm that coastal downtowns have been better anchored to high incomes. Column (1) confirms the long-run decline in the income of interior downtowns, by an average of 4.0 percentile points every 10 years, but as indicated by the positive

TABLE 7
Decentralization of income and metropolitan coastal proximity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample years:		1910–2010[e]		1950–1980	1980–2010	1990–2010 (Kneebone)	
1(CBD)[a]	−0.040***	−0.085***	−0.015***	−0.023***	0.005**	0.018***	0.018**
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.008)
1(CBD) × 1(Coastal metro)[b]	0.032***	0.034***	0.020**	0.030***	0.029***	0.025**	0.025**
	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.011)	(0.011)
Initial percentile rank by income ($r_{i,t}$)		−0.181***	−0.205***	−0.313***	−0.124***	−0.108***	−0.108***
		(0.009)	(0.006)	(0.010)	(0.003)	(0.003)	(0.003)
Log distance to seaport			−0.003	−0.003	−0.007***	−0.007***	−0.007***
			(0.003)	(0.005)	(0.002)	(0.002)	(0.002)
Log population density			−0.035***	−0.048***	−0.021***	−0.020***	−0.020***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log average house age[c]				−0.075***	0.005*	0.008***	0.008***
				(0.010)	(0.002)	(0.003)	(0.003)
1(CBD) × ΔCBD job share[d]							0.027
							(0.241)
1(CBD) × Δ3–10 mi job share[e]							−0.382**
							(0.147)
Metro–years f.e.	✓	✓	✓	✓	✓	✓	✓
R^2	0.004	0.098	0.207	0.338	0.107	0.099	0.099
Neighbourhoods	297,522	297,522	297,520	105,529	175,794	98,006	98,006
Metros	293	293	293	224	293	86	86

Notes: Each column displays estimates from a separate regression. Dependent variable is 10-year forward change in percentile rank by income ($\Delta r_{i,t}$); mean, 0, standard deviation, 0.16. Standard errors, clustered on metropolitan area–year, in parentheses; $^{*}p$<0.10, $^{**}p$<0.05, $^{***}p$<0.01. Regressions use observations of 60,400 neighbourhoods in 293 metropolitan areas, 1910 to 2010. [a]Neighbourhood is within 5km of principal city CBD. [b]Metropolitan area CBD is within 1km of an ocean or a Great Lake. [c]Available 1950 and later. [d]Changes in share of metro jobs within 3 miles of CBD, 1998–2006 (Kneebone, 2009). [e]Changes in share of metro jobs within 3–10 miles of CBD, 1998 to 2006 (Kneebone, 2009). [f]Sample for which 10-year forward change in percentile rank by income is defined.

estimated effect of the interaction term, downtown neighbourhoods in coastal metros declined by an average of just 0.8 percentile points every 10 years. We have verified that this result is robust to using a continuous treatment and interaction instead of an indicator for downtown proximity.[33] This result is also robust to alternative measures of metropolitan natural heterogeneity versus a simple metro coastal indicator.[34]

Column (2) shows that conditioned on initial income, coastal downtowns tended to decrease less in income versus interior downtowns. Controlling for initial income corresponds to the conditioning statement of Proposition 4. Further, this result is robust in our 1910 to 2000 sample to controlling for neighbourhood distance to the nearest seaport and population density, as seen in column (3).

Columns (4) and (5) compare two distinct periods: the decentralization of income before 1980 and the gentrification of city centres after that, respectively. In addition, these regressions restrict the sample to years in which we have information on neighbourhood average house age, an additional control. In the first period, the negative coefficient estimate on city centre proximity confirms the suburbanization of income. In the second period, the positive estimate reflects the

33. For example, the estimated coefficient on log distance to city centre is 0.028 (c.r.s.e.=0.002), and the coefficient on log distance to city centre times coastal metro indicator is −0.010, c.r.s.e.=0.005.

