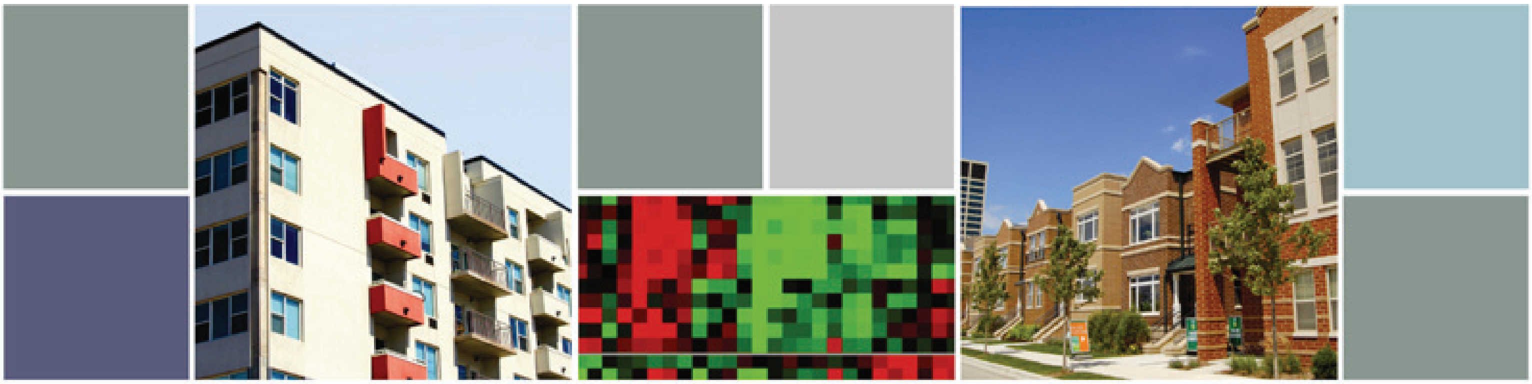

Dynamic Neighborhoods

New Tools for Community and Economic Development

A project of

Living Cities
THE NATIONAL COMMUNITY DEVELOPMENT INITIATIVE

Appendices

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APPENDICES

APPENDIX A
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CMAP Chicago Metropolitan Agency for Planning

CNT
Sustainable Communities
Attainable Results

THE CLEVELAND FOUNDATION

DataPlace

ECONSULT CORPORATION®

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METROPOLITAN POLICY PROGRAM
THE BROOKINGS INSTITUTION

NEIGHBORHOOD PROGRESS

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APPENDIX B
Data Sources and Preparation Procedures

In order to conduct the Evolution analysis, the project acquired historical, parcel-level data on property characteristics and real estate transactions in the four sample cities and their counties. As described in the Evolution report, the data for different cities was acquired from different sources. Consequently, data cleanup and preparation procedures had to be customized for each dataset. Below is a detailed description of the data sources and clean up procedures that were adopted for each city.

I. Chicago

Overview

The Chicago Real Estate Transactions data was acquired from a leading national real estate data vendor, which in turn acquires data from the County Assessor and Recorder of Deeds offices.

The cleanup process consists of fifteen steps:

1. Import the data, Standardize essential variables
2. Remove invalid property identifiers and unnecessary variables
3. Append the data, Construct "age" variable
4. Adjust property identifiers to account for condos
5. Import 2005 Tax roll data, Fill in missing property type information
6. Construct new property identifiers and "account" and "salesnum" variables, Control for new construction
7. Eliminate non-residential properties
8. Eliminate foreclosures and subsequent sales
9. Eliminate non-arm's length transactions
10. Import XY coordinates
11. De-duplicate same property sales within 30 days
12. Eliminate outliers based on appreciation rate
13. Apply inflation-adjusted price ceiling and floor
14. Reconstruct "account" and "salesnum" variables
15. Prepare dataset for analysis

Step One: Import the Data, Standardize Essential Variables

There are two batches of data of real estate transaction records. Each dataset covers a different time period:

Years Covered	Number of Files

1985 – 1990	1
1991 – 2006	5 (append)

The 85-90 and 91-06 data ultimately need to be appended together. However, the dataset is too large to fit into memory at this stage, so this will be done in step three.

In order to be able to combine these files, we first need to rename the variables in both datasets to the same variable names (we will use the 91-06 names as the final names), and then we will need to recast the variables in both datasets to the same data type. This is done as follows:

Variable	85-90	91-96	Final
recordingdate	str8	long	str
propertyindicator	byte	byte	byte
documenttype	str2	str2	str
transactiontype	byte	str2	str
saleamount	double	long	(either)

Step Two: Remove Invalid Property Identifiers and Unnecessary Variables

The only records which are kept are records with a string APN identifier of exactly 14 characters that are not all zeros and do not include any extraneous characters. These extraneous characters are found to be " " (space), "-", "`", "B", "E", "K", "U", and "Z".

To make the datasets more manageable, we also remove variables that won't be used at any point in the data preparation or analysis, such as mailing addresses. In any case, the files are indexed so that it is easy to merge any of this information back in if needed.

Step Three: Append the Data, Construct "age" Variable

The 85-90 and 91-06 datasets are now appended together after steps one and two have been performed on both separately.

We can now generate age variables *year*, *month*, *date* and *age* from the *recordingdate* variable. The *age* variable counts the months as an ordered sequence starting at 0 with the first month in the dataset (January 1985). Dates that have incomplete information with respect to the day of the month (such as 1990-12-00) are kept. However, records with dates that have missing month information (such as 1990-00-12) are discarded (this affects just over three hundred records).

Step Four: Adjust Property Identifiers to Account for Condos

We noticed that a number of properties have the same property ID even though the "unit number" in the property address field is different. In the vast majority of cases, these units are coded as condos, and refer to different units in the same building. If we were to keep the original property identifier, we wouldn't be able to distinguish between the different individual properties that make up the condominium.

In order to account for this issue, we construct a new property identifier *apn_unit* consisting of a concatenation of the original APN and unit number. Note that when we import property type information from the tax roll file in the next step (see below) we will still be using the original property identifier, since the new one will not be found in the tax roll dataset.

Additionally, in some cases the unit number of the condo properties was missing. We divided these properties into three cases and resolved them as follows: when the unit number was missing for a few records and the other records with the same APN had multiple values of unit numbers, the records with a missing unit number were deleted. However, when only one unique unit number was present, this unit number was copied onto the records with missing unit numbers. In the third case, when all the unit numbers were missing for the same APN, they were grouped together as if they were one property.

Step Five: Import 2005 Tax Roll Data, Fill In Missing Property Type Information

Up to this point, many records still have indeterminate property type codes because the information is missing or they are coded as missing or miscellaneous (misc/miss). This missing information disproportionately affects the 1985-90 portion of the data, where the property type is coded as either missing or miscellaneous for 73% of the records (while this is true for only 29% of the 91-06 data).

The first step is to extract as much information as we can from the original dataset. In particular:

1. For properties that have missing property type in sales between 1991 and 2006, if there is a subsequent sale of the same property that has a valid *propertyindicator* code, then the value of the non-missing code is copied back for the missing code. Similarly, for repeat sales in which sales between 1985 and 1990 are always coded as misc/miss, and the first sale from 1991 onwards is coded as something other than missing, we use the code from this first sale to copy back onto the misc/miss sales from between 1985 and 1990. There are three considerations at play here:

    1. Properties do not change land use often (the actual percentage of properties with repeat sales that do change property type during the 20 years for which we have observations is between 4% and 10%). So in copying back property type codes from later transactions we are allowing a little more noise in exchange for a larger sample size.
    2. The property type code that we find in the 1991-2006 dataset is more likely to be accurate than the property code we can extract from the 2005 tax roll data (see below) since it was entered at the time of sale.
    3. If a property is coded as something other than missing or miscellaneous between 1985 and 1990, that means that at some point the property was coded correctly, and a miscellaneous code is a "genuine" miscellaneous code.

After this step, we still have a number of properties that have missing property type information, or (in the case of the pre-1991 data) miscellaneous property type.

The 2005 tax roll data contains property type information for about 96% of the APNs in the dataset. We merge our current dataset with the tax records data by using the APN field. The tax roll data variables are renamed as *tax_propertyindicator* and *tax_yearbuilt*. We then implement the following steps:

1. Generate a *yearbuilt_useful* variable equal to 1 if *0 < tax_yearbuilt < year,* where *year* is the year of sale. We will only use the *tax_propertyindicator* field if *yearbuilt_useful* is equal to 1: the assumption here is that if a property was labeled as residential in 2005 and was built before the date of the sale in question, we can safely assume that it was residential at the time of sale. Note that about 27% of APNs have *tax_yearbuilt* equal to 0: these cases are treated as missing values and the *tax_propertyindicator* information is not used.

2. For records between 1985 and 1990, replace the *propretyindicator* code with the *tax_propertyindicator* values if *yearbuilt_useful* is equal to 1 and the old code is misc/miss. For records from 1991 onwards, only replace if the old code is missing. The rationale is that (based on our conversations with the data vendor) we believe that between 1985 and 1990 both misc/miss are indeterminate, while from 1991 onwards missing codes are indeterminate and miscellaneous codes are genuinely miscellaneous.

Step Six: Construct New Property Identifiers and “account” and “salesnum” Variables; Control for New Construction

In order to limit the analysis to genuine repeat sales, we need to take into account any changes that properties might undergo in between sales, to the extent that they are reflected in the data we have. The easiest case is when there are changes in property type (where, for instance, the same property goes from being a vacant parcel to a single family home). We know for certain that at least 4% of repeat sales properties changed type over the 1985-2006 time period, and estimate that the actual number is between 4% and 10% (we cannot know for sure due to the large number of missing cases). In order to account for these changes, we infer that a property has changed property type by setting the *new_construction* variable to a new value “P”. This adds a new “New Construction” modifier to the *new_construction* variable already included in the dataset, which either had a value of “N” for a new construction or “M” if it is not.

Based on this *apn_unit* number and the *new_construction* flag, we then create the “account” and “salesnum” variables that will be respectively used as the panel and time variables in the repeat sales index. The *account* variable effectively constructs a new property ID every time that a change in property type occurs. Note that the previous *apn_unit* variable does not do this: if a property changed from residential to commercial and then back to residential, the old *apn_unit* variable would treat the two residential sales as the same property.

Step Seven: Eliminate Non-Residential Properties; Identify Apartment Units

We can now eliminate all of the non-residential sales from the dataset. This is done based on the *propertyindicatorcode* field in the dataset. Note that at this stage we are also eliminating the remaining properties with missing or miscellaneous property type information.

Additionally, we will flag all apartment properties (*propertyindicatorcode* equal to 22), since the analysis will focus on single-family and condo units, and not apartment units.

Step Eight: Eliminate Foreclosures

Foreclosures are now dropped, since these are clearly non-arm's length transactions – i.e. they do not reflect the actual market value of the property. Similarly, the sale immediately following the foreclosure is also dropped, under the assumption that it might be "tainted" by the foreclosure and not reflect the true market value of the property. However, if at least two years elapse between the foreclosure and the following sale, then we assume that the sale will no longer be impacted by the foreclosure and the transaction is kept.

Step Nine: Eliminate Non Arms-Length Transactions

Non-arm's length transactions are identified based on the type of deed used to record the transaction (*documenttype)* and on the type of transaction as coded by the data vendor (*transactiontype)*. In particular, only transactions recorded with Grant deeds, deeds of trust, or multi-county deeds are kept, since all other deed types are typically used for non-arm's length transactions.[1] We also keep only transactions that are marked as resales, new construction, or time shares in the original dataset.

Step Ten: Merge XY Coordinates

The XY coordinates for each APN come from several sources, including geocoding based on property address, 2005 parcel centroids provided by the Chicago Metropolitan Agency for Planning, and the original dataset.

These sources were combined into one master file containing a complete list of unique parcel IDs and related coordinates. Records that could not be matched to XY coordinates from any of these sources were dropped from the dataset.

Step Eleven: De-duplicate Same Property Sales Within 30 Days

In this step we do two things:

[1] The relevant deed types were identified in each city based on conversations with real estate lawyers and County officials.

- De-duplicate all of the transactions for the same property that take place within a 30 day period and have the same sale price, under the assumption that for our purposes this is really one real estate transaction that involves multiple documents or parties.
- If the same property sells more than once within 30 days but for different sale prices, then we only keep the transaction that has the highest selling price, under the assumption that the higher price is more likely to be the final or true sale reflecting the market value.

Note that when we tag sales within 30 days of each other, it is possible for a string of sales to actually stretch over a longer period of time, so long as the sales are within 30 days of one another. For example, a property could sell on Jan 1, then Jan 20, then Feb 1, Feb 20, and all four sales would be tagged. This happens rarely (there are less than a hundred of these cases), and when it does, the string of sales is at most four sales and all of the sales typically have the same sale price. Therefore we choose to keep only one of these transactions (the one with the highest price) whenever this occurs.

Step Twelve: Eliminate Outliers Based on Appreciation Rate

Even after cleaning the data as described above, we observe records that show extreme swings in price that are clearly due to data issues rather than true market trends. In order to control for this factor we identify all pairs of transactions on the same property that have either doubled or halved in price over a three month period, and had a minimum absolute change of $25,000. Since we have no way of knowing which of the transactions in the pair reflects the actual market value of the property, we will eliminate both sales.

Step Thirteen: Apply Inflation-Adjusted Price Ceiling and Floor

For these purposes, we calculate an inflation-adjusted sale price in 2006 dollars, using the MSA-level annual CPI.

We then eliminate all sales below the inflation-adjusted price of $5,000 and above the inflation-adjusted price of $5,000,000.

Step Fourteen: Reconstruct "account" Variable

After creating the "account" and "salesnum" variables in Step Six, the procedures in Step Seven – Step Thirteen will have created gaps in the panel and time variables. Although having gaps would not affect the repeat sales index calculation since only the ordering of the variables is important, as a matter of consistency we will reconstruct the "account" variable as *account2* and the "salesnum" variable as *salesnum2* so that it does not contain any gaps.

Step Fifteen: Prepare Dataset for Analysis

In the final step, we generate regression variables required for estimating the repeat sales index.

II. Cleveland

Overview

The Cleveland Real Estate Transactions data was acquired from the Northeast Ohio Community and Neighborhood Data for Organizing (NEO CANDO). The data is then cleaned to make it consistent with the other cities and ready for analysis.

The cleanup process consists of nine steps:

1. Import the Data, Locate "age" variable
2. Identify apartment units
3. Construct new property identifiers and "account" and "salesnum" variables, Control for new construction
4. Eliminate non-arm's length transactions
5. De-duplicate same property sales within 30 days
6. Eliminate outliers based on appreciation rate
7. Apply inflation-adjusted price ceiling and floor
8. Reconstruct "account" and "salesnum" variables
9. Prepare dataset for analysis

Step One: Import the Data, Locate "age" Variable

Only data for residential properties was acquired. The *age* variable was generated as the number of months from the initial month in the dataset (January 1976), with zero-based indexing.

Step Two: Identify Apartment Units

All the records in the dataset are transactions on residential properties. However, since the analysis will use single-family and condo units, and not apartment units, we need to flag the records that are apartment units because we may remove them later. In particular, any transaction with the *land_use* variable containing the substring "Apartment" or equal to "Four family dwelling" or "Four To Six Family" is considered an apartment unit. All other values of the *land_use* variable are considered single family or condo units.

Step Three: Construct New Property Identifiers, Control for New Construction

In order to limit the analysis to genuine repeat sales, we need to take into account any changes that properties might undergo in between sales, to the extent that they are reflected in the data we have. Therefore, we create a *new_property* variable flag to indicate whenever a property undergoes changes in land use. This variable will be used in addition to the *new_construction* variable already in the dataset to determine when a parcel, if it sold more than once, should be treated as separate properties or as a repeat sale.

Based on the *parcel* number, the *new_property* and the *new_construction* flags, we then create the "account" and "salesnum" variables that will be respectively used as the panel and time variables in the repeat sales index. The *account* variable effectively constructs a new property ID every time that a change in land use occurs. Note that the previous *parcel* variable does not do this: if a property changed from an apartment to a condo and then back to an apartment, the old *parcel* variable would treat the two residential sales as the same property.

Step Four: Eliminate Non Arms-Length Transactions

Non-arm's length transactions are identified based on the type of deed used to record the transaction (*deed_type).* In particular, we keep the record if its *deed_type* is either "Corporation", "Deed", "Fiduciary", "Limited warranty", "Survivorship", "Trustee", or "Warranty", since all other deed types are typically used for non-arm's length transactions.

Step Five: De-duplicate Same Property Sales within 30 Days

In this step we do two things:

- De-duplicate all of the transactions for the same property that take place within a 30 day period and have the same sale price;
- If the same property sells more than once within 30 days but for different sale prices, then we only keep the transaction that has the highest selling price.

Step Six: Eliminate Outliers Based on Appreciation Rate

Even after cleaning the data as described above, we observe records that show extreme swings in price that are clearly due to data issues rather than true market trends. In order to control for this factor we identify all pairs of transactions on the same property that have either doubled or halved in price over a three month period, and had a minimum absolute change of $25,000. Since we have no way of knowing which of the transactions in the pair reflects the actual status of the property, we will eliminate both sales.

Step Seven: Apply Inflation-Adjusted Price Ceiling and Floor

The dataset contains an October 2006 inflation-adjusted price in the variable *sales_price_oct06*. We use this variable to eliminate all sales below the inflation-adjusted price of $5,000 and above the inflation-adjusted price of $5,000,000.

Step Eight: Reconstruct "account" and "salesnum" Variables

After creating the "account" and "salesnum" variables in Step Three, the procedures in steps four through seven will have created gaps in the panel and time variables. Although having gaps would not affect the repeat sales index calculation since only the ordering of the variables is important, as a matter of consistency we will reconstruct the "account" variable as *account2* and the "salesnum" variable as *salesnum2* so that it does not contain any gaps.

Step Nine: Prepare Dataset for Analysis

In the final step, we generate regression variables required for estimating the repeat sales index.

III. Dallas

Overview

The Dallas Real Estate Transactions data was acquired from the Dallas County Assessment District. The data is then cleaned to make it consistent across cities and ready for analysis.

The cleanup procedure consists of nine steps:

1. Import the data, Remove invalid transactions, Append the data
2. Standardize essential variables, Construct “age” variable
3. Construct “account” and “salesnum” variables, Control for new construction
4. Import XY coordinates
5. De-duplicate same property sales within the same month
6. Eliminate outliers based on appreciation rate
7. Apply inflation-adjusted price ceiling and floor
8. Reconstruct “account” and “salesnum” variables
9. Prepare dataset for analysis

Step One: Import the Data, Remove Invalid Transactions, Append the Data

There are three batches of data of real estate transaction records: “totsales.dta”, “totsales98_04.dta”, and “th_condo.dta”. The first two files contain records for single-family properties, and the third file contains records for condo properties.

In each dataset, the variable *id* uniquely identifies the property. However, the variable does not have unique values across the single-family and condo datasets, so we concatenated a “C” to the *id* variable of all condo properties to make the identification possible across all records when we appended the datasets.

The datasets also contain a few cases of duplicate transaction records, although the vast majority of records are unique. In one of these cases, a record in the condo dataset actually belonged to one of the other datasets (we inferred this because all housing attributes were the same, and only the date of transaction and the price were different). In every other case, the records were exactly the same across two datasets, so they were dropped in one of the datasets. The detailed records and the actions undertaken are as follows:

File	*id*	Action Performed
“th_condo_2”	000001609930000000	Dropped
	26449450200030000	Dropped
	26449450200050000	Dropped
	800729000K0340000	Dropped
	28141500020010000C	The “C” was dropped – this was actually a repeat sale with a record in the single-family properties datasets.
“totsales98_04”	14107220500650000	Dropped
	00815400050350000	Dropped

The next step is to rename variable names so that the three datasets would work as one dataset when appended together. Fortunately, only a few changes had to be made: in “totsales.dta”, the variable *yr* was renamed to *year*, and the variable *yearbuilt* was renamed to *yrbuilt*, and in “totsales98_04.dta”, the variable *yearbuilt* was renamed to *yrbuilt*. After renaming the variables, the datasets were appended together.

Step Two: Standardize Essential Variables; Construct “age” Variable

In the original datasets, the *year* variable was coded in either two-digit or four-digit formats. The majority of the two-digit years ranged from 79-99 (the dataset is supposed to start in 1979 and end in 2004), and these were resolved by adding 1900. There were also forty duplicate records that had either years 1922, 1930 or 1978, and these records were all dropped. However, there were also 5,581 transactions with the year “0”, which may have been either the year 2000 or missing. We tested both hypotheses by assuming one case, implementing the rest of the data cleaning procedure, and checking whether the distribution of the number of sales made sense in the year 2000. The assumption is that the number of sales should be similar over a short multi-year period.

When these records were assumed to be missing and thus eliminated at this step, the final dataset resulting from the cleaning procedure had an even distribution of sales throughout all the years, including 2000. Therefore, a decision was made to eliminate the records that had a year “0”.

The *age* variable was generated as the number of months from the initial month in the dataset (January 1979), with zero-based indexing.

Step Three: Construct “account” and “salesnum” Variables, Control for New Construction

In order to limit the analysis to genuine repeat sales, we need to take into account any changes that properties might undergo in between sales, including in particular new construction on the same property. In order to account for this phenomenon, a new unique identifier (*account*) is created by concatenating the original identifier (*id)* and the year built (*yrbuilt*) variable. We then create the "account" and "salesnum" variables that will be respectively used as the panel and time variables in the repeat sales index. The *account* variable effectively constructs a new property ID every time that a property undergoes a new construction.

Step Four: Merge XY Coordinates

The XY coordinates for each APN come from two sources: a parcel shapefile from the Dallas County Assessment District, and from a geocoding procedure based on addresses provided in matching files. The geocoded coordinates were used only when coordinates were not available in the parcel shapefile. Records that could not be matched to XY coordinates from either of these sources were dropped from the dataset.

Step Five: De-duplicate Same Property Sales Within the Same Month

In this step we do two things:

- De-duplicate all of the transactions for the same property that take place within the same month and have the same sale price;
- If the same property sells more than once within the same month days but for different sale prices, then we only keep the transaction that has the highest selling price.

Note that unlike the transaction records for the other cities, the records for Dallas had year and month information but not a date variable. Therefore the scope of this procedure is limited to same month transactions rather than transactions occurring within 30 days.

Step Six: Eliminate Outliers Based on Appreciation Rate

Even after cleaning the data as described above, we observe records that show extreme swings in price that are clearly due to data issues rather than true market trends. In order to control for this factor we identify all pairs of transactions on the same property that have either doubled or halved in price over a three month period and had a minimum absolute change of $25,000. Since we have no way of knowing which of the transactions in the pair reflects the actual status of the property, we will eliminate both sales.

Step Seven: Apply Inflation-Adjusted Price Ceiling and Floor

For these purposes, we calculate an inflation-adjusted sale price in 2004 dollars, using the MSA-level annual CPI.

We then eliminate all sales below the inflation-adjusted price of $5,000 and above the inflation-adjusted price of $5,000,000.

Step Eight: Reconstruct "account" and "salesnum" Variables

After creating the "account" and "salesnum" variables in Step Three, the procedures in Step Four – Step Seven will have created gaps in the panel and time variables. Although having gaps would not affect the repeat sales index calculation since only the ordering of the variables is important, as a matter of consistency we will reconstruct the "account" variable as *account2* and the "salesnum" variable as *salesnum2* so that it does not contain any gaps.

Step Nine: Prepare Dataset for Analysis

In the final step, we generate regression variables required for estimating the repeat sales index. The name of the final file is *dallas_clean.dta*.

IV. Seattle

Overview

The Seattle Real Estate Transactions data was provided by Chris Cunningham of the Atlanta Federal Reserve Bank and from the King County Assessor. The data was then cleaned to make it consistent with the other cities and ready for analysis.

The data preparation procedure consists of twelve steps:

1. Import the data, Drop invalid transactions, Construct "age" variable
2. Import XY coordinates
3. Fill in missing principal use information
4. Drop records with conflicting *propertyclass* and *propertytype*
5. Construct new property identifiers and "account" and "salesnum" variables, Control for New Construction
6. Eliminate non-residential properties
7. Eliminate foreclosures and subsequent sales
8. Eliminate non-arm's length transactions
9. De-duplicate same property sales within 30 days
10. Eliminate outliers based on appreciation rate
11. Apply inflation-adjusted price ceiling and floor
12. Reconstruct "account" and "salesnum" variables
13. Prepare dataset for analysis

Step One: Import the Data, Drop Invalid Transactions, Construct "age" Variables

The variable *propertyid* identifies unique properties, and for all but fourteen records out of the entire dataset of 1.6 million records, *propertyid* is a string of length 10. These fourteen records are dropped.

We also eliminate transaction records at this point that do not have coordinate information. In all, there are about 45,000 such cases. Since this is a very small group of records, and there is no reliable address information that can be used to geocode them, these cases are dropped from the dataset.

We then generate the age variables *year*, *month*, *date* and *age* from the formatted *saledate* variable. The *age* variable counts the number of months from the first month in the dataset (January 1982), with the variable starting at 0.

Step Two: Import XY coordinates

Coordinates for each property are imported from parcel shapefiles provided by the GIS department of the King County Department of Assessments.

Step Three: Fill In Missing Land Use Information

Up to this point, many records still have indeterminate land use codes ("principal use" in this dataset) because the information is missing or they are coded as missing or miscellaneous. We want to extract as much information as we can from the original dataset without losing sample size. In particular, for properties that have missing or miscellaneous principal use in sales, if there is a subsequent sale of the same property that has a valid *principaluse* code, then the value of the non-missing code is copied back for the missing or miscellaneous code.

Step Four: Drop Records with Conflicting *propertyclass* and *propertytype*

Before describing the procedure in this step, it is useful to mention briefly the three variables available in the dataset that describe property characteristics. These three variables are *principaluse*, *propertytype*, and *propertyclass*. The *principaluse* variable is the main variable used to determine land use information, while the *propertytype* variable is used to determine vacant properties and new constructions.

The variable *propertyclass*, on the other hand, contains both land use and property type information. It determines the type of property as reported on the Excise Tax affidavit, and also what "part of the property" is being sold. We have learned from the King County Assessors Office that this variable is often not a systematic classification of what is being sold, and is prone to inconsistencies. The inconsistency that concerns us here are transactions that do not match on the *propertytype* and *propertyclass* variables. For example, a transaction may have *propertytype* "LAND WITH NEW BUILDING" while the *propertyclass* variable says "Land Only." When this occurs, we have no way of knowing whether the transaction refers to a sale of the land, or a sale of the land and the building, since the two can be sold separately. Therefore, in this step we eliminate all properties that conflict between these two variables whenever one indicates a land only sale and the other indicates a sale of the land with the property. This step results in about 34,000 transactions being dropped.

Step Five: Construct New Property Identifiers and "account" and "salesnum" Variables, Control for New Construction

In order to limit the analysis to genuine repeat sales, we need to take into account any changes that properties might undergo in between sales, to the extent that they are reflected in the data we have. Therefore, we create a *new_property* variable flag to indicate whenever a property undergoes changes in property type. This variable will be used in addition to the *new_construction* variable already in the dataset to determine when a property, if it sold more than once, should be treated as two separate properties or as a repeat sale.

Based on the *propertyid* string, the *new_property* and the *new_construction* flags, we then create the "account" and "salesnum" variables that will be respectively used as the panel and time variables in the repeat sales index. The *account* variable effectively constructs a new property

ID every time that a change in property type occurs. Note that the previous *propertyid* variable does not do this: if a property changed from residential to commercial and then back to residential, the old *propertyid* variable would treat the two residential sales as the same property.

Step Six: Eliminate Non-Residential Properties

We can now eliminate all of the non-residential sales from the dataset. This is done based both on the *principaluse* and the *propertyclass* fields.

Note that a value of "0" in either variable means missing or miscellaneous. If the record has a missing value only in one variable, then we can still infer whether the property is residential through the other variable. However, if both *principaluse* and *propertyclass* are equal to zero, then we cannot determine if the property is residential or not, so we drop the record from the dataset.

Step Seven: Eliminate Foreclosures

Foreclosures are now dropped, and if the sale immediately following the foreclosure takes place within two years of the foreclosure, then that record is deleted as well.

Step Eight: Eliminate Other Non Arms-Length Transactions

Non-arm's length transactions are identified based on the type of sale instrument of the transaction (*saleinstrument)*. In particular, transactions with the following sale instrument values were dropped: Corporate Warranty Deed, Quit Claim Deed, Trust Deed (Deed of Trust), Executor's Deed, Fiduciary Deed, Sheriff's Deed, Bargain and Sales Deed.

Step Nine: De-duplicate Same Property Sales within 30 Days

In this step we do two things:

- De-duplicate all of the transactions for the same property that take place within a 30 day period and have the same sale price;
- If the same property sells more than once within 30 days but for different sale prices, then we only keep the transaction that has the highest selling price.

Note that when we tag sales within 30 days of each other, it is possible for a string of sales to actually stretch over a longer period of time, so long as the sales are within 30 days of one another. For example, a property could sell on Jan 1, then Jan 20, then Feb 1, Feb 20, and all four sales would be tagged. This happens only seven times, so we choose to keep only one of these transactions (the one with the highest price) whenever this occurs.

Step Ten: Eliminate Outliers Based on Appreciation Rate

Even after cleaning the data as described above, we observe records that show extreme swings in price that are clearly due to data issues rather than true market trends. In order to control for this factor we identify all pairs of transactions on the same property that have either doubled or halved in price over a three month period, and had a minimum absolute change of $25,000. Since we have no way of knowing which of the transactions in the pair reflects the actual status of the property, we will eliminate both sales.

Step Eleven: Apply Inflation-Adjusted Price Ceiling and Floor

For these purposes, we calculate an inflation-adjusted sale price in 2006 dollars, using the MSA-level annual CPI.

We then eliminate all sales below the inflation-adjusted price of $5,000 and above the inflation-adjusted price of $5,000,000.

Step Twelve: Reconstruct "account" and "salesnum" Variables

After creating the "account" and "salesnum" variables in Step Three, the procedures in Step Four – Step Seven will have created gaps in the panel and time variables. Although having gaps would not affect the repeat sales index calculation since only the ordering of the variables is important, as a matter of consistency we will reconstruct the "account" variable as *account2* and the "salesnum" variable as *salesnum2* so that it does not contain any gaps.

Step Thirteen: Prepare Dataset for Analysis

In the final step, we generate regression variables required for estimating the repeat sales index. The name of the final file is *seattle_clean.dta*.

APPENDIX C
The Role of Amenities in Housing Markets: Formal Model of Neighborhood Change

A metropolitan area is composed on *N* households and *J* housing submarkets, or neighborhoods. Each household occupies one housing unit and each housing unit is occupied by only one household, and the subscript *i* uniquely identifies a household and a housing unit. Each household has a utility function defined over housing and other goods, where household *i*'s utility is $U_i = U_i(x_i, a_j, f_i, z)$, where x represents structural attributes of the household's housing unit, a_j represents a vector of amenities associated with the neighborhood, *j*, in which the housing unit is located, f_i indicates the density, or ratio of housing units to total land area of the property on which housing unit *i* is located, and *z* represents a vector of all non-housing, non-locational commodities. By assumption, $\partial U/\partial f < 0$, meaning that consumers receive more utility in single-family than multi-unit housing, all else equal, and utility declines with density of development at the site.[2]

We are interested in the determinants of housing prices differentials across neighborhoods. The theory of compensating differentials tells us that housing must be priced at each site so the occupant is charged for the value of locational amenities at the site. Let housing price per square foot equal

$$P = \pi q + \lambda x + \theta a + \theta a g - \beta f \,, \tag{1}$$

where *q* denotes the quantity of land on which the structure is built, π is the value of the land per square foot of housing, *x* represents the structural attributes of the housing unit, λ is the per-unit value of the attributes, *a* denotes the amenities associated with the housing unit's location, θ is the per-unit value of amenities, and *g* is the expected future growth rate of the amenities, and *f* is the ratio of housing unit to total land area. To simplify exposition, we have dropped subscripts and all terms are assumed to be expressed in present discounted value. Together, $\theta a + \theta a g$ are the value of amenities that exist at the site presently and into the future. We separate them to emphasize the importance of expectations about future neighborhood amenities, *g*. For healthy neighborhoods we expect $g > 0$, but where $g = 0$, the fourth term on the right hand side drops out, and where $g < 0$, current housing prices will be dragged down by negative expectations. It is clear from (1) that prices offset amenities, meaning that households have no incentive to move and the market is in a spatial equilibrium.

The supply of land at a given location is, by definition, fixed, but the supply of housing at a given site is price-elastic. Specifically, each land owner wants to maximize profits from the land, net of construction costs. Since consumers are willing to pay less per housing unit when there are more units on a site, land owners face a tradeoff between increasing the density of development at a site and receiving less income per unit. In addition, marginal construction costs (per square foot of housing) are increasing in density, with $C = \mu x + \tau f$, where μ is the per-

[2] A possible extension of the model would be to add multiple groups of households with different income and/or preferences. This would result in segregation of groups by type across neighborhoods. Another possible extension of the model would be to allow for the existence of multiple housing quality submarkets within the region, each characterized by a different equilibrium price and elasticity of supply.

unit cost of the structural attributes and τ is the incremental additional cost as density is increased. We take τ to include both the physical costs of construction as well as the regulatory costs of obtaining permission to build at greater densities. The profit per square foot of housing is simply $P-C$, and therefore the profit per square foot of land, *p*, is $f(P-C)$. After substitution, we obtain

$$p = f(P-C) = f(\theta a + \theta ag + \pi q + (\lambda - \mu)x) - f^2(\beta - \tau). \tag{2}$$

The land owner selects the density of development, *f*, that maximizes the residual value of land. The first order condition is:

$$\frac{\partial p}{\partial F} = \theta a + \theta ag + \pi q + (\lambda - \mu)x - 2f(\beta - \tau) = 0\,. \tag{3}$$

Solving (3) for the profit-maximizing density level, f^*, yields

$$f^* = \frac{\theta a + \theta ag + \pi q + (\lambda - \mu)x}{2(\beta - \tau)}. \tag{4}$$

Substituting (4) into (2) produces

$$p^* = \frac{(\theta a + \theta ag + \pi q + (\lambda - \mu)x)^2}{4(\beta - \tau)}, \tag{5}$$

the equilibrium profit per square foot of land. Similarly, the equilibrium price per square foot of housing is obtained by substituting (4) into (1), yielding:

$$P^* = \frac{(\theta a + \theta ag + \pi q)(\beta + 2\tau) + (\beta(\lambda + \mu) + 2\lambda\tau)x}{2(\beta + \tau)}. \tag{6}$$

Finally, variation in housing price and density across neighborhoods are determined by amenities. Comparative statics indicate the response of equilibrium density, land price, and housing price to changes in amenities.

$$\frac{\partial f^*}{\partial a} = \frac{\theta + \theta g}{2(\beta + \tau)} \tag{7}$$

$$\frac{\partial p^*}{\partial a} = \frac{(1+g)\theta(a(1+g)\theta + \pi q + (\lambda - \mu)x)}{2(\beta + \tau)} = (\theta + \theta g)f^* \tag{8}$$

$$\frac{\partial P^*}{\partial a} = \theta + \theta g - \frac{\beta(\theta + \theta g)}{2(\beta + \tau)} = \theta + \theta g - \frac{\delta f^*}{\delta a}\beta \tag{9}$$

Equations (7), (8), and (9) demonstrate that as neighborhoods become more attractive — i.e., as amenities increase — density, housing prices, and land prices all increase. The marginal cost of increasing density, τ, also plays an important role in determining the rate at which amenities are capitalized into prices. A higher value of τ indicates that a given increase in density requires a higher cost, which implies that housing supply is less elastic. Thus, where τ is high, we expect a given increase in amenities to result in a greater increase in housing prices, and a smaller increase in density. By contrast, where τ is low, amenity growth should result in a larger increase in density and a smaller increase in price.[3] Empirically, our focus is on estimating the effect of amenities on density and housing prices, as land prices are difficult to observe directly in already developed areas.

[3] Glaeser, Gyourko, and Saks (2005) make a similar argument at the level of MSA housing markets.

APPENDIX D
EVOLUTION METRICS AND METHODOLOGY

This Appendix outlines the procedures that were used to develop the metrics described in Section III.C and describes the methodologies adopted for the Evolution analysis presented in Section IV. The metrics and analytics are presented below in the order in which they appear in the Report.

I. Metrics

A. Sales Price Indices

Sales price indices are used to estimate changes in housing values for a particular level of geography. There are numerous methodologies that can be used to estimate indices, from taking simple raw median values to more complex methods such as repeat sales indices that are designed to measure housing values while controlling for changes in the quality of the housing stock. The project developed several sales price indices, as discussed below.

1. The Dynamic Taxonomy Project Repeat Sales Index

This metric is a spatially smoothed and temporally smoothed repeat sales price index (RSI), used to measure quality-adjusted change in housing values. The index is estimated at the tract, city and county level. For a detailed presentation of the procedures and methodologies used to develop the index, please see Appendix D.