34. For example, using the standard deviation of our hedonic measure of natural value yields similar results: the estimated coefficient on downtown proximity is −0.038, c.r.s.e. =0.004, and the estimated coefficient on downtown proximity times the metropolitan standard deviation of hedonic natural value is 0.119, c.r.s.e. =0.035.

gentrification of downtowns experienced in the past few decades. In columns (3) and (4), the attenuation of the estimated coefficient on downtown proximity compared with columns (1) and (2) suggests that some of the decline of downtowns can be attributed to observable characteristics such as housing age, proximity to ports, or population density.

Notably, the coefficient of interest on the interaction between neighbourhood city centre proximity and metropolitan coastal proximity remains stable across specifications. Our estimates suggest that coastal downtowns have had a 3-percentile-point advantage over interior downtowns in terms of conditional changes in income rank.

Finally, these results do not appear to be driven by less job decentralization in coastal metropolitan areas. An alternative explanation for our results might be that naturally heterogeneous cities also keep employment more centralized, perhaps due to greater transportation costs associated with industrial or commercial activities. In columns (6) and (7), we show that our results are robust to controls for the degree of job decentralization in a metropolitan area. Kneebone (2009) uses ZIP Code Business Patterns data to estimate the changes in metropolitan employment shares over 1998–2006 in 3-, 3- to 10-, and greater than 10-mile rings around the CBDs of many metropolitan areas, of which eighty-six match our metropolitan area definitions. Column (6) repeats regressions (4) and (5) on the Kneebone-restricted sample. In column (7), we include the first two measures of job decentralization (as the three shares sum to 1). The estimated effect of downtown proximity and coastal proximity is identical across columns (6) and (7), suggesting that limited job decentralization in coastal cities does not contribute to our results. Interestingly, increases in the job share of neighbourhoods within 3 miles of the central business district appear to bolster the incomes of central neighbourhoods, although the effect is imprecisely estimated. Job-share increases in a 3- to 10-mile ring around the CBD appear to be negatively and significantly related to incomes in the city centre, consistent with the importance of job access to the recent gentrification of central cities. In addition, the estimated coefficient on downtown proximity becomes more positive, consistent with intensifying gentrification of central cities starting in 1990.

These differences in patterns of decentralization and gentrification add a cross-city perspective to literature that have documented historical changes in the location of income within U.S. cities. LeRoy and Sonstelie (1983) report that downtown neighbourhoods in eighteenth- and nineteenth-century Milwaukee, Philadelphia, Pittsburgh, and Toronto tended to feature higher incomes at least until the introduction of the streetcar in the 1850s and 1860s “caused the first major flight of the affluent to the suburbs” (p. 81). This decentralization would be repeated later on a larger scale between central cities and their outlying suburbs, leading to the dominant U.S. pattern today of poor centres and rich suburbs (Brueckner and Rosenthal, 2009). Subsequently, many central cities have experienced rising incomes and gentrification in the past several decades.

Figure 7 confirms these patterns for a fixed sample of twenty-nine metropolitan areas over 10 census years—a broader section of cities than in previous work. Each panel displays the pattern of income and residential location: the horizontal axis measures distance from the city centre, up to 15 km, and the vertical axis measures average household income on a percentile rank scale.[35] Plotted lines show lowess regressions, fitted separately for coastal versus interior cities.[36]

35. Only six cities in our sample had neighbourhoods beyond 15 km from the city centre in 1880. Overall, the median city’s maximum extent was 6 km from the city centre.