2. Smoothed Median Indices and Prices

The Fourier method used in estimating the repeat sales index is a general method used to smooth a function over a period of time. It offers advantages over standard smoothers such as the simple moving average, because it is less sensitive to periods with small sample size. This property of the smoother makes it very attractive for use in this project because sample size is a significant issue at the tract level.

Using the Fourier method, the project developed a Median Price Index and a smoothed median price. The Median Sales Price Index is a spatially weighted measure that is entirely comparable to the repeat sales index except that it is not quality adjusted, as it considers all transactions in a dataset, rather than being limited to repeat sales only. By being able to directly compare this index (actual price growth) with the repeat sales index (constant quality price growth), key insights into the change in the quality of the housing stock of a neighborhood can be gained.

Unlike the Median Sales Price Index, the smooth median price does not use any spatial weighting, which makes this measure essentially a smoothed version of the raw monthly median prices. By smoothing the monthly prices, the index is a much more robust estimator of the monthly median sales price, since monthly data at the tract level can be sparse.

The equations to estimate both indices are the same, except for the fact that the Median Sales Price Index also applies spatial smoothing:

$$p_{i,t} = \alpha_1 z_i + \alpha_2 z_i^2 + \sum_{q=1}^{3} \left[\lambda_q \left(\sin(qz_i)\right) - \gamma_q \left(\cos(qz_i) - 1\right)\right] + u_{i,t} \tag{1}$$

Where:

$p_{i,t}$ is the sale price of house i at time t

$z_i = 2\pi t_i / \max\{t_i\}$, i.e the linear transformation of the time variable t_i to the interval $[0, 2\pi]$

$\alpha_1, \alpha_2, \{\lambda_q\} \{\gamma_q\}$ are estimated coefficients

$u_{i,t}$ is the error term

The modifications performed on the repeat sales index estimation procedure are relevant here as well. In particular, Equation (1) is estimated using the quantile regression, three Fourier expansions, and a six-month cutoff period. Spatial weighting in the Median Sales Price Index is applied by using the same quadratic weighting function as the repeat sales index: all properties in the tract are set to one, while properties in adjacent tracts have a declining weight of $\left[1 - d_i / \max\{d_i\}\right]^2$. Since both indices consider all sales and not just repeat sales, the "flexible burn-in" period simply begins estimation at the fifth weight.

A shortcoming of estimating Equation (1) is that neighborhoods with a very small overall sample size may have negative values estimated for $\hat{p}_{i,t}$. Negative values rarely occur in tracts and only when sales data within the tract is extremely sparse, and are due to the regression imposing this particular functional form. To address this issue, a tract with an estimated negative smoothed median value anywhere along the time interval in either index is disregarded for all subsequent analysis.

B. Volatility of the Repeat Sales Price Index

Housing prices in neighborhoods can be characterized in terms of price appreciation and price volatility. From an investment point of view, one would expect that with all other things being equal, investors would demand higher appreciation in high volatility neighborhoods. Two measures of volatility were developed to assess risk: temporal and cross-sectional volatility.

Temporal volatility is a measure of the risk associated with a neighborhood over a long time interval. It is calculated as the standard deviation of the appreciation rates derived from the monthly repeat sales index from 1990 to the final year of the sample.

$$v_{temporal} = sd\left(\left\{\frac{RSI_{i,t} - RSI_{i,t-1}}{RSI_{i,t-1}} \,\middle|\, t = \{1,\ldots,T\}\right\}\right) \tag{2}$$

Where:

$RSI_{i,t}$ is the repeat sales index in tract i at time t

T is the final month of the index

Cross-sectional volatility is a measure of risk with a neighborhood during a short, fixed time interval. The cross-sectional volatility of the repeat sales index is calculated as the coefficient of variation of raw prices for five years starting in 1990 and for the final five years of data:

$$v_{cross\_sectional} = \frac{sd\left(prices_{five\_years}\right)}{mean\left(prices_{five\_years}\right)} \tag{3}$$

C. Changes in Quality

Neighborhood change can be reflected in increased prices for a given house, but it can also be reflected in increased investment in housing, resulting in larger, higher quality houses. An estimate of housing quality is the difference between actual price growth and constant quality price growth, which can be calculated as the difference between the median sales price index (actual price growth) and the repeat sales index (constant quality price growth). If the difference is calculated for the final time period of the sample, the measure reflects the change in quality over the entire sample period.[4]

The quality metric is then calculated as a fraction of the median price in order to normalize the results:

$$\Delta Q_i = \frac{MED_{i,T} - RSI_{i,T}}{MED_{i,T}} \tag{4}$$

Where:

ΔQ_i is the change in quality of housing in tract i from time 0 to the final year of the sample

$MED_{i,T}$ is the median sales price index in tract i in the final year of the sample

$RSI_{i,T}$ is the repeat sales index in tract i in the final year of the sample

Note that Equation (4) assumes that the median sales price index and the repeat sales price index in all tracts have the same value at $t = 0$. If a measure of quality change starting at a time $t > 0$

[4] It should be noted that this metric might tend to underestimate change in housing quality in places where there is significant remodeling activity, since this will inflate the repeat sales index values (which cannot control for all remodeling) and consequently reduce the difference between the repeat sales index and the median. At the same time, the metric might overestimate change in quality in places where there is significant abandonment, since the units in worse conditions are more likely to drop out of the sample, inflating the median prices.

is desired, then both the median sales price index and the repeat sales index are adjusted so that $MED_{i,0} = RSI_{i,0}$.

III. Analytical Methods

This section describes the analytical methods used to answer specific questions about neighborhood evolution.

A. Neighborhood Convergence

Neighborhood convergence exists when low performing neighborhoods improve and "catch up" to more successful neighborhoods. For neighborhoods to catch up, they will have to improve faster than successful neighborhoods, and the difference between neighborhoods will eventually have to diminish. By using housing prices as a measure of neighborhood value, this means that prices will have to rise faster in low-priced areas than prices rise in expensive neighborhoods, and the variation between prices in high and low price neighborhoods will have to decrease.

Formally, these two kinds of changes are modeled as "beta convergence" and "sigma convergence" (Barro, 1990). Beta convergence occurs when lower-priced neighborhoods appreciate faster than expensive neighborhoods do, and sigma convergence occurs when the variation of prices across neighborhoods decreases.

The equation to estimate the extent of beta convergence is as follows:

$$\frac{1}{T}\log\left(\frac{y_{i,T}}{y_{i,t_0}}\right) = \alpha - \left(\frac{1-e^{-\beta T}}{T}\right)\cdot\log\left(y_{i,t_0}\right) + u_i \qquad (11)$$

Where:

$y_{i,T}$ is the median price in tract i in the final year of the sample
y_{i,t_0} is the median price in tract i in the first year
T is the length of the sample in years
α is a fixed effect
β is the beta convergence parameter
u_i is random error

The estimated value of β indicates whether or not beta convergence exists: if $\beta < 0$, there is beta convergence; if $\beta \geq 0$, there is not beta convergence.

To assess the extent of sigma convergence in each city, a simple test of equality of the variance in the first year with the variance in the final year of the sample is conducted based on its F statistic and p-value.

B. Transition Matrices: How Much and How Fast do Neighborhoods Change?

The extent to which neighborhoods change relative to other neighborhoods in their region is assessed by using a transition matrix. A transition matrix is a general analytic tool that shows the transition probabilities of a given state space between two periods of time. For the purposes of this project, the state spaces are the quintiles of the temporally smooth median prices of a tract.

If M is a transition matrix, then its (i, j)-th element is

$$[M]_{i,j} = \Pr(T_s = j \mid T_r = i) \tag{5}$$

Where:

T_r and T_s are the quintiles of the temporally smooth median price of tract T at times r and s, where $r < s$

i, j are possible quintiles and also the row and columns of the matrix

Due to fact that the temporally-smooth median price may be missing at time r, or have a negative smooth median price during some time period, the set $\{T\}$ is limited to tracts that have non-missing values at all $r < s$ and positive values over the entire time frame. A missing value is the result of a tract not having "burned-in" yet, and is a concern only during early time periods. A negative value occurs only on a small subset of tracts that have very small sample size, as discussed above.

The average K-year transition matrix $\overline{M}$ is calculated by taking the average of all possible K-year transition matrices $M_1, M_2, \ldots, M_N$, where the (i, j)-th element of the $\overline{M}$ is

$$\left[\overline{M}\right]_{i,j} = \tfrac{1}{N} \sum_{n=1}^{N} [M_n]_{i,j} \tag{6}$$

M_1 begins from the first month of the fourth year for which data in the city or region exists. M_2 begins from the second month of the fourth year, and so on until M_N which ends at the last month of available data. The four-year time period was chosen by using an "elbow" criterion: about 90% of the tracts for each city had an estimated temporally-smoothed median value by the fourth year, while increasing this time period does not include significantly more tracts in the matrix $\overline{M}$.

C. <u>Patterns of Change: Trend Break Analysis</u>

Significant changes in the trend of housing prices, whether caused by large changes in economic drivers, or changes in the nature of the impacts of drivers ("tipping," for example) are potentially important neighborhood dynamics that can be identified statistically. Formally, structural breaks in the data can be tested by estimating the following model for all values of t:

$$y_{i,t} = t + D_B + (D_B \cdot t) \tag{7}$$

Where:

$y_{i,t}$ is the median price in tract i in year t
D_B is defined as $\{0\ if\ t \leq B; 1\ if\ t > B\}$
B is a potential structural break

A standard Wald test ascertains whether the parameters of a simple time trend model are equal across the two samples $(t < B)$ and $(t > B)$. The maximum Wald statistic across the regressions for all t is defined as the Quandt statistic (Hansen, 2001). This is then used with the Andrews (1994) critical value to test for the existence of a structural break in the interval $(0, \max\{t\})$.

If the Quandt test confirms a structural break, a simple time trend model is estimated twice for each possible B, once for $(t < B)$ and once for $(t > B)$:

$$y_{i,t} = t \tag{8}$$

Where:

t is the time in years
$y_{i,t}$ is the median price in tract i in the final year of the sample

The sum of squared errors (SSE) for the two sub-samples are combined to form the sum of squared errors for each B. The maximum SSE_B identifies the structural break. If a structural break is identified, the sample is split into two, and all of the steps above are iterated on each of the new sub-samples. The process is repeated until all structural breaks are identified.

References

[1] Andrews, Donald W.K. "Tests for Parameter Instability and Structural Change With Unknown Change Point," Econometrica Vol. 61, No. 4 (1993), pp. 821-856.

[2] Barro, R.J., and Xavier Sala i Martin. "Economic Growth and Convergence Across the United States," NBER Working Paper No. 3419 (1990). Cambridge, Mass.: National Bureau of Economic Analysis.

[3] Brzinsky-Fay, C. and Kohler, U. "Sequence analysis with Stata," The Stata Journal. Vol. 6, No. 4. (2006), pp. 435-460.

[4] Hansen, B.E. "The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity," Journal of Economic Perspectives Vol. 15, No. 4 (2001), pp. 117-128.

[5] Hastie, T., Tibshirani, R., and Friedman, Jerome. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. New York: Springer (2001).

[6] McMillen, D.P. and Dombrow, J. "A Flexible Fourier Approach to Repeat Sales Price Indexes," Real Estate Economics Vol. 29, No. 2 (2001), pp. 207-225.

APPENDIX E
CONVERGENCE TABLES

To assess the extent of sigma convergence in each city, the project conducted a series of tests of the equality of the variance in the first year with the variance in the final year of the sample, based on its *F* statistic and *p*-value. The null hypothesis for these tests is that the ratio of the price variance in the first year of the study period to the variance in the final year is equal to one (i.e. prices are as dispersed at the end of the study period as they were in the initial year). The project then tested three alternative hypotheses: that the ratio is not one, that it is less than one, and that it is greater than one. If sigma convergence is occurring, we would expect the ratio to be greater than one, meaning that prices are less dispersed at the end of the study period than they were at the beginning.

The results of this analysis are reported in Tables 1 through 4 below. In particular, the key test result is reported in bold at the bottom right of each table: if we observe sigma convergence, the ratio between the variance in 1990 and the variance in 2006 should be greater than 1. If the p-value for this hypothesis is less than 0.05 (as it is for three out of the four cities) we find statistical evidence of the occurrence of sigma convergence.

Table 1. Sigma Convergence in Chicago (Variance Ratio Test, 1990-2006)

Variable	**Obs**	**Mean**	**Std. Err.**	**Std. Dev.**	**[95% Conf. Interval]**	
ln_median_1990	1231	11.32606	.0178182	.6251612	11.2911	11.36101
ln_median_2006	1307	12.41962	.014142	.5112686	12.39188	12.44737
Combined	2538	11.88921	.0156658	.7892187	11.85849	11.91993
ratio = sd (ln_median_y1990) / sd (ln_median_y2006)						f = 1.4952
Ho: ratio = 1						Degrees of freedom = 1230, 1306
Ha: ratio < 1 Pr(F < f) = 1.0000			Ha: ratio != 1 2*Pr(F > f) = 0.0000			**Ha: ratio > 1** **Pr(F > f) = 0.0000**

Table 2. Sigma Convergence in Cleveland (Variance Ratio Test, 1990-2006)

Variable	**Obs**	**Mean**	**Std. Err.**	**Std. Dev.**	**[95% Conf. Interval]**	
ln_median_1990	467	10.90033	.0368908	.7972171	10.82784	10.97282
ln_median_2006	473	11.65834	.0260456	.566454	11.60716	11.70952
Combined	940	11.28175	.0256923	.7877108	11.23133	11.33217

ratio = sd (ln_median_y1990) / sd (ln_median_y2006)		f = 1.9807
Ho: ratio = 1		Degrees of freedom = 466, 472
Ha: ratio < 1 Pr(F < f) = 1.0000	Ha: ratio != 1 2*Pr(F > f) = 0.0000	**Ha: ratio > 1** **Pr(F > f) = 0.0000**

Table 3. Sigma Convergence in Seattle (Variance Ratio Test, 1990-2006)

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
ln_median_1990	369	11.75254	.0201313	.3867087	11.71295	10.97282
ln_median_2006	371	12.8482	.0177645	.3421677	12.81327	11.70952
Combined	740	12.30185	.0242066	.6584903	12.25433	12.34937
ratio = sd (ln_median_y1990) / sd (ln_median_y2006)						f = 1.2773
Ho: ratio = 1						Degrees of freedom = 368, 370
Ha: ratio < 1 Pr(F < f) = 0.9905			Ha: ratio != 1 2*Pr(F > f) = 0.0190			**Ha: ratio > 1** **Pr(F > f) = 0.0095**

Table 4. Sigma Convergence in Dallas (Variance Ratio Test, 1990-2004)

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
ln_median_1990	473	11.09645	.0315517	.6862039	11.03445	11.15845
ln_median_2006	492	11.66797	.0308581	.6844665	11.60734	11.7286
Combined	965	11.38784	.0238928	.7422177	11.34095	11.43472
ratio = sd (ln_median_y1990) / sd (ln_median_y2006)						f = 1.0051
Ho: ratio = 1						Degrees of freedom = 472, 491
Ha: ratio < 1 Pr(F < f) = 0.5224			**Ha: ratio != 1** **2*Pr(F > f) = 0.9552**			Ha: ratio > 1 Pr(F > f) = 0.4776

APPENDIX F
DRIVERS ANALYSIS: METHODOLOGY AND TECHNICAL NOTES

1. Statistical Challenges

In addition to the conceptual challenges discussed in Chapter V, the analysis of the drivers of neighborhood change presents several statistical issues:

Endogeneity:

Two of our key outcome measures, housing prices and housing quantity, embody the classic example of endogeneity. The price of housing depends in part on the quantity of housing produced, and the quantity of housing produced will depend on the price that the housing will sell for. The standard econometric approach to endogeneity is either to focus on the reduced form models or to find identifying restrictions that allow consistent estimation of the underlying structural model. Since estimating a structural model would require too many assumptions and more data than was available, the project chose to estimate reduced form models of price and quantities. These reduced form models yield a net effect of a variable as it acts through both the supply and demand equations in its effects on price and quantity.

Aside from the classic supply and demand endogeneity problem, there are other types of endogeneity issues that must be kept in mind in the statistical analysis. For example crime is likely to be one of our explanatory variables in the house price and quantity equations. However, some would argue that lower crime itself is an outcome measure and to the extent that higher income people tend to purchase more expensive houses, and to the extent that higher income households are associated with lower crime, then high house prices effectively cause lower crime rather than vice versa. This makes it difficult to cleanly infer causality. The project addressed this issue to the extent possible by adopting Edward Glaeser's approach of regressing change on initial conditions[5] as well as by experimenting with various lag structures in the time series models.

Spatial correlation:

Our outcome measures are based on census tract level data. There is likely to be correlation across census tracts in our outcome measures for three reasons:

- Neighborhood boundaries may extend beyond the individual census tracts;

[5] This modeling approach was popularized by Barro in an influential paper on cross-country growth (Robert Barro, "Economic Growth in a Cross Section of Countries," *The Quarterly Journal of Economics*, Vol. 106, Issue 2 (1991), pp. 407-43), and adopted for urban growth models by Glaeser et al. (Edward Glaeser, Jose Scheinkman, and Andrei Shleifer, "Economic Growth in a Cross-Section of Cities," *Journal of Monetary Economics,* Vol. 36 (1995), 117-143).

- Events in neighborhoods may have impacts on adjacent neighborhoods; and
- The econometric method used to construct the Repeat Sales Index induces a special correlation because it uses observations in adjacent neighborhoods to estimate the Index.

The first of these issues means that when neighborhoods extend beyond tract boundaries they are likely to move together because they are experiencing the same kinds of economic phenomena. The second issue implies cross jurisdictional externalities, i.e. actions in one neighborhood that cause events in another. The third of these issues is a statistical artifact. In order to understand neighborhood dynamics we have to be able to distinguish between co-movements in neighborhoods that are the result of common economic factors and co-movements that are the result of one neighborhood imposing externalities on another. The difficulty of distinguishing between these two phenomena is compounded by the spatial correlation induced by the index construction method. In order to address these issues the project experimented with several approaches, including an instrumental variable approach and controlling for the neighboring tracts value of the dependent variable, and finally settled for a model specification that includes the neighboring tract values of the explanatory variables in the estimation.

Stationarity

Statistical analysis of time series data must address the issue of stationarity. Essentially, data with "unit roots" or trends can result in spurious correlation across series where there is, in fact, no underlying correlation. Typically, the issue of stationarity is addressed through differencing the data. In our analysis of the drivers of neighborhood dynamics, this implied focusing on changes in house prices and investment rather than on levels.

Lag Structure

The project is interested in understanding the dynamics of neighborhood change. This implies that we are interested not only in what factors are driving change, but also in the time horizon over which these drivers result in neighborhood change. We have very little theoretical guidance on the timing of impacts. However, we do expect that prices adjust relatively rapidly to changes in neighborhood characteristics when they are known. Housing supply, on the other hand is likely to adjust more slowly. The econometric analysis, therefore, experimented with alternative lag structures in the driver relationships. This was challenging, however, due to both the lack of theoretical guidance on the length and pattern of the lag in impact and to the limited number of years for which data was available, which reduced the number of degrees of freedom the project could work with in specifying different time lags.

2. Model Specification

As mentioned above, the project settled for a reduced form specification, estimating separate models for change in price and change in quantity of housing. Change in price was estimated primarily using the repeat sales index developed by the project. Models using median price change as the dependent variable are also included for comparison purposes.[6]

The project estimated three different sets of models, selected as to maximize the overlap in time and geography across different datasets: 1990-2000 decennial models; 1994-2004 time series models; and 1999-2004 time series models. A more detailed description of each of these sets of models is reported below.

Decennial Models

The 1990-2000 model is essentially a model that regresses the log of the price index in 2000 or the quantity index on initial conditions in 1990. As such, these models are explaining decadal growth rates.

The model is specified as follows:

$$\log(RSI_{j,2000}) = \alpha + \beta_1 * S_{j,1990} + \beta_2 * M_{j,1990} + \beta_3 * C_j + \varepsilon_j$$

Where

- *j* is an indexing term for the Census Tract of the observation.
- $RSI_{j,2000}$ is the value of the RSI for Census Tract *j* in 2000 normalized to 1990.
- α is a constant term.
- β are the parameters measuring the effects of the independent variables on the RSI.
- $S_{j,1990}$ are factors related to the supply of housing in 1990 that control for any supply effects. These factors are related to the temporally lagged housing supply (units built in the previous decade) and to the elasticity of supply (measured in terms of density[7]).
- $M_{j,1990}$ are variables measuring neighborhood amenities.
- C_j are city dummy variables controlling for regional effects.
- ε_j is an error term.

Additionally, models measuring the effects of the variables on changes in median prices and the quantity of residential units are specified in a similar way using the appropriate dependent variable.[8]

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[6] Indexes of median house prices reflect both the changes in the underlying price of a constant quality house and the changes in the quality of houses in the market. Since median housing price indexes are based on all sales in a given time period, changes in the index are, in part, dependent on the distribution of the types of houses sold. For that reason, a median-based price index is less reliable as an indicator of the underlying change in the price of housing. We examine the median index for two reasons: 1) to look for areas of consistency with the RSI and 2) to see if apparent differences between median and RSI models can be reasonably explained by changes in quality over time.

[7] This is a very imperfect proxy for supply elasticity, as other important factors (such as zoning restrictions) contribute to limiting the supply of new housing units in response to increases in demand.

[8] We ran each regression by combining all four cities into one sample, and controlled for city-level effects by adding a dummy variable for each city. Since this may fail to account for specific differences in coefficient estimation for each city, we ran a standard pooling test to see if tracts from all the cities could in fact be combined into one

1994-2004 Time Series Models

In addition to the decennial model, the project specified several time series models. The main one is a time series model covering every year between 1994 and 2004. This model was designed to capture shorter term and more detailed effects of potential drivers of neighborhood change, as it measures the effect of a change in amenities in one year on change in housing price and quantity the following year, over a ten year period. By comparison, the decennial models measure the effect of initial conditions on change over one ten-year time period.

A key factor distinguishing this analysis is the project's focus on changes in neighborhoods and away from the estimation of factors driving the price of an individual home, as in hedonic house price research. However, as discussed above, this focus introduces important methodological problems, as it is likely that there will be correlation in our outcome measures across neighborhoods.

In order to address this issue identified above, the team considered three methodologies:

1. Including the value of the outcome variable in neighboring tracts directly in the estimation;
2. An instrumental variable approach, including the neighbor tract values, but addressing the issues of endogeneity inherent in (1); and
3. Including the driver explanatory variables in neighboring tracts in the estimation.

The project settled on the final strategy, including the demographic, housing, amenity, and infrastructure characteristics of nearby neighborhoods in the RSI and housing quantity equations. This approach has a number of theoretically attractive features: we know that amenities in neighboring tracts, and not just amenities in the containing tract, affect prices; as a result, if we do not include the neighboring amenities, there may be omitted variable bias in the estimated effects of amenities. In addition, the effects of these neighboring amenities may be inherently interesting. Finally, in the case of the RSI model, the spatial dependence induced by including transactions from neighboring tracts will be mitigated.

Using this basic variable specification, we considered three econometric estimators: ordinary least squares (OLS), fixed effects (FE), and random effects (RE).

The estimation of the determinants of neighborhood change is inherently fraught with omitted variable bias. There are three kinds of drivers of change in our analysis: drivers that are quantifiable, and obtainable; drivers that are quantifiable, but unobtainable, either due to cost or data problems; and unquantifiable drivers, such as people's expectations concerning the future of the neighborhood. We do not presume to have a complete set of quantifiable drivers, and we are cognizant of the last set of unquantifiable drivers. To address the unquantifiable drivers, we experimented with fixed effects regression. This technique is an estimate like a linear regression,

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regression. The test results showed that three of the four cities (Chicago, Cleveland and Seattle) could be pooled, and the key results are consistent across all four cities.

except that a fixed effect is allowed for each tract—a quantified unquantifiable. The method focuses on the variation within tracts over time, rather than between different tracts.

Fixed-effects estimators are the most likely to lead to unbiased parameter estimates of the three estimators, but they do not allow for the estimation of the effects of time invariant data on the outcome variables. Since we believe that starting points--in terms of demographic, geographic, and housing characteristics—have a significant effect on changes in prices, this is a major limiting factor. Under stringent assumptions, a random effects estimator can be used, which allows time invariant data to be used alongside time varying data.[9] The estimates of the parameter of the time-varying independent variables in the RE estimation are quite similar to those of the FE estimator.[10]

The specification for the baseline 1994-2004 time series price model is as follows:

$$\log(RSI_{j,t}) = \alpha + \beta_1 {*} S_{j,1990} + \beta_2 {*} s_{j,1990} + \beta_3 {*} M_{j,1990} + \beta_4 {*} m_{j,1990} + \beta_5 {*} N_{j,t} + \beta_6 {*} n_{j,t} + \beta_4 {*} C_j + \beta_5 {*} Y_{j,t} + \varepsilon_{j,t}$$

Where

j is an indexing term for the Census Tract of the observation.

t is an indexing term for the year of the observation.

$RSI_{j,t}$ is value of the RSI for Census Tract *j* at time *t* normalized to 1994.

α is a constant term.

β are the parameters measuring the effects of the independent variables on the RSI.

$S_{j,1990}$ are factors related to the supply of housing in 1990 that control for any supply effects in the random effects specification of the model. These factors are related to the temporally lagged housing supply (units built in the previous decade) and to the elasticity of supply (measured in terms of density[11]).

$s_{j,1990}$ are spatially-lagged supply variables. All variables in 'S' have a spatially lagged version in 's'.

$M_{j,1990}$ are variables measuring neighborhood amenities in 1990, used as starting point conditions in the random effects model. These variables are not included in the fixed effects specification.

$m_{j,1990}$ are spatially-lagged amenities variables in 1990. Almost all variables in 'M' have a spatially lagged version in 'm', with the exception of a few variables that are highly spatially correlated. As for 'M', these variables are discarded in the fixed effects model.

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[9] The tract-level random effect must be uncorrelated with the explanatory variables.

[10] Statistical tests suggest that the fixed effects estimator is the preferred estimator, however the insights gained by including the time invariant parameters through the random effects model, in our judgment outweigh the cost of the bias associated with such models.

[11] This is a very imperfect proxy for supply elasticity, as other important factors (such as zoning restrictions) contribute to limiting the supply of new housing units in response to increases in demand.

$N_{j,t}$ are time-varying amenities variables used in both the random effects and fixed effects model specifications. Almost all variables in 'N' have a spatially lagged version in 'n', with the exception of a few variables that are highly spatially correlated.

$n_{j,t}$ are spatially-lagged time-varying amenities variables.

C_j are city dummy variables controlling for regional effects in the random effects specification.

$Y_{j,t}$ are yearly dummy variables controlling for time effects.

$\varepsilon_{j,t}$ is an error term.

Due to data limitations, the corresponding quantity model could not be estimated across the entire sample. However, since the required data on quantity was available in Chicago (and since Chicago represents over half of the entire sample of census tracts) the project estimated a Chicago-only version of the 1994-2004 time series models including both price and quantity. These models also include additional variables on public services and interventions that were not available for the other cities.

In addition to the baseline model, several model extensions were used to look at specific questions of interest. These model extensions include:

1. HMDA Lag: a 1-year lag for each HMDA variable was included as dependent variables in addition to all other variables in the base model, in order to look at possible temporal lag effects of HMDA variables.
2. Sub-Prime Lag: a temporal lag of the percentage of sub-prime loans in the tract for each year from 1 to 5 years was included as dependent variables in addition to all other variables in the base model, in order to look at the longer-term impacts of sub-prime lending.
3. Density Segmentations: To further investigate the interaction between change in amenities and supply elasticity, the model is run on two subsets of the sample, identifying the neighborhoods with the highest density (above 75th percentile) as well as the ones with the lowest (below the 25th percentile).

<u>1999-2004 Time Series Models</u>

The specification for the baseline 1999-2004 time series model is as follows:

$$\log(RSI_{j,t}) = \alpha + \beta_1 * N_{j,t} + \beta_2 * n_{j,t} + \beta_3 * Y_{j,t} + \varepsilon_{j,t}$$

Where

j is an indexing term for the Census Tract of the observation.

t is an indexing term for the year of the observation.

$RSI_{j,t}$ is value of the RSI for Census Tract *j* at time *t* normalized to 1999.

α is a constant term.

β are the parameters measuring the effects of the independent variables on the RSI.

$N_{j,t}$ are time-varying amenities variables. The variables in 'N' in this model include all time-varying amenities variables used in the 1994-2004 model as well as several additional variables available in this time period, including personal credit information, test scores, and parks.

$n_{j,t}$ are spatially lagged time-varying amenities variables. Some variables in 'N' are not included as spatially lagged variables in 'n' due to degrees of freedom limitations (see below).

$Y_{j,t}$ are yearly dummy variables controlling for time effects.

$\varepsilon_{j,t}$ is an error term.

A quantity model using changes in number of residential properties as the dependent variable was estimated across all cities as well.

The 1999-2004 models are similar to the 1994-2004 model, but are estimated using only fixed effects. A random effects estimation was not possible due to the difficulties in finding appropriate starting point conditions for the observations. The only two years with enough data on starting conditions are 1990 and 2000, and one was too far removed from the beginning of the time series to be relevant, while the other was too close to satisfy the assumption that the time invariant characteristics be uncorrelated with the other regressors.

Moreover, due to the shorter time span of the model and the fixed effects estimation procedure used, a number of spatially lagged variables were excluded in order to conserve degrees of freedom. Only variables that seemed most likely to have effects on the neighboring tracts were included as spatially lagged regressors. Also due to the short span of the time series, this model is deemed slightly less reliable than the other two.

APPENDIX G
VARIABLES AND DATA SOURCES

			Own Tract			*Neighbor*			
Dependent Variables		**Source**	Mean	Median	SD	***Mean***	***Median***	***SD***	**Years Available**
	DNT Repeat Sales Index	Administrative Data	0.085	0.073	0.12				1985-2006
	% Change in Residential Parcels	County Assessor's Office, NEOCANDO	0.021	0	0.70				1999-2004
Supply									
	Population Density, per sq. mi. (1990)	Census	12674	9730	10903	*12401*	*10472*	*8073*	1990, 2000
	% of Housing Units Built in 1980-1990	Census	0.088	0.026	0.16	*0.088*	*0.047*	*0.12*	1990, 2000
Amenities									
Physical	% of Housing Units Vacant (1990)	Census	0.107	0.088	0.084	*0.11*	*0.1*	*0.062*	1990, 2000
	Mean Rooms per Housing Unit (1990)	Census	4.957	5.04	0.947	*4.94*	*5.00*	*0.70*	1990, 2000
	Land Use: Industrial Parcels as % of total parcels	County Assessor's Office, NEOCANDO	0.036	0.008	0.079	*0.038*	*0.020*	*0.044*	1990-2005
	Land Use: Vacant Parcels as % of total parcels	County Assessor's Office, NEOCANDO	0.089	0.055	0.089	*0.088*	*0.075*	*0.069*	1990-2005
Transportation	Distance to CBD, in miles	ESRI	5.14	4.70	3.17				N/A
	Mean Commute Time, in minutes (1990)	Census	27.36	27.13	6.99				1990, 2000
	Presence of Transit Stops	Administrative Data	0.106	0	0.407	*0.113*	*0*	*0.231*	1990-2005
	Employees in Nearby Zip Code as % of total county employees	ZCBP and ESRI	0.022	0.015	0.026	*0.022*	*0.015*	*0.022*	1994-2004
	Distance to closest employment sub-center	ZCBP and ESRI	8.031	7.278	4.73	*8.02*	*7.25*	*4.63*	1998-2004
	# Regional Amenities	RW Ventures	0.024	0	0.19	*0.026*	*0*	*0.097*	1990-2004
Consumption	Presence of Art Galleries	Dun and Bradstreet	0.11	0.00	0.32	*0.12*	*0.00*	*0.19*	90, '95, '00, '02, '06
	# Bank Locations, normalized by population (000's)	FDIC	1.55	0.00	43.95	*2.08*	*0.16*	*24.38*	1994-2006
	# Bookstores	Dun and Bradstreet	0.38	0.00	0.99	*0.40*	*0.20*	*0.60*	90, '95, '00, '02, '06
	# Drycleaners	Dun and Bradstreet	0.31	0.00	0.62	*0.32*	*0.25*	*0.31*	90, '95, '00, '02, '06
	# Eating and Drinking Establishments, normalized by population (000's)	Dun and Bradstreet	7.82	1.05	133.18	*8.32*	*1.38*	*71.55*	90, '95, '00, '02, '06
	# Hardware Stores	Dun and Bradstreet	0.25	0.00	0.56	*0.25*	*0.20*	*0.26*	90, '95, '00, '02, '06
	# Hotels and Motels	Dun and Bradstreet	0.54	0.00	2.00	*0.61*	*0.17*	*1.53*	90, '95, '00, '02, '06
	# Meat and Fish Stores	Dun and Bradstreet	0.18	0.00	0.73	*0.18*	*0.11*	*0.34*	90, '95, '00, '02, '06
	Presence of Movie Theaters	Dun and Bradstreet	0.043	0.00	0.20	*0.048*	*0.00*	*0.11*	90, '95, '00, '02, '06
	# Photocopy Stores	Dun and Bradstreet	0.17	0.00	0.79	*0.20*	*0.00*	*0.55*	90, '95, '00, '02, '06
	# Retail Stores, normalized by population (000's)	Dun and Bradstreet	22.62	4.02	383.00	*20.85*	*5.35*	*166.46*	90, '95, '00, '02, '06
	# Supermarkets	Dun and Bradstreet	0.23	0.00	0.53	*0.24*	*0.17*	*0.28*	90, '95, '00, '02, '06
Public Services	Presence of Anchor Institutions	Dun and Bradstreet	0.16	0	0.36	*0.16*	*0.13*	*0.19*	90, '95, '00, '02, '06

	# Social Service Establishments, normalized by population (000's)	Dun and Bradstreet	2.88	0.32	45.68	2.69	0.48	21.05	90, '95, '00, '02, '06
	Presence of Employment Agencies	Dun and Bradstreet	0.23	0	0.42	0.23	0.17	0.26	90, '95, '00, '02, '06
	Presence of Libraries	Dun and Bradstreet	0.15	0	0.36	0.16	0.14	0.16	90, '95, '00, '02, '06
	# of Fire Stations	Administrative Data	0.14	0	0.40	0.15	0.14	0.16	1990-2004
	# of Police Stations	Administrative Data	0.027	0	0.16	0.030	0	0.063	1990-2004
	Park area as % of total tract area	ESRI	0.038	0	0.095	0.039	0.020	0.049	98, '00, '01, '03, '04
	Mean Elementary school math test score	From state websites	57.12	58.00	24.79	57.02	56.14	20.34	1999-2004
	HMDA % FHA Loans	HMDA	0.085	0.057	0.095	0.085	0.065	0.073	1993-2005
	LIHTC Units as % of total housing units	HUD USER	0.026	0	0.29	0.024	0.0012	0.084	1987-2004
	Public Housing Units as % of total housing units	HUD, courtesy of Stuart Rosenthal	0.042	0	0.26	0.041	0	0.11	1990-2004
	TIF Area as % of total tract area	Administrative Data	0.19	0.012	0.30	0.18	0.089	0.23	1986-2006
Social Interactions	% Age 0-18 (1990)	Census	0.27	0.27	0.11	0.27	0.27	0.084	1990, 2000
	% Age 19-34 (1990)	Census	0.30	0.28	0.11	0.30	0.27	0.076	1990, 2000
	% Age 65+ (1990)	Census	0.14	0.12	0.090	0.13	0.13	0.055	1990, 2000
	Median Household Income (1990)	Census	25790	24233	15268	25635	24490	12178	1990, 2000
	% Education more than High School (1990)	Census	0.41	0.34	0.23	0.40	0.34	0.20	1990, 2000
	Unemployment Rate (1990)	Census	0.13	0.10	0.12	0.13	0.11	0.090	1990, 2000
	% Population Foreign Born (1990)	Census	0.13	0.079	0.13	0.12	0.095	0.11	1990, 2000
	% Population Black (1990)	Census	0.37	0.12	0.42	0.37	0.21	0.37	1990, 2000
	% Population Hispanic (1990)	Census	0.16	0.046	0.23	0.16	0.070	0.19	1990, 2000
	HMDA Median Income of borrowers (originated loans, owner-occupied)	HMDA	58.33	50.00	42.80	57.97	51.33	28.91	1993-2005
	HMDA Loan Approval Rate	HMDA	0.72	0.73	0.16	0.72	0.72	0.13	1993-2005
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	HMDA	0.27	0.048	0.36	0.28	0.087	0.32	1993-2005
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	HMDA	0.18	0.042	0.27	0.18	0.068	0.23	1993-2005
	Income Diversity: standard deviation over mean income	TransUnion	0.42	0.41	0.11	0.41	0.40	0.088	1999-2004
	Mean Credit Available (in $K)	TransUnion	47.74	35.22	41.92	47.47	37.54	33.78	1999-2004
	Ratio of Balance to Credit Line	TransUnion	0.44	0.42	0.17	0.44	0.43	0.13	1999-2004
	% Population in Credit Database	TransUnion	0.12	0.11	0.065	0.12	0.12	0.039	1999-2004
	Total Bank Deposits, normalized by population (000's)	FDIC	951	0	39438	1398	6.26	21769	1994-2006
	Homicide Rate, normalized by population (000's)	Administrative Data	0.593	0	13.732	0.63	0.15	5.55	1999-2004
	Violent Crime Rate, normalized by population (000's)	Administrative Data	42.116	17.674	307	41.24	21.63	120	1999-2004
	Property Crime Rate, normalized by housing units (000's)	Administrative Data	174	55.786	1567	162	68.29	667	1999-2004