36. See Online Appendix Table B2 for our classification of cities.

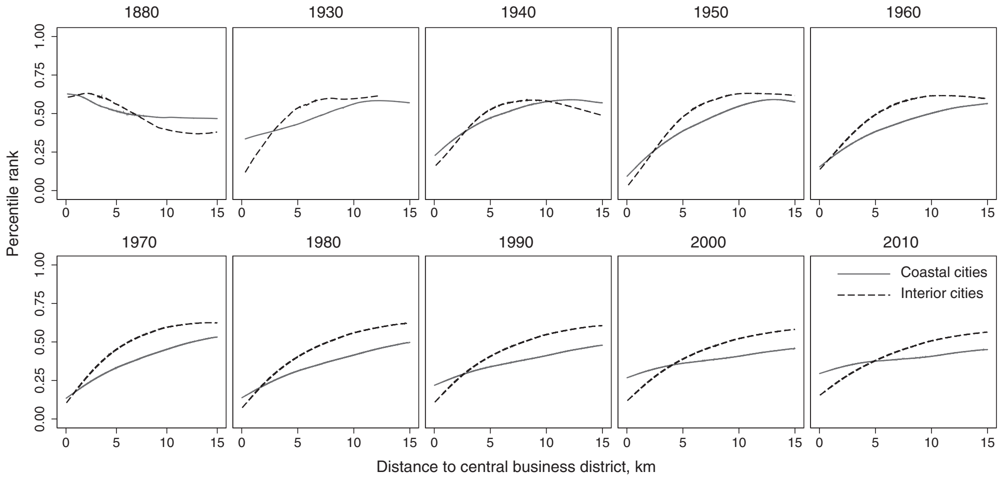

FIGURE 7

Income and residential location for coastal and interior cities, 1880–2010

Notes: Each plot shows, for a different census year, the pattern of neighbourhood average household income on the vertical axis versus neighbourhood distance to the city centre (up to 15 km) on the horizontal axis. The smoothed lines are from lowess regressions. Two groups of cities are shown in each panel: coastal cities are represented by a solid line and interior cities by a dashed line. The sample is a fixed group of twenty-nine metropolitan areas with some missing city observations from 1930 to 1950. Coastal and interior cities are classified in Online Appendix Table B2.

The first panel shows that in 1880 income declined with distance to the city centre in both coastal and interior cities. This pattern is consistent with the fact that many of these cities were still recently founded as of 1880, and the best-developed areas were clustered near downtown.[37]

However, as early as 1930, we see a divergence in the fortunes of downtowns in coastal versus interior cities: while all downtowns declined, those in interior cities tended to decline faster than downtowns in coastal cities, at least until 1960. Further, the second row of Figure 7 shows that, from 1970 onward, coastal city downtowns tended to improve faster in income than interior city downtowns. Thus, the pattern seen in Figure 7 is consistent with Proposition 4. Throughout both the widespread decentralization of income and the more recent gentrification of central cities, coastal city downtowns have been better anchored to high incomes.

7. CONCLUSION

We combine new theory and a novel database of consistent-boundary neighbourhoods to study both neighbourhood dynamics and differences across cities in patterns of neighbourhood change, suburbanization, and persistence. Our theory and results highlight the role of natural amenities in neighbourhood dynamics. Persistent natural amenities anchor neighbourhoods to high incomes over time, and they affect neighbourhood dynamics citywide. Downtown neighbourhoods in coastal cities have been both less susceptible to suburbanization and more responsive to gentrification versus interior cities. Finally, cities with greater internal natural heterogeneity tend to exhibit more persistent spatial distributions of income.

37. In Online Appendix Figure B1, we show that the pattern of income varied across metropolitan areas. For example, peripheral incomes in Columbus, Louisville, and Washington, DC, exceeded incomes in the core. And in Philadelphia, Boston, Cleveland, and New York City, incomes were highest not in the core but at some distance from the centre. But most sample cities continued to feature the highest incomes closest to the centre in 1880.

Although our stylized model assumes a closed city for simplicity, our insights should hold in an open city setting. Even if migration across cities causes changes in a city's nominal income distribution, the sorting between workers' income rank and neighbourhood aggregate amenities still holds. That said, there are many interesting questions to be examined in a model that considers household mobility across cities. For example, cross-city sorting of households on preferences for natural amenities may have important implications for income inequality and the political economy of coastal cities, complementing recent research by Moretti (2013) and Eeckhout *et al*. (2014). Further, the push to implement place-based policies, as well as their consequences, may vary with natural heterogeneity and these sorting patterns. These interesting topics are left for future research.

Finally, we have focused on neighbourhood sorting by income in this article. But our insights extend to sorting on other characteristics as well. For example, the strong correlation between race and income in the U.S. means that many of the patterns we find apply to racial segregation dynamics as well.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

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