	# Social Capital Organizations, normalized by population (000's)	Dun and Bradstreet	5.62	1.45	89.51	*5.81*	*1.79*	*45.00*	90, '95, '00, '02, '06
	% Household Moved in less than 5 years ago (1990)	Census	0.50	0.49	0.17	*0.50*	*0.49*	*0.13*	1990, 2000
	% Household Moved in Over 10 years ago (1990)	Census	0.36	0.36	0.17	*0.36*	*0.36*	*0.13*	1990, 2000
Other									
	HMDA % Loans for owner-occupied units	HMDA	0.90	0.92	0.091	*0.90*	*0.91*	*0.060*	1993-2005
	Sub-prime loans as % of total home purchase loans	HMDA	0.20	0.13	0.19	*0.20*	*0.15*	*0.16*	1993-2005

NOTES

DNT Repeat Sales Index	Statistics are for 1-year changes in index from 1994-2004
% Residential Parcels	Statistics are for 1-year changes in index from 1999-2004
# Transit Stops	Includes Chicago's CTA Rail System, Cleveland's RTA Rail Systems, and Dallas's Light Rail System
Employees in Nearby Employment Center as % of total county employees	Proportion of employees in nearest zip code to the total number of county employees
# Art Galleries, normalized by population	SIC Code 8412
# Bookstores, normalized by population	SIC Code 5942
# Drycleaners, normalized by population	SIC Code 7215
# Eating and Drinking Establishments, normalized by population	SIC Code 5812
# Hardware Stores, normalized by population	SIC Code 5251
# Hotels and Motels, normalized by population	SIC Code 7011
# Meat and Fish Stores, normalized by population	SDIC Code 5421
# Movie Theaters, normalized by population	SIC Codes 7832, 7833
# Photocopy Stores, normalized by population	SIC Code 7331
# Retail Stores, normalized by population	SIC Codes 5411, 5912, 5921, 5932, 5421, 5431, 5441, 5451, 5461, 5499, 5311, 5331, 5399, 5735, 5736, 5941, 5942, 5943, 5944, 5945, 5946, 5947, 5948, 5949, 5961, 5962, 5963, 5992, 5993, 5994, 5995, 5999, 5611, 5621, 5632, 5641, 5651, 5661, 5699, 5731, 5734, 5211, 5231, 5251, 5261, 5712, 5713, 5714, 5719, 5722, 5511, 5521, 5531, 5551, 5561, 5571, 5599, 5541, 5983, 5984, 5989, 5271
# Supermarkets, normalized by population	SIC Codes 5411, only supermarkets with greater than 20 employees
Presence of Anchor Institution	SIC Codes 8062, 8221, 8222
# Social Service Establishments, normalized by population	SIC Codes 8611, 8641, 8651, 8661, 8699
# Employment agencies	SIC Code 7361
# Libraries	SIC Code 8231
Mean Elementary school math test score	Tracts are assigned values as the average values of schools within the boundary; otherwise, the values from the school closest to the tract centroid are used

Elementary School Student to Teacher Ratio	Tracts are assigned values as the average values of schools within the boundary; otherwise, the values from the school closest to the tract centroid are used
LIHTC Units as % of total housing units	LIHTC Units are counted when the project is completed
Public Housing Units as % of total housing units	Public Housing Units are counted when the project is completed or demolished
% Population in Credit Database	The ratio of the sample size of individuals in the credit sample to the total population; sampling across census tracts is assumed to be simple random
# Social Capital Establishments, normalized by population	SIC Codes 8611, 8641, 8651, 8661, 8699
Sub-prime loans as % of total home purchase loans	Inclues home purchase, improvement, refinance, and multi-dwelling sub-prime loans

APPENDIX H

Drivers Model Results

This appendix reports the full results of the models developed to identify the key drivers of neighborhood change. For each of these models, the project developed numerous iterations before arriving at the final one presented here. In many instances, the discussion of the findings in the Report is based on observations that were consistent across all the different iterations, and can thus be interpreted as more robust.

The appendix is divided in two sections: one concerning the models for all neighborhoods presented in Section V, and one concerning the specialized drivers analysis reported in Section VI. The first section reports the results of the decennial models for price and quantity, the 1994-2004 time series base model and its extensions, and the 1999-2004 time series model on price and quantity. The second section then includes a model that shows the drivers for Improvement in Place between 1994 and 2000 and a model that details the specialized drivers specifically for Immigrant Communities.

All model results are organized in tables that show coefficients, standard error, and statistical significance in columns, and the particular drivers of change in rows. The coefficients are standardized, to enable comparisons in the magnitude of the effect across different drivers of change. For convenience, the drivers have been organized based on the broad categories of amenities discussed in Section III.B.

A. Overall Drivers Models

1 Decennial Models (1990-2000)

Supply		**RSI**	Std. Err.	Sig	**Median Price**	Std. Err.	Sig	**Quantity**	Std. Err.	Sig
	Population Density (1990)	0.000	0.000		0.000	0.000		0.000	0.000	*
	% of Housing Units Built in 1980-1990	0.032	0.067		-0.033	0.143		0.402	0.090	**
Amenities										
Physical	% of Housing Units Vacant (1990)	0.476	0.187	*	0.242	0.318		-0.279	0.225	
	Mean Rooms per Housing Unit (1990)	0.087	0.021	**	0.043	0.031		0.018	0.024	
Transportation	Distance to CBD, in miles	-0.025	0.003	**	-0.008	0.006		-0.003	0.004	
	Mean Commute Time, in minutes (1990)	0.000	0.000		-0.007	0.007		-0.002	0.002	
	Presence of Transit Stops (1990)	-0.005	0.020		0.046	0.035		0.010	0.018	
Consumption	Presence of Art Galleries (1990)	0.420	10.500		50.853	23.115	*	85.424	24.905	**
	# Eating and Drinking Establishments, normalized by population (1990)	-0.688	0.593		2.600	1.074	*	11.201	0.905	**
	# Hotels and Motels (1990)	-5.049	7.650		26.581	19.837		-4.564	21.733	
	Presence of Movie Theaters (1990)	-39.759	13.663	**	-52.139	31.987		147.833	37.906	**
	# Retail Stores, normalized by population (1990)	0.013	0.186		-2.265	0.688	**	-0.259	0.480	
	# Supermarkets (1990)	14.780	16.607		118.713	38.543	**	-21.046	19.133	
Public Services	Presence of Anchor Institutions (1990)	-0.006	0.007		0.031	0.019		-0.012	0.011	
	# Social Service Establishments, normalized by population (1990)	-0.158	0.116		-1.407	0.249	**	-0.140	0.333	
	Presence of Libraries (1990)	-17.631	13.883		46.359	24.020		-71.134	26.444	**
	LIHTC Units as % of total housing units (1990)	-0.003	0.150		0.296	0.282		0.436	0.200	*
	Public Housing Units as % of total housing units (1990)	-0.102	0.052		-0.495	0.326		0.037	0.026	
	% Age 0-18 (1990)	-0.340	0.233		-0.271	0.411		-0.045	0.321	
Social Interactions	% Age 19-34 (1990)	-0.001	1.000		-0.067	0.447		0.060	0.240	
	% Age 65+ (1990)	0.498	0.187	**	0.296	0.384		-0.074	0.218	
	Median Household Income (1990)	0.000	0.000	**	0.000	0.000		0.000	0.000	

% Education more than High School (1990)	0.093	0.089		-0.415	0.159	**	0.075	0.129	
Unemployment Rate (1990)	0.732	0.227	**	-0.306	0.502		-0.325	0.254	
% Population Foreign Born (1990)	-0.129	0.079		-0.330	0.204		-0.009	0.069	
% Population Black (1990)	0.024	0.043		0.102	0.075		0.018	0.051	
% Population Hispanic (1990)	0.405	0.063	**	0.101	0.120		0.178	0.041	**
# Social Capital Organizations, normalized by population (1990)	3.709	1.775	*	4.561	3.508		-7.753	5.499	
% Household Moved in less than 5 years ago (1990)	-0.248	0.197		-0.712	0.381		0.019	0.238	
% Household Moved in over 10 years ago (1990)	-0.457	0.190	*	-1.160	0.368	**	0.051	0.196	
Control Variables									
Cleveland (dummy)	-0.109	0.044	*	-0.357	0.091	**	-0.070	0.032	*
Dallas (dummy)	-0.232	0.028	**	-0.232	0.066	**	-0.123	0.034	**
Seattle (dummy)	0.042	0.030		0.292	0.074	**	-0.054	0.025	*
Intercept	0.553	0.226	*	1.643	0.510	**	-0.022	0.220	
# Observations	1405			1405			1405		
R^2	0.33			0.22			0.52		

2 1994-2004 Time Series Models

a Base Model (1994-2004)

		RSI Random Eff.	Std. Err.	Sig.	RSI Fixed Effects	Std. Err.	Sig.
Supply							
	Population Density (1990)	1.0868	0.6508				
	Population Density (1990) (neighbor)	*0.3938*	*1.0643*				
	% of Housing Units Built in 1980-1990	-0.0250	0.0446				
	% of Housing Units Built in 1980-1990 (neighbor)	*0.0020*	*0.0667*				
Amenities							
Physical	% of Housing Units Vacant (1990)	0.0678	0.0904				
	% of Housing Units Vacant (1990) (neighbor)	*0.2266*	*0.1349*				
	Mean Rooms per Housing Unit (1990)	0.0210	0.0119				
	Mean Rooms per Housing Unit (1990) (neighbor)	*-0.0917*	*0.0165*	**			
Transportation	Distance to CBD, in miles	0.0040	0.0024				
	Mean Commute Time, in minutes (1990)	0.0394	0.0773				
	Presence of Transit Stops	-1.2557	0.8969		-1.3969	1.3304	
	Presence of Transit Stops (neighbor)	*3.2379*	*1.6109*	*	*8.2839*	*2.2032*	**
	Employees in Nearby Zip Code as % of total county employees	-7.3198	22.1812		-2.6217	23.8336	
	Employees in Nearby Zip Code as % of total county employees (neighbor)	*-38.3265*	*28.3900*		*-25.0932*	*31.7635*	
	# Regional Amenities (neighbor)	*0.1381*	*0.0529*	**			
Consumption	Presence of Art Galleries	6.6840	6.9625		4.8583	7.9644	
	Presence of Art Galleries (neighbor)	*-3.0385*	*14.4690*		*7.0956*	*16.1264*	
	# Eating and Drinking Establishments, normalized by population, log	0.0735	0.3675		0.6146	0.5253	
	# Eating and Drinking Establishments, normalized by population, log (neighbor)	*-0.5685*	*0.9636*		*0.2474*	*0.9896*	
	# Hotels and Motels, log	-8.8545	4.7605		-22.0907	6.7763	**
	# Hotels and Motels, log (neighbor)	*-21.2546*	*8.8193*	*	*-29.4830*	*11.3834*	**
	Presence of Movie Theaters	16.0529	17.6405		25.5299	19.6384	
	Presence of Movie Theaters (neighbor)	*143.7311*	*43.2925*	**	*171.6231*	*45.5234*	**
	# Retail Stores, normalized by population, log	-0.3026	0.2073		0.5543	0.3046	
	# Retail Stores, normalized by population, log (neighbor)	*-1.6557*	*0.4224*	**	*-0.5179*	*0.4503*	
	# Supermarkets, log	12.6438	5.6699	*	11.3815	8.6882	
	# Supermarkets, log (neighbor)	*62.2710*	*10.1750*	**	*71.9418*	*10.7697*	**
Public Services	Presence of Anchor Institutions	0.0003	0.0016		-0.0017	0.0025	
	Presence of Anchor Institutions (neighbor)	*-0.0034*	*0.0025*		*0.0024*	*0.0028*	
	# Social Service Establishments, normalized by population, log	0.0933	0.1435		-0.3270	0.2070	
	# Social Service Establishments, normalized by population, log (neighbor)	*0.8035*	*0.2771*	**	*0.7053*	*0.2879*	*

	Presence of Libraries	10.2466	5.9229		5.3116	6.8982	
	Presence of Libraries (neighbor)	*10.7108*	*12.9046*		*-6.8968*	*14.3683*	
	HMDA % FHA Loans	-0.0361	0.0242		-0.0399	0.0243	
	HMDA % FHA Loans (neighbor)	*-0.2702*	*0.0387*	**	*-0.2798*	*0.0387*	**
	LIHTC Units as % of total housing units	2.7093	4.2333		3.2549	5.0075	
	LIHTC Units as % of total housing units (neighbor)	*-7.1290*	*7.8341*		*-12.2645*	*9.0180*	
	Public Housing Units as % of total housing units	3.9415	2.2652		-7.5799	4.6790	
	Public Housing Units as % of total housing units (neighbor)	*-9.4088*	*3.5371*	**	*8.9830*	*3.9057*	*
	% Age 0-18 (1990)	0.0041	0.1025				
Social Interactions	*% Age 0-18 (1990) (neighbor)*	*0.6147*	*0.1680*	**			
	% Age 19-34 (1990)	0.0336	0.0933				
	% Age 19-34 (1990) (neighbor)	*-0.0685*	*0.1370*				
	% Age 65+ (1990)	0.1347	0.1020				
	% Age 65+ (1990) (neighbor)	*0.7012*	*0.1348*	**			
	Median Household Income (1990)	-0.1907	0.7628				
	Median Household Income (1990) (neighbor)	*-2.9048*	*1.1760*	*			
	% Education more than High School (1990)	-0.2310	0.0624	**			
	% Education more than High School (1990) (neighbor)	*0.1898*	*0.0825*	*			
	Unemployment Rate (1990)	-0.2262	0.0920	*			
	Unemployment Rate (1990) (neighbor)	*0.2327*	*0.1322*				
	% Population Foreign Born (1990)	-0.0629	0.0758				
	% Population Foreign Born (1990) (neighbor)	*-0.1452*	*0.0995*				
	% Population Black (1990)	0.1773	0.0397	**			
	% Population Black (1990) (neighbor)	*0.3630*	*0.0485*	**			
	% Population Hispanic (1990)	0.1107	0.0559	*			
	% Population Hispanic (1990) (neighbor)	*0.3670*	*0.0708*	**			
	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0214	0.0037	**	0.0218	0.0037	**
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.0752*	*0.0079*	**	*0.0738*	*0.0080*	**
	HMDA Loan Approval Rate	0.0811	0.0174	**	0.0782	0.0173	**
	HMDA Loan Approval Rate (neighbor)	*0.2770*	*0.0305*	**	*0.2804*	*0.0300*	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.1395	0.0196	**	-0.1996	0.0201	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.5487*	*0.0335*	**	*-0.6900*	*0.0344*	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.0662	0.0206	**	-0.1172	0.0213	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.3894*	*0.0305*	**	*-0.6209*	*0.0333*	**
	# Social Capital Organizations, normalized by population, log	0.1375	0.5978		-1.4226	0.7295	
	# Social Capital Organizations, normalized by population, log (neighbor)	*-0.8843*	*1.3199*		*-4.0852*	*1.4538*	**
	% Household Moved in less than 5 years ago (1990)	0.0346	0.0961				
	% Household Moved in less than 5 years ago (1990) (neighbor)	*-0.4940*	*0.1328*	**			
	% Household Moved in over 10 years ago (1990)	-0.0295	0.0983				
	% Household Moved in over 10 years ago (1990) (neighbor)	*-0.2263*	*0.1301*				
Other							

HMDA % loans for owner-occupied units	0.0288	0.0238		0.0371	0.0238	
HMDA % loans for owner-occupied units (neighbor)	*0.3270*	*0.0405*	**	*0.3495*	*0.0395*	**
Sub-prime loans as % of total home purchase loans	7.0765	1.4867	**	6.3701	1.4849	**
Sub-prime loans as % of total home purchase loans (neighbor)	*15.1922*	*2.3925*	**	*17.7420*	*2.3783*	**
Control Variables						
1995 (year dummy)	0.0255	0.0050	**	0.0279	0.0049	**
1996 (year dummy)	0.0689	0.0053	**	0.0686	0.0052	**
1997 (year dummy)	0.1326	0.0057	**	0.1330	0.0056	**
1998 (year dummy)	0.2121	0.0059	**	0.2093	0.0058	**
1999 (year dummy)	0.3267	0.0062	**	0.3288	0.0061	**
2000 (year dummy)	0.4283	0.0065	**	0.4330	0.0065	**
2001 (year dummy)	0.4984	0.0062	**	0.5043	0.0062	**
2002 (year dummy)	0.5608	0.0063	**	0.5651	0.0064	**
2003 (year dummy)	0.6363	0.0067	**	0.6402	0.0068	**
2004 (year dummy)	0.7119	0.0078	**	0.7198	0.0078	**
Cleveland (dummy)	0.1362	0.0238	**			
Dallas (dummy)	0.0780	0.0211	**			
Seattle (dummy)	0.1033	0.0258	**			
Intercept	-0.1755	0.1382		-0.2640	0.0436	**
# Observations	14713			14713		
# Census Tracts	1368			1368		
R^2	0.84			0.84		

b Time Series Model Extensions

Lag Effects of HMDA Variables (1994-2004)

Supply		RSI	Std. Err.	Sig
	Population Density (1990)	1.8881	0.7072	**
	Population Density (1990) (neighbor)	*-0.9822*	*1.1290*	
	% of Housing Units Built in 1980-1990	-0.0553	0.0489	
	% of Housing Units Built in 1980-1990 (neighbor)	*0.0933*	*0.0671*	
Amenities				
Physical	% of Housing Units Vacant (1990)	0.0499	0.0998	
	% of Housing Units Vacant (1990) (neighbor)	*0.3038*	*0.1489*	*
	Mean Rooms per Housing Unit (1990)	0.0047	0.0131	
	Mean Rooms per Housing Unit (1990) (neighbor)	*-0.0966*	*0.0178*	**
Transportation	Distance to CBD, in miles	0.0042	0.0026	
	Mean Commute Time, in minutes (1990)	0.0941	0.0840	
	Presence of Transit Stops	-0.9362	0.9752	
	Presence of Transit Stops (neighbor)	*-1.4652*	*1.7443*	
	Employees in Nearby Zip Code as % of total county employees	-16.0110	21.0671	
	Employees in Nearby Zip Code as % of total county employees (neighbor)	*-7.0083*	*26.9550*	
	# Regional Amenities (neighbor)	*0.0715*	*0.0563*	
Consumption	Presence of Art Galleries	7.3440	6.9283	
	Presence of Art Galleries (neighbor)	*-4.0026*	*13.3420*	
	# Eating and Drinking Establishments, normalized by population, log	0.0014	1.0000	
	# Eating and Drinking Establishments, normalized by population, log (neighbor)	*-2.3492*	*0.8272*	**
	# Hotels and Motels, log	-9.1653	5.0918	
	# Hotels and Motels, log (neighbor)	*-9.5366*	*8.7492*	
	Presence of Movie Theaters	-1.0521	17.5350	
	Presence of Movie Theaters (neighbor)	*45.2554*	*40.0490*	
	# Retail Stores, normalized by population, log	0.0575	0.3026	
	# Supermarkets, log	17.4280	6.5030	**
Public Services	Presence of Anchor Institutions	-0.0002	0.0022	
	Presence of Anchor Institutions (neighbor)	*-0.0013*	*0.0024*	
	# Social Service Establishments, normalized by population, log	-0.0444	0.2018	
	# Social Service Establishments, normalized by population, log (neighbor)	*0.0198*	*0.2200*	
	Presence of Libraries	9.9624	5.9300	
	HMDA % FHA Loans	-0.1027	0.0266	**
	HMDA % FHA Loans (neighbor)	*-0.3112*	*0.0454*	**
	HMDA % FHA Loans, 1 year lag	-0.0322	0.0239	

	HMDA % FHA Loans, 1 year lag (neighbor)	*-0.1281*	*0.0413*	**
	LIHTC Units as % of total housing units	-4.3896	4.4792	
	LIHTC Units as % of total housing units (neighbor)	*-25.5113*	*8.0477*	**
	Public Housing Units as % of total housing units	7.8224	2.4833	**
	Public Housing Units as % of total housing units (neighbor)	*-17.9170*	*3.5479*	**
Social Interactions	% Age 0-18 (1990)	-0.0125	0.1250	
	% Age 0-18 (1990) (neighbor)	*0.7370*	*0.1780*	**
	% Age 19-34 (1990)	0.0920	0.1034	
	% Age 19-34 (1990) (neighbor)	*-0.1727*	*0.1439*	
	% Age 65+ (1990)	0.0672	0.1102	
	% Age 65+ (1990) (neighbor)	*0.8028*	*0.1454*	**
	Median Household Income (1990)	-0.1680	0.8400	
	Median Household Income (1990) (neighbor)	*-3.3708*	*1.2484*	**
	% Education more than High School (1990)	-0.3016	0.0679	**
	% Education more than High School (1990) (neighbor)	*0.0892*	*0.0875*	
	Unemployment Rate (1990)	-0.2746	0.1010	**
	Unemployment Rate (1990) (neighbor)	*0.2541*	*0.1412*	
	% Population Foreign Born (1990)	-0.1800	0.0818	*
	% Population Foreign Born (1990) (neighbor)	*-0.0648*	*0.1045*	
	% Population Black (1990)	0.1634	0.0422	**
	% Population Black (1990) (neighbor)	*0.1469*	*0.0483*	**
	% Population Hispanic (1990)	0.1421	0.0597	*
	% Population Hispanic (1990) (neighbor)	*0.2692*	*0.0732*	**
	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0459	0.0074	**
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.0539*	*0.0074*	**
	HMDA Median Income of borrowers (originated loans, owner-occupied), 1 year lag	0.0360	0.0071	**
	HMDA Median Income of borrowers (originated loans, owner-occupied), 1 year lag (neighbor)	*0.0523*	*0.0074*	**
	HMDA Loan Approval Rate	0.0672	0.0173	**
	HMDA Loan Approval Rate (neighbor)	*0.2262*	*0.0305*	**
	HMDA Loan Approval Rate, 1 year lag	0.0524	0.0167	**
	HMDA Loan Approval Rate, 1 year lag (neighbor)	*0.2428*	*0.0296*	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.0519	0.0096	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.1658*	*0.0182*	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied), 1 year lag	-0.0288	0.0094	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied), 1 year lag (neighbor)	*-0.1204*	*0.0177*	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.0061	0.0111	
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.1006*	*0.0210*	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied), 1 year lag	-0.0569	0.0109	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied), 1 year lag (neighbor)	*-0.2217*	*0.0207*	**
	# Social Capital Organizations, normalized by population, log	-0.3435	0.6481	
	# Social Capital Organizations, normalized by population, log (neighbor)	*0.2839*	*1.2905*	
	% Household Moved in less than 5 years ago (1990)	-0.0230	0.1095	

	% Household Moved in less than 5 years ago (1990) (neighbor)	*0.1921*	*0.1444*	
	% Household Moved in over 10 years ago (1990)	-0.0139	0.1069	
	% Household Moved in over 10 years ago (1990) (neighbor)	*0.3315*	*0.1417*	*
Other				
	HMDA % loans for owner-occupied units	0.0609	0.0240	*
	HMDA % loans for owner-occupied units (neighbor)	*0.3489*	*0.0436*	**
	HMDA % loans for owner-occupied units, 1 year lag	0.0041	0.0241	
	HMDA % loans for owner-occupied units, 1 year lag (neighbor)	*-0.1648*	*0.0427*	**
	Sub-prime loans as % of total home purchase loans	5.1314	1.4831	**
	Sub-prime loans as % of total home purchase loans (neighbor)	*16.1236*	*2.6090*	**
	Sub-prime loans as % of total home purchase loans, 1 year lag	0.3423	1.4883	
	Sub-prime loans as % of total home purchase loans, 1 year lag (neighbor)	*-4.9564*	*2.4296*	*
Control Variables				
	1995 (year dummy)	-0.6350	0.0077	**
	1996 (year dummy)	-0.5849	0.0070	**
	1997 (year dummy)	-0.5178	0.0066	**
	1998 (year dummy)	-0.4480	0.0063	**
	1999 (year dummy)	-0.3625	0.0057	**
	2000 (year dummy)	-0.2680	0.0057	**
	2001 (year dummy)	-0.1910	0.0059	**
	2002 (year dummy)	-0.1303	0.0053	**
	2003 (year dummy)	-0.0675	0.0047	**
	Cleveland (dummy)	0.1351	0.0256	**
	Dallas (dummy)	0.1058	0.0227	**
	Seattle (dummy)	0.1168	0.0275	**
	Intercept	0.0175	0.1591	
	# Observations	13211		
	# Census Tracts	1364		
	R^2	0.85		

Lag Effect of Sub-prime Lending

Supply		RSI	Std. Err.	Sig.
	Population Density (1990)	2.3753	0.7662	**
	Population Density (1990) (neighbor)	*2.8365*	*1.2226*	*
	% of Housing Units Built in 1980-1990	-0.0402	0.0529	
	% of Housing Units Built in 1980-1990 (neighbor)	*0.1359*	*0.0727*	
Amenities				
Physical	% of Housing Units Vacant (1990)	0.1049	0.1081	
	% of Housing Units Vacant (1990) (neighbor)	*0.6202*	*0.1615*	**
	Mean Rooms per Housing Unit (1990)	-0.0126	0.0147	
	Mean Rooms per Housing Unit (1990) (neighbor)	*-0.0257*	*0.0207*	
Transportation	Distance to CBD, in miles	-0.0019	0.0292	
	Mean Commute Time, in minutes (1990)	0.1321	0.0944	
	Presence of Transit Stops	-1.5250	1.1822	
	Presence of Transit Stops (neighbor)	*-1.7750*	*2.1914*	
	Employees in Nearby Zip Code as % of total county employees	-21.2001	19.6297	
	Employees in Nearby Zip Code as % of total county employees (neighbor)	*22.8033*	*25.0586*	
	# Regional Amenities (neighbor)	*0.1932*	*0.0600*	**
Consumption	Presence of Art Galleries	9.5954	8.7231	
	Presence of Art Galleries (neighbor)	*-51.1424*	*14.7810*	**
	# Eating and Drinking Establishments, normalized by population, log	-1.0994	0.9560	
	# Eating and Drinking Establishments, normalized by population, log (neighbor)	*-2.5014*	*1.4376*	
	# Hotels and Motels, log	-3.7919	7.2921	
	# Hotels and Motels, log (neighbor)	*-44.6110*	*11.2088*	**
	Presence of Movie Theaters	-8.8933	20.2120	
	Presence of Movie Theaters (neighbor)	*-106.0586*	*51.2360*	*
	# Retail Stores, normalized by population, log	-0.3246	0.4845	
	# Retail Stores, normalized by population, log (neighbor)	*-0.3525*	*0.7663*	
	# Supermarkets, log	31.8770	8.3013	**
	# Supermarkets, log (neighbor)	*51.8692*	*11.2029*	**
Public Services	Presence of Anchor Institutions	-0.0025	0.0024	
	Presence of Anchor Institutions (neighbor)	*0.0004*	*0.0024*	
	# Social Service Establishments, normalized by population, log	0.8106	0.3603	*
	# Social Service Establishments, normalized by population, log (neighbor)	*1.0649*	*0.3480*	**
	Presence of Libraries	4.8988	9.2430	
	Presence of Libraries (neighbor)	*32.8237*	*21.8825*	
	HMDA % FHA Loans	-0.1832	0.0341	**
	HMDA % FHA Loans (neighbor)	*-0.7708*	*0.0544*	**
	LIHTC Units as % of total housing units	-13.2813	4.9557	**

	LIHTC Units as % of total housing units (neighbor)	*-52.6368*	*9.3660*	**
	Public Housing Units as % of total housing units	3.2099	3.6476	
	Public Housing Units as % of total housing units (neighbor)	*-13.7962*	*4.5683*	**
Social Interactions	% Age 0-18 (1990)	0.0144	1.3091	
	% Age 0-18 (1990) (neighbor)	*0.2857*	*0.2012*	
	% Age 19-34 (1990)	0.0140	1.1667	
	% Age 19-34 (1990) (neighbor)	*-0.4410*	*0.1581*	**
	% Age 65+ (1990)	0.0213	0.1253	
	% Age 65+ (1990) (neighbor)	*0.5646*	*0.1690*	**
	Median Household Income (1990)	-0.4299	0.8956	
	Median Household Income (1990) (neighbor)	*-7.4838*	*1.3364*	**
	% Education more than High School (1990)	-0.1545	0.0754	*
	% Education more than High School (1990) (neighbor)	*0.1453*	*0.0982*	
	Unemployment Rate (1990)	-0.0703	0.1172	
	Unemployment Rate (1990) (neighbor)	*0.4706*	*0.1628*	**
	% Population Foreign Born (1990)	-0.2245	0.0905	*
	% Population Foreign Born (1990) (neighbor)	*-0.1076*	*0.1145*	
	% Population Black (1990)	0.1048	0.0460	*
	% Population Black (1990) (neighbor)	*0.0503*	*0.0535*	
	% Population Hispanic (1990)	0.1411	0.0678	*
	% Population Hispanic (1990) (neighbor)	*0.0869*	*0.0820*	
	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0482	0.0080	**
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.1421*	*0.0154*	**
	HMDA Loan Approval Rate	0.0149	0.0194	
	HMDA Loan Approval Rate (neighbor)	*0.1998*	*0.0335*	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.0174	0.0103	
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.1691*	*0.0194*	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	0.0090	0.0115	
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.0735*	*0.0201*	**
	# Social Capital Organizations, normalized by population, log	-0.0038	1.0000	
	# Social Capital Organizations, normalized by population, log (neighbor)	*-2.3866*	*1.3560*	
	% Household Moved in less than 5 years ago (1990)	-0.0931	0.1178	
	% Household Moved in less than 5 years ago (1990) (neighbor)	*0.1175*	*0.1780*	
	% Household Moved in over 10 years ago (1990)	-0.0150	0.1154	
	% Household Moved in over 10 years ago (1990) (neighbor)	*0.1331*	*0.1751*	
Other				
	HMDA % loans for owner-occupied units	0.0790	0.0255	**
	HMDA % loans for owner-occupied units(neighbor)	*0.5345*	*0.0442*	**
	Sub-prime loans as % of total home purchase loans	5.1045	1.6519	**
	Sub-prime loans as % of total home purchase loans (neighbor)	*3.9819*	*2.8042*	
	Subprime loans as % of total home purchase loans (1 year lag)	0.3857	2.7550	

Subprime loans as % of total home purchase loans (1 year lag) (neighbor)	*3.8213*	*1.6056*	*
Subprime loans as % of total home purchase loans (2 year lag)	-8.1679	2.6780	**
Subprime loans as % of total home purchase loans (2 year lag) (neighbor)	*-1.7490*	*1.5209*	
Subprime loans as % of total home purchase loans (3 year lag)	-12.4810	2.6669	**
Subprime loans as % of total home purchase loans (3 year lag) (neighbor)	*-5.5747*	*1.4866*	**
Subprime loans as % of total home purchase loans (4 year lag)	-5.9694	2.3688	*
Subprime loans as % of total home purchase loans (4 year lag) (neighbor)	*0.7980*	*1.4509*	
Control Variables			
1999 (year dummy)	0.1040	0.0038	**
2000 (year dummy)	0.1920	0.0046	**
2001 (year dummy)	0.2749	0.0050	**
2002 (year dummy)	0.3490	0.0054	**
2003 (year dummy)	0.4143	0.0055	**
2004 (year dummy)	0.4716	0.0060	**
Cleveland (dummy)	0.1038	0.0280	**
Dallas (dummy)	0.1193	0.0253	**
Seattle (dummy)	0.1675	0.0298	**
Intercept	-0.4014	0.2147	
# Observations	9031		
# Census Tracts	1330		
R^2	0.83		

Density Segmentation

Supply		RSI High Density	Std. Err.	Sig.	RSI Low Density	Std. Error	Sig.
	Population Density (1990)	0.0376	0.9400		11.2885	4.7035	*
	Population Density (1990) (neighbor)	*3.5822*	*1.8092*	*	*-0.2306*	*2.5622*	
	% of Housing Units Built in 1980-1990	-0.0448	0.1179		0.0548	0.0498	
	% of Housing Units Built in 1980-1990 (neighbor)	*0.5150*	*0.2525*	*	*0.0962*	*0.1002*	
Amenities							
Physical	% of Housing Units Vacant (1990)	-0.3048	0.2275		-0.1668	0.1062	
	% of Housing Units Vacant (1990) (neighbor)	*-0.1892*	*0.3379*		*0.4146*	*0.2126*	
	Mean Rooms per Housing Unit (1990)	-0.0331	0.0274		-0.0074	0.0161	
	Mean Rooms per Housing Unit (1990) (neighbor)	*0.0045*	*0.0450*		*0.0242*	*0.2951*	
Transportation	Distance to CBD, in miles	0.0212	0.0084	*	-0.0040	0.0035	
	Mean Commute Time, in minutes (1990)	0.1346	0.1726		0.1667	0.1048	
	Presence of Transit Stops	0.9855	1.6991		-0.6503	1.5861	
	Presence of Transit Stops (neighbor)	*14.7954*	*3.5911*	**	*-0.2108*	*2.6350*	
	Employees in Nearby Zip Code as % of total county employees	-0.0088	0.1257		0.0016	0.0050	
	Employees in Nearby Zip Code as % of total county employees (neighbor)	*0.0053*	*0.0331*		*0.0058*	*0.0193*	
	# Regional Amenities (neighbor)	*-0.2755*	*0.1602*		0.2992	0.1169	*
Consumption	Presence of Art Galleries	21.4254	31.0513		3.2142	7.6529	
	Presence of Art Galleries (neighbor)	*-42.1919*	*46.8799*		*21.0083*	*26.9337*	
	# Eating and Drinking Establishments, normalized by population, log	-2.1477	4.3831		0.8154	0.3793	*
	# Eating and Drinking Establishments, normalized by population, log (neighbor)	*-7.5290*	*2.9759*	*	*0.3974*	*1.4719*	
	# Hotels and Motels, log	23.1712	19.3093		-0.4338	4.8200	
	# Hotels and Motels, log (neighbor)	*27.2983*	*32.8895*		*-41.2203*	*13.1275*	**
	Presence of Movie Theaters	23.6386	43.7752		50.7975	28.0649	
	Presence of Movie Theaters (neighbor)	*31.8067*	*102.6023*		*289.7314*	*85.2151*	**
	# Retail Stores, normalized by population, log	4.7885	1.9625	*	-0.5702	0.1973	**
	# Retail Stores, normalized by population, log (neighbor)	*-0.0018*	*1.0000*		*-1.1016*	*0.7200*	
	# Supermarkets, log	11.7131	32.5364		1.5457	4.5462	
	# Supermarkets, log (neighbor)	*71.2321*	*26.6787*	**	*-39.7385*	*22.4511*	
Public Services	Presence of Anchor Institutions	0.0033	0.0077		0.0039	0.0016	*
	Presence of Anchor Institutions (neighbor)	*-0.0090*	*0.0055*		*0.0029*	*0.0041*	
	# Social Service Establishments, normalized by population, log	-0.9425	1.4500		0.1335	0.1376	
	# Social Service Establishments, normalized by population, log (neighbor)	*-1.5929*	*1.3164*		*-0.0711*	*0.4444*	
	Presence of Libraries	4.0163	40.1630		-9.1297	3.6086	*
	Presence of Libraries (neighbor)	*13.4984*	*58.6887*		*-2.0751*	*13.8340*	
	HMDA % FHA Loans	0.0129	0.0586		-0.0847	0.0370	*
	HMDA % FHA Loans (neighbor)	*-0.4798*	*0.0950*	**	*-0.0789*	*0.0751*	

	LIHTC Units as % of total housing units	20.3112	17.6619		-1.9305	5.0803	
	LIHTC Units as % of total housing units (neighbor)	*-43.1427*	*20.9431*		*17.7228*	*12.3936*	
	Public Housing Units as % of total housing units	20.4999	6.0651	**	2.6001	2.0473	
	Public Housing Units as % of total housing units (neighbor)	*10.3582*	*11.5091*		*-5.9795*	*5.1996*	
Social Interactions	% Age 0-18 (1990)	0.1216	0.2702		0.0679	0.1281	
	% Age 0-18 (1990) (neighbor)	*1.0890*	*0.5018*	*	*-0.1827*	*0.2900*	
	% Age 19-34 (1990)	-0.3502	0.2350		-0.1155	0.1013	
	% Age 19-34 (1990) (neighbor)	*0.4431*	*0.3787*		*-0.2090*	*0.2518*	
	% Age 65+ (1990)	-0.6148	0.2479	*	0.0909	0.1151	
	% Age 65+ (1990) (neighbor)	*3.2615*	*0.4443*	**	*0.2998*	*0.2361*	
	Median Household Income (1990)	-2.1086	2.1516		0.3282	0.8005	
	Median Household Income (1990) (neighbor)	*2.6797*	*3.4355*		*-1.9571*	*1.6309*	
	% Education more than High School (1990)	-0.2047	0.1599		0.0160	0.0696	
	% Education more than High School (1990) (neighbor)	*0.2702*	*0.2252*		*-0.2516*	*0.1277*	*
	Unemployment Rate (1990)	-0.5122	0.2237	*	-0.2916	0.1257	*
	Unemployment Rate (1990) (neighbor)	*0.9049*	*0.3952*	*	*0.9020*	*0.2819*	**
	% Population Foreign Born (1990)	0.0800	0.1509		-0.2368	0.1067	*
	% Population Foreign Born (1990) (neighbor)	*-1.0667*	*0.2168*	**	*0.2774*	*0.1533*	
	% Population Black (1990)	0.0346	0.1281		0.0800	0.0479	
	% Population Black (1990) (neighbor)	*0.0217*	*0.1550*		*0.1525*	*0.0751*	*
	% Population Hispanic (1990)	-0.0965	0.1253		0.2217	0.0678	**
	% Population Hispanic (1990) (neighbor)	*0.8249*	*0.1633*	**	*-0.0382*	*0.1124*	
	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0081	0.0312		-0.0101	0.0160	
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.1349*	*0.0492*	**	*0.1423*	*0.0345*	**
	HMDA Loan Approval Rate	0.2260	0.0427	**	0.0322	0.0262	
	HMDA Loan Approval Rate (neighbor)	*0.5459*	*0.0821*	**	*0.0414*	*0.0567*	
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.1879	0.0516	**	-0.0535	0.0272	*
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*0.0462*	*0.0872*		*-0.3529*	*0.0570*	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.1091	0.0462	*	-0.0423	0.0313	
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.2618*	*0.0729*	**	*-0.1306*	*0.0558*	*
	# Social Capital Organizations, normalized by population, log	-0.6828	5.2523		1.2713	0.5859	*
	# Social Capital Organizations, normalized by population, log (neighbor)	*1.9898*	*4.6274*		*1.8650*	*2.0272*	
	% Household Moved in less than 5 years ago (1990)	-0.4081	0.2000	*	0.2032	0.1155	
	% Household Moved in less than 5 years ago (1990) (neighbor)	*-0.6733*	*0.4261*		*0.1384*	*0.2611*	
	% Household Moved in over 10 years ago (1990)	0.0862	0.2102		0.2749	0.1180	*
	% Household Moved in over 10 years ago (1990) (neighbor)	*-1.0329*	*0.4035*	*	*0.1440*	*0.2441*	
Other							
	HMDA % loans for owner-occupied units	0.0040	0.0571		0.0015	0.0300	
	HMDA % loans for owner-occupied units (neighbor)	*0.5161*	*0.0947*	**	*-0.3391*	*0.0745*	**
	Sub-prime loans as % of total home purchase loans	-0.8496	3.8618		11.1413	2.0942	**
	Sub-prime loans as % of total home purchase loans (neighbor)	*5.3129*	*6.6411*		*22.0110*	*4.1609*	**

Control Variables						
1995 (year dummy)	0.0228	0.0111	*	0.0430	0.0103	**
1996 (year dummy)	0.0580	0.0119	**	0.0807	0.0110	**
1997 (year dummy)	0.1356	0.0129	**	0.1327	0.0120	**
1998 (year dummy)	0.2209	0.0140	**	0.2076	0.0124	**
1999 (year dummy)	0.3657	0.0156	**	0.2939	0.0131	**
2000 (year dummy)	0.4853	0.0188	**	0.3762	0.0140	**
2001 (year dummy)	0.5562	0.0185	**	0.4419	0.0141	**
2002 (year dummy)	0.6245	0.0208	**	0.4865	0.0154	**
2003 (year dummy)	0.7392	0.0202	**	0.5421	0.0158	**
2004 (year dummy)	0.8447	0.0228	**	0.5820	0.0183	**
Cleveland (dummy)	0.4350	0.1431	**	0.0522	0.0408	
Dallas (dummy)	0.5795	0.1756	**	0.0768	0.0373	*
Seattle (dummy)	0.3412	0.0945	**	0.1495	0.0402	**
Intercept	-0.9573	0.4935		-0.2185	0.2300	
# Observations	3732			3733		
# Census Tracts	340			343		
R^2	0.74			0.71		

Chicago Random Effects Models (1994-2004)

Supply		**RSI**	Std.Err	Sig.	**Median Price**	Std. Err	Sig.	**Quantity**	Std. Err	Sig.
	Population Density (1990)	0.0151	0.0237		-0.0206	0.0237		-0.0271	0.0206	
	Population Density (1990) (neighbor)	*-0.0316*	*0.0268*		*0.0378*	*0.0268*		*-0.0613*	*0.0225*	**
	% of Housing Units Built in 1980-1990	-0.0813	0.0234	**	0.0015	0.0234		0.0183	0.0219	
	% of Housing Units Built in 1980-1990 (neighbor)	*0.0258*	*0.0244*		*-0.0540*	*0.0244*	*	*-0.0426*	*0.0204*	*
Amenities										
Physical	% of Housing Units Vacant (1990)	-0.0225	0.0253		0.0188	0.0253		0.0173	0.0240	
	% of Housing Units Vacant (1990) (neighbor)	*-0.0253*	*0.0293*		*-0.0572*	*0.0293*		*-0.0632*	*0.0260*	*
	Mean Rooms per Housing Unit (1990)	-0.0308	0.0338		-0.1065	0.0338	**	-0.0645	0.0312	*
	Mean Rooms per Housing Unit (1990) (neighbor)	*-0.0469*	*0.0426*		*0.1269*	*0.0426*	*	*-0.1101*	*0.0367*	**
	Land Use: Industrial Parcels as % of total parcels	0.0320	0.0166		-0.0521	0.0166	*			
	Land Use: Industrial Parcels as % of total parcels (neighbor)	*0.0161*	*0.0142*		*0.0637*	*0.0142*	**			
	Land Use: Vacant Parcels as % of total parcels	-0.0525	0.0185	**	0.0261	0.0185				
	Land Use: Vacant Parcels as % of total parcels (neighbor)	*-0.0396*	*0.0209*		*0.0822*	*0.0209*	**			
Transportation	Distance to CBD, in miles	0.0047	0.0309		0.0578	0.0309		0.0419	0.0287	
	Mean Commute Time, in minutes (1990)	0.0091	0.0238		-0.0013	0.0236		-0.0525	0.0227	*
	Presence of Transit Stops	-0.0151	0.0135		-0.0056	0.0135		-0.0275	0.0127	*
	Presence of Transit Stops (neighbor)	*0.0437*	*0.0144*	**	*0.0014*	*0.0144*		*0.0231*	*0.0129*	
	Employees in Nearby Zip Code as % of total county employees	0.0324	0.0314		-0.0187	0.0314		0.0450	0.0301	
	Employees in Nearby Zip Code as % of total county employees (neighbor)	*-0.0305*	*0.0362*		*0.0365*	*0.0362*		*0.0154*	*0.0340*	
Consumption	Presence of Art Galleries	-0.0096	0.0087		-0.0054	0.0087		0.0214	0.0083	**
	Presence of Art Galleries (neighbor)	*-0.0493*	*0.0118*	**	*0.0372*	*0.0118*	*	*0.0333*	*0.0115*	**
	# Bookstores, log	0.0133	0.0092		0.0171	0.0092		-0.0058	0.0088	
	# Bookstores, log (neighbor)	*0.0468*	*0.0135*	**	*0.0102*	*0.0135*		*-0.0041*	*0.0128*	
	# Drycleaners, log	-0.0014	0.0075		0.0194	0.0075	*	0.0167	0.0072	*
	# Drycleaners, log (neighbor)	*-0.0077*	*0.0090*		*0.0330*	*0.0090*	**	*-0.0026*	*0.0086*	
	# Hardware Stores, log	0.0021	0.0086		0.0178	0.0086	*	-0.0052	0.0082	
	# Hardware Stores, log (neighbor)	*0.0050*	*0.0089*		*-0.0149*	*0.0089*		*-0.0087*	*0.0084*	

	# Hotels and Motels, log	0.0038	0.0140		0.0400	0.0140	*	0.0418	0.0131	**
	# Hotels and Motels, log (neighbor)	0.0059	0.0225		-0.0076	0.0225		0.0780	0.0204	**
	# Meat and Fish Stores, log	0.0030	0.0078		0.0160	0.0078	*	0.0134	0.0076	
	# Meat and Fish Stores, log (neighbor)	0.0330	0.0093	**	0.0197	0.0093	*	0.0256	0.0090	**
	Presence of Movie Theaters	0.0046	0.0089		0.0065	0.0089		-0.0037	0.0086	
	Presence of Movie Theaters (neighbor)	0.0068	0.0115		0.0197	0.0115		0.0301	0.0107	**
	# Photocopy Stores, log	-0.0251	0.0097	**	0.0167	0.0097		-0.0045	0.0094	
	# Photocopy Stores, log (neighbor)	-0.0388	0.0144	**	-0.0133	0.0144		0.0008	0.0136	
	# Supermarkets, log	0.0227	0.0101	*	-0.0079	0.0101		-0.0127	0.0098	
	# Supermarkets, log (neighbor)	0.0114	0.0114		0.0232	0.0114	*	-0.0379	0.0106	**
Public Services	Presence of Anchor Institutions	-0.0251	0.0090	**	-0.0065	0.0090		-0.0018	0.0087	
	Presence of Anchor Institutions (neighbor)	0.0076	0.0108		-0.0050	0.0108		0.0789	0.0426	
	# Social Service Establishments, normalized by population, log	-0.0229	0.0137		0.0112	0.0137		0.0053	0.0129	
	# Social Service Establishments, normalized by population, log (neighbor)	0.0023	0.0195		0.0036	0.0195		-0.0701	0.0171	**
	Presence of Employment Agencies	-0.0020	0.0070		0.0044	0.0070		-0.0028	0.0068	
	Presence of Employment Agencies (neighbor)	0.0300	0.0095	**	-0.0096	0.0095		0.0013	0.0092	
	Presence of Libraries	0.0051	0.0094		0.0029	0.0094		0.0095	0.0091	
	Presence of Libraries (neighbor)	0.0234	0.0102	*	-0.0184	0.0102		0.0161	0.0096	
	# of Fire Stations	-0.0012	0.0156		-0.0231	0.0156		0.0066	0.0154	
	# of Police Stations	0.0403	0.0106	**	-0.0060	0.0106		-0.0065	0.0105	
	HMDA % FHA Loans	-0.0161	0.0083		-0.0359	0.0083	**	0.0168	0.0074	*
	HMDA % FHA Loans (neighbor)	-0.0523	0.0117	**	-0.0277	0.0117		0.0837	0.0103	**
	LIHTC Units as % of total housing units	0.0936	0.0147	**	0.0321	0.0147	*	0.0057	0.0131	
	LIHTC Units as % of total housing units (neighbor)	-0.0163	0.0134		0.0005	0.0135		0.0278	0.0117	*
	Public Housing Units as % of total housing units	-0.0405	0.0264		-0.0767	0.0264	*	-0.0213	0.0219	
	Public Housing Units as % of total housing units (neighbor)	-0.0238	0.0118	*	0.0005	0.0119		-0.0386	0.0105	**
	TIF Area as % of total tract area	0.0250	0.0063	**	0.0212	0.0063	*	-0.0067	0.0060	
	% Age 0-18 (1990)	0.0248	0.0415		-0.0312	0.0415		-0.0603	0.0387	
Social Interactions	% Age 0-18 (1990) (neighbor)	0.1323	0.0529	*	0.0016	0.0533		0.0136	0.0450	
	% Age 19-34 (1990)	0.0049	0.0366		-0.0013	0.0371		0.0610	0.0349	
	% Age 19-34 (1990) (neighbor)	-0.0469	0.0401		0.0392	0.0401		-0.0644	0.0362	

% Age 65+ (1990)	0.0901	0.0314	**	-0.0292	0.0314		-0.0478	0.0298	
% Age 65+ (1990) (neighbor)	*0.0919*	*0.0311*	**	*0.1294*	*0.0311*	**	*-0.0018*	*0.0265*	
Median Household Income (1990)	0.1142	0.0347	**	-0.0024	0.0348		0.0401	0.0341	
Median Household Income (1990) (neighbor)	*-0.1880*	*0.0438*	**	*-0.0346*	*0.0438*		*-0.0319*	*0.0398*	
% Education more than High School (1990)	-0.0787	0.0440		-0.0070	0.0440		-0.0021	0.0412	
% Education more than High School (1990) (neighbor)	*0.1264*	*0.0538*	*	*-0.0713*	*0.0538*		*-0.0943*	*0.0456*	*
Unemployment Rate (1990)	0.0097	0.0291		0.0475	0.0291		-0.0042	0.0286	
Unemployment Rate (1990) (neighbor)	*0.1424*	*0.0378*	**	*-0.0266*	*0.0378*		*0.0051*	*0.0347*	
% Population Foreign Born (1990)	-0.0325	0.0371		-0.0424	0.0371		-0.0172	0.0348	
% Population Foreign Born (1990) (neighbor)	*-0.0442*	*0.0424*		*-0.0178*	*0.0424*		*-0.0355*	*0.0385*	
% Population Black (1990)	0.2169	0.0635	**	-0.1554	0.0635	*	0.3181	0.0624	**
% Population Black (1990) (neighbor)	*0.3352*	*0.0769*	**	*0.6233*	*0.0769*	**	*0.1409*	*0.0699*	*
% Population Hispanic (1990)	0.0881	0.0474		-0.0784	0.0474		0.2314	0.0437	**
% Population Hispanic (1990) (neighbor)	*0.2546*	*0.0531*	**	*0.2243*	*0.0531*	**	*0.0636*	*0.0470*	
HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0421	0.0093	**	0.1141	0.0093	**	-0.0025	0.0092	
HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.1606*	*0.0135*	**	*0.1380*	*0.0135*	**	*0.0653*	*0.0126*	**
HMDA Loan Approval Rate	0.0206	0.0088	*	-0.0194	0.0088	*	0.0516	0.0077	**
HMDA Loan Approval Rate (neighbor)	*0.1112*	*0.0148*	**	*0.0253*	*0.0148*		*0.1162*	*0.0131*	**
HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.0813	0.0286	**	-0.1290	0.0286	**	-0.1604	0.0237	**
HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.4053*	*0.0485*	**	*-0.1845*	*0.0485*	**	*-0.1771*	*0.0411*	**
HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.0208	0.0208		-0.0393	0.0208		-0.1307	0.0186	**
HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.2064*	*0.0271*	**	*-0.0509*	*0.0271*		*-0.1227*	*0.0244*	**
# Social Capital Organizations, normalized by population, log	-0.0043	0.0126		-0.0864	0.0126	**	0.0429	0.0117	**
# Social Capital Organizations, normalized by population, log (neighbor)	*-0.0856*	*0.0178*	**	*-0.1026*	*0.0178*	**	*0.0881*	*0.0158*	**
% Household Moved in less than 5 years ago (1990)	0.0610	0.0544		-0.2292	0.0544	**	-0.0884	0.0482	
% Household Moved in less than 5 years ago (1990) (neighbor)	*0.0446*	*0.0776*		*0.2110*	*0.0776*	*	*0.0354*	*0.0604*	
% Household Moved in over 10 years ago (1990)	0.0196	0.0547		-0.1279	0.0548	*	-0.1043	0.0494	*
% Household Moved in over 10 years ago (1990) (neighbor)	*0.0954*	*0.0776*		*0.1018*	*0.0776*		*0.0449*	*0.0618*	

Other									
HMDA % loans for owner-occupied units	0.0140	0.0063	*	0.0401	0.0063	**	0.0353	0.0058	**
HMDA % loans for owner-occupied units (neighbor)	*0.0619*	*0.0088*	**	*0.0015*	*0.0088*		*0.0805*	*0.0081*	**
Sub-prime loans as % of total home purchase loans	0.0210	0.0102	*	-0.0032	0.0102		0.0021	0.0087	
Sub-prime loans as % of total home purchase loans (neighbor)	*0.0445*	*0.0161*	**	*-0.0448*	*0.0161*	*	*-0.0292*	*0.0139*	*
Control Variables									
1995 (year dummy)	-0.0037	0.0052		-0.0127	0.0052	*	0.0234	0.0049	**
1996 (year dummy)	0.0124	0.0055	*	-0.0270	0.0055	**	0.0406	0.0052	**
1997 (year dummy)	0.0584	0.0060	**	-0.0029	0.0060		0.0636	0.0057	**
1998 (year dummy)	0.1142	0.0064	**	0.0318	0.0064	**	0.0890	0.0061	**
1999 (year dummy)	0.2034	0.0072	**	0.0804	0.0072	**	0.1220	0.0069	**
2000 (year dummy)	0.2770	0.0083	**	0.1259	0.0083	**	0.1441	0.0078	**
2001 (year dummy)	0.3338	0.0081	**	0.1658	0.0081	**	0.1382	0.0076	**
2002 (year dummy)	0.3933	0.0081	**	0.2214	0.0081	**	0.1330	0.0077	**
2003 (year dummy)	0.4687	0.0086	**	0.2752	0.0086	**	0.1786	0.0081	**
2004 (year dummy)	0.5436	0.0101	**	0.3219	0.0101	**	0.2109	0.0094	**
Intercept	-0.0143	0.0146		0.0091	0.0146		-0.0504	0.0144	**
# Observations	7916			8041			8458		
# Census Tracts	738			747			804		
R^2	0.73			0.44			0.31		

3 1999-2004 Time Series Models

Amenities		RSI	Std. Err.	Sig.	Quantity	Std. Error	Sig.
Transportation	Presence of Transit Stops	-0.0764	0.0487		-0.0176	0.0314	
	Presence of Transit Stops (neighbor)	*-0.0913*	*0.0326*	**	*-0.0456*	*0.0207*	*
	Employees in Nearby Zip Code as % of total county employees	-0.0118	0.0494		0.1268	0.0313	**
	Distance to closest employment sub-center	0.0045	0.0318		-0.0003	0.0201	
Consumption	Presence of Art Galleries	-0.0262	0.0177		0.0070	0.0113	
	# Bookstores, log	0.0179	0.0208		0.0064	0.0132	
	# Drycleaners, log	0.0026	0.0221		0.0038	0.0139	
	# Hardware Stores, log	-0.0442	0.0204	*	-0.0109	0.0126	
	# Hardware Stores, log (neighbor)	*-0.0852*	*0.0200*	**	*0.0021*	*0.0122*	
	# Hotels and Motels, log	-0.0152	0.0376		-0.0092	0.0229	
	# Hotels and Motels, log (neighbor)	*-0.0046*	*0.0442*		*0.0862*	*0.0270*	**
	# Meat and Fish Stores, log	0.0081	0.0237		0.0149	0.0145	
	Presence of Movie Theaters	-0.0204	0.0159		-0.0137	0.0102	
	Presence of Movie Theaters (neighbor)	*-0.0569*	*0.0190*	**	*0.0102*	*0.0124*	
	# Photocopy Stores, log	-0.0634	0.0229	**	-0.0602	0.0143	**
	# Supermarkets, log	-0.0004	0.0260		-0.0141	0.0162	
	# Supermarkets, log (neighbor)	*-0.0522*	*0.0268*		*0.0022*	*0.0168*	
Public Services	Presence of Anchor Institutions	-0.0237	0.0170		0.0049	0.0109	
	Presence of Anchor Institutions (neighbor)	*0.0642*	*0.0193*	**	*0.0256*	*0.0122*	*
	# Social Service Establishments, normalized by population, log	0.0673	0.0413		0.0217	0.0261	
	Presence of Employment Agencies	0.0130	0.0156		-0.0244	0.0099	**
	Presence of Employment Agencies (neighbor)	*0.1147*	*0.0208*	**	*0.0169*	*0.0129*	
	Presence of Libraries	0.0345	0.0222		-0.0054	0.0141	
	Presence of Libraries (neighbor)	*0.0580*	*0.0200*	**	*0.0469*	*0.0123*	**
	Park area as % of total tract area	0.0185	0.0245		-0.0140	0.0157	
	Park area as % of total tract area (neighbor)	*0.0837*	*0.0209*	**	*0.0101*	*0.0134*	
	Mean Elementary school math test score	0.0367	0.0112	**	-0.0178	0.0075	**
	HMDA % FHA Loans	-0.1371	0.0121	**	0.0053	0.0073	
	LIHTC Units as % of total housing units	-0.1483	0.0323	**	0.0361	0.0203	
	LIHTC Units as % of total housing units (neighbor)	*-0.1190*	*0.0261*	**	*-0.0035*	*0.0154*	
	Public Housing Units as % of total housing units	-0.0968	0.0767		-0.1346	0.0483	**
	Public Housing Units as % of total housing units (neighbor)	*-0.0283*	*0.0214*		*-0.0593*	*0.0125*	**
Social Interactions	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0882	0.0175	**	0.0275	0.0116	**
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.1770*	*0.0241*	**	*-0.0249*	*0.0147*	
	HMDA Loan Approval Rate	0.0367	0.0150	**	-0.0169	0.0093	
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.1879	0.0443	**	-0.1128	0.0258	**
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.6851*	*0.0675*	**	*-0.2919*	*0.0399*	**

	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	0.0389	0.0346		-0.1297	0.0211	**
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.1565*	*0.0518*	**	*-0.1840*	*0.0312*	**
	Income Diversity: standard deviation over mean income	0.0704	0.0130	**	-0.0023	0.0077	
	Mean Credit Available	-0.0104	0.0183		0.1980	0.0119	**
	Ratio of Balance to Credit Line	-0.0587	0.0137	**	-0.0230	0.0084	**
	% Population in Credit Database	0.0144	0.0128		0.0582	0.0083	**
	Total Bank Deposits, normalized by population, log	-0.0101	0.0268		0.0849	0.0164	**
	Homicide Rate	-0.0048	0.0092		-0.0081	0.0055	
	Violent Crime Rate	-0.0613	0.0344		-0.0078	0.0213	
	Property Crime Rate	0.0668	0.0557		-0.0446	0.0348	
	# Social Capital Organizations, normalized by population, log	-0.1140	0.0389	**	-0.0488	0.0246	*
Other							
	HMDA % loans for owner-occupied units	0.0975	0.0108	**	0.0300	0.0067	**
	Sub-prime loans as % of total home purchase loans	0.0862	0.0152	**	0.0307	0.0091	**
Control Variables							
	2000 (year dummy)	0.1149	0.0081	**	0.0068	0.0050	
	2001 (year dummy)	0.2175	0.0087	**	0.0175	0.0054	**
	2002 (year dummy)	0.3238	0.0099	**	0.0140	0.0061	*
	2003 (year dummy)	0.4325	0.0106	**	0.0588	0.0066	**
	2004 (year dummy)	0.5373	0.0122	**	0.0543	0.0076	**
	Intercept	-0.0366	0.0101	**	-0.0666	0.0066	**
	# Observations	7046			7267		
	# Census Tracts	1262			1306		
	R^2	0.71			0.24		

B. Specialized Drivers Models

1 Improvement in Place

Supply		RSI	Std. Err.	Sig.
	Population Density (1990)	0.02	0.07	
	% of Housing Units Built in 1980-1990	-0.10	0.06	*
Amenities				
Physical	% of Housing Units Vacant (1990)	-0.07	0.08	
	Mean Rooms per Housing Unit (1990)	0.04	0.07	
Transportation	Distance to CBD, in miles	-0.35	0.09	***
	Mean Commute Time, in minutes (1990)	0.08	0.10	
	Presence of Transit Stops	0.05	0.03	
	Presence of Transit Stops (neighbor)	*0.09*	*0.03*	***
	Employees in Nearby Zip Code as % of total county employees	-0.19	0.05	***
Consumption	Presence of Art Galleries	-0.04	0.04	
	Presence of Art Galleries (neighbor)	*0.15*	*0.05*	***
	# Bookstores, log	0.01	0.03	
	# Bookstores, log (neighbor)	*0.14*	*0.04*	***
	# Drycleaners, log	-0.01	0.03	
	# Drycleaners, log (neighbor)	*-0.06*	*0.04*	
	# Hardware Stores, log	-0.01	0.04	
	# Hardware Stores, log (neighbor)	*0.06*	*0.03*	*
	# Hotels and Motels, log	0.12	0.06	**
	# Hotels and Motels, log (neighbor)	*0.08*	*0.06*	
	# Meat and Fish Stores, log	-0.06	0.04	
	# Meat and Fish Stores, log (neighbor)	*0.01*	*0.04*	
	Presence of Movie Theaters (neighbor)	*0.05*	*0.03*	
	# Photocopy Stores, log	-0.08	0.05	
	# Photocopy Stores, log (neighbor)	*-0.06*	*0.04*	*
	# Supermarkets, log	0.00	0.04	
	# Supermarkets, log (neighbor)	*-0.05*	*0.04*	
Public Services	Presence of Anchor Institutions	-0.09	0.04	**
	Presence of Anchor Institutions	*0.04*	*0.04*	
	# Social Service Establishments, normalized by population, log	-0.02	0.04	
	# Social Service Establishments, normalized by population, log	*-0.06*	*0.06*	
	Presence of Employment Agencies	0.06	0.02	**
	Presence of Employment Agencies (neighbor)	*0.05*	*0.03*	
	Presence of Libraries	0.00	0.03	
	Presence of Libraries (neighbor)	*0.05*	*0.03*	
	HMDA % FHA Loans	0.10	0.03	***
	LIHTC Units as % of total housing units	0.07	0.04	*
	Public Housing Units as % of total housing units	-0.09	0.05	
	Public Housing Units as % of total housing units (neighbor)	*0.00*	*0.04*	
Social Interactions	% Age 0-18 (1990)	-0.07	0.12	
	% Age 19-34 (1990)	0.00	0.10	
	% Age 65+ (1990)	0.01	0.12	
	Median Household Income (1990)	-0.15	0.12	
	% Education more than High School (1990)	-0.09	0.10	
	Unemployment Rate (1990)	0.29	0.09	***
	% Population Foreign Born (1990)	0.04	0.12	
	% Population Black (1990)	-0.07	0.15	
	% Population Hispanic (1990)	-0.02	0.12	
	HMDA Median Income of borrowers (originated loans, owner-occupied)	-0.01	0.02	
	HMDA Loan Approval Rate	-0.02	0.03	

	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.32	0.10	***
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.19	0.07	***
	# Social Capital Organizations, normalized by population, log	0.01	0.05	
	# Social Capital Organizations, normalized by population, log (neighbor)	*-0.11*	*0.05*	**
	% Household Moved in less than 5 years ago (1990)	-0.33	0.13	**
	% Household Moved in over 10 years ago (1990)	-0.18	0.14	
Other				
	HMDA % loans for owner-occupied units	-0.04	0.02	
	Sub-prime loans as % of total home purchase loans	0.07	0.03	**
Control Variables				
	1995 (year dummy)	0.05	0.02	**
	1996 (year dummy)	0.08	0.02	***
	1997 (year dummy)	0.15	0.03	***
	1998 (year dummy)	0.27	0.03	***
	1999 (year dummy)	0.38	0.03	***
	2000 (year dummy	0.46	0.03	***
	Cleveland (dummy)	-0.02	0.09	
	Dallas (dummy)	-0.46	0.10	***
	Intercept	0.00	0.04	
	# Observations	935		
	# Census Tracts	135		
	R^2	0.60		

2 Immigrant Communities

Amenities		RSI	Std. Err.	Sig.	Chi2	Bonferroni p-value
Transportation	Presence of Transit Stops	-0.0088	0.0124			
	Interaction	-0.0466	0.0850		0.30	1
	Presence of Transit Stops (neighbor)	*0.0014*	*0.0120*			
	Interaction	*0.0636*	*0.0701*		*0.82*	*1*
	Employees in Nearby Zip Code as % of total county employees	-0.0855	0.0190	***		
	Interaction	0.3697	0.1079	***	11.75	0.0293
Consumption	Presence of Art Galleries	0.0174	0.0076	**		
	Interaction	-0.0165	0.0260		0.40	1
	# Bookstores, log	0.0157	0.0083	*		
	Interaction	-0.0255	0.0240		1.14	1
	# Drycleaners, log	0.0031	0.0067			
	Interaction	0.0055	0.0167		0.11	1
	# Hardware Stores, log	-0.0192	0.0077	**		
	Interaction	0.0338	0.0231		2.15	1
	# Hardware Stores, log (neighbor)	*-0.0227*	*0.0081*	***		
	Interaction	*0.0434*	*0.0240*	*	*3.26*	*1*
	# Hotels and Motels, log	-0.0406	0.0123	***		
	Interaction	-0.0361	0.0520		0.48	1
	# Hotels and Motels, log (neighbor)	*-0.1400*	*0.0188*	***		
	Interaction	*0.0966*	*0.0751*		*1.65*	*1*
	# Meat and Fish Stores, log	0.0000	0.0075			
	Interaction	0.0129	0.0210		0.38	1
	Presence of Movie Theaters	0.0091	0.0062			
	Interaction	-0.0107	0.0201		0.28	1
	Presence of Movie Theaters (neighbor)	*0.0267*	*0.0073*	***		
	Interaction	*-0.0778*	*0.0384*	**	*4.11*	*1*
	# Photocopy Stores, log	-0.0061	0.0084			
	Interaction	-0.0572	0.0322	*	3.15	1
	# Supermarkets, log	0.0242	0.0097	**		
	Interaction	0.0165	0.0387		0.18	1
	# Supermarkets, log (neighbor)	0.0431	0.0110	***		
	Interaction	0.0202	0.0365		*0.31*	*1*
Public Services	Presence of Anchor Institutions	-0.0177	0.0084	**		
	Interaction	0.0529	0.0264	**	4.00	1

	Presence of Anchor Institutions (neighbor)	*0.0447*	*0.0099*	***		
	Interaction	*-0.0250*	*0.0291*		*0.74*	*1*
	# Social Service Establishments, normalized by population, log	-0.0114	0.0134			
	Interaction	0.0782	0.0610		1.64	1
	Presence of Employment Agencies	-0.0047	0.0063			
	Interaction	0.0078	0.0191		0.17	1
	Presence of Employment Agencies (neighbor)	*0.0102*	*0.0087*			
	Interaction	*-0.0300*	*0.0298*		*1.01*	*1*
	Presence of Libraries	-0.0035	0.0085			
	Interaction	0.0321	0.0301		1.14	1
	Presence of Libraries (neighbor)	*0.0154*	*0.0088*	*		
	Interaction	*-0.0297*	*0.0320*		*0.80*	*1*
	HMDA % FHA Loans	-0.0274	0.0059	***		
	Interaction	-0.0274	0.0185		2.19	1
	LIHTC Units as % of total housing units	0.0594	0.0135	***		
	Interaction	-0.0003	0.0581		0.00	1
	LIHTC Units as % of total housing units (neighbor)	*-0.0084*	*0.0105*			
	Interaction	*-0.1720*	*0.0438*	***	*15.42*	*0.0041*
	Public Housing Units as % of total housing units	-0.1003	0.0508	**		
	Interaction	0.1846	0.6719		0.08	1
	Public Housing Units as % of total housing units (neighbor)	*0.0429*	*0.0127*	***		
	Interaction	*-0.0088*	*0.0343*		*0.07*	*1*
Social Interactions	HMDA Median Income of borrowers (originated loans, owner-occupied)	0.0943	0.0133	***		
	Interaction	0.0096	0.0310		0.10	1
	HMDA Median Income of borrowers (originated loans, owner-occupied) (neighbor)	*0.1912*	*0.0134*	***		
	Interaction	*-0.0069*	*0.0364*		*0.04*	*1*
	HMDA Loan Approval Rate	0.0373	0.0069	***		
	Interaction	-0.0006	0.0235		0.00	1
	HMDA % Applicants Race: Black (originated loans, owner-occupied)	-0.2205	0.0208	***		
	Interaction	0.0311	0.0875		0.13	1
	HMDA % Applicants Race: Black (originated loans, owner-occupied) (neighbor)	*-0.6929*	*0.0329*	***		
	Interaction	*0.0989*	*0.1218*		*0.66*	*1*
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied)	-0.0595	0.0167	***		
	Interaction	-0.0262	0.0415		0.40	1
	HMDA % Applicants Race: Hispanic (originated loans, owner-occupied) (neighbor)	*-0.2972*	*0.0228*	***		
	Interaction	*-0.1283*	*0.0565*	**	*5.16*	*1*
	# Social Capital Establishments, normalized by population	-0.0231	0.0125	*		
	Interaction	0.0215	0.0483		0.20	1

Other						
	HMDA % loans for owner-occupied units	0.0194	0.0048	***		
	Interaction	0.0128	0.0184		0.48	1
	Sub-prime loans as % of total home purchase loans	0.0721	0.0067	***		
	Interaction	-0.0853	0.0290	***	8.65	0.1572
Control Variables						
	1995 (dummy)	0.0225	0.0040	***		
	Interaction	-0.0018	0.0124		0.02	1
	1996 (dummy)	0.0555	0.0041	***		
	Interaction	-0.0136	0.0127		1.14	1
	1997 (dummy)	0.1077	0.0043	***		
	Interaction	-0.0178	0.0132		1.83	1
	1998 (dummy)	0.1765	0.0046	***		
	Interaction	-0.0212	0.0142		2.22	1
	1999 (dummy)	0.2670	0.0049	***		
	Interaction	-0.0040	0.0152		0.07	1
	2000 (dummy)	0.3363	0.0054	***		
	Interaction	0.0117	0.0170		0.47	1
	2001 (dummy)	0.3945	0.0055	***		
	Interaction	0.0444	0.0172	***	6.69	0.4652
	2002 (dummy)	0.4452	0.0056	***		
	Interaction	0.0805	0.0178	***	20.58	0.0003
	2003 (dummy)	0.5026	0.0058	***		
	Interaction	0.1135	0.0185	***	37.84	0
	2004 (dummy)	0.5639	0.0065	***		
	Interaction	0.1313	0.0209	***	39.55	0
	Intercept	0.0204	0.0115	*		
	# Observations	14108				
	# Census Tracts	1325				
	R^2	0.86				
	Interaction Test	df = 48			7.14	0

APPENDIX I

DNT Neighborhood Typology: Methodology, Tables and Maps

A. Methodology

Variable Selection

Before finalizing the typology, the project experimented with several different methods (including regression trees, EM algorithms, and k-means and hierarchical clustering) as well as different combinations of variables, testing the results based on statistical criteria as well as feedback from local partners in each of the four cities. In particular, as we neared a final iteration, typology outputs were evaluated based on how well they seemed to group together neighborhoods that are perceived as fundamentally similar by the people who know them best.

In addition to the feedback from local partners, criteria for the selection of the variables included their importance in the Drivers models, their relevance to defining neighborhood types, and the availability and reliability of the data.

At the end, the typology is based on the two basic dimensions that characterize neighborhoods: "People" (i.e. the characteristics of the residents of a neighborhood) and "Place" (i.e. the characteristics of the built environment of the neighborhood, including business presence, housing stock, and so forth.) Each of these dimensions was given equal weight in the typology, to ensure that both categories are equally important in determining the final neighborhood groupings regardless of how many variables were chosen under either category.

Before selecting actual variables, the project identified within each dimension a set of sub-categories that appeared to define neighborhood type. For example, within the "People" dimension, "Age Structure" is a sub-category that contains all the different age group variables. Again, each of these sub-categories was given equal weight within its dimension.[12]

This layered structure—composed of dimensions, sub-categories, and variables—helps ensure that each factor is given appropriate weight in determining neighborhood type regardless of how many variables are used to measure it. For example, if the sub-category "Age Structure" included four age brackets, and thus four different variables, and "Income Diversity" included only one variable, a non-weighted version of the typology would give "Age Structure" four times more importance than "Income Diversity." By weighting the variables within each sub-category and dimension, all sub-categories become equally important.

[12] The only exception is Income, which was weighed more heavily since it affects so many other neighborhood characteristics.

The final hierarchy of categories, subcategories and variables, along with their final weights, is displayed in the table below.

Dimension	Sub-Category	Variable	Weight	Data Source
People	Income	Median income	1/6	Census
	Diversity	Herfindahl index of Census groups	1/12	Census
	Age Structure	% Age 0-18	1/48	Census
		% Age 19-34	1/48	Census
		% Age 35-64	1/48	Census
		% Age 65 and up	1/48	Census
	Household	% Single parent households	1/12	Census
	Foreign	% Foreign born	1/12	Census
	Turnover	% Households moved in less than 5 years	1/24	Census
		% Households moved in over 10 years	1/24	Census
Place	Housing Type	% Single family units	1/18	Census
	Vacancy Rates	% Vacant housing units	1/18	Census
	Tenure	% Owner	1/18	Census
	Housing Age	Median age of housing stock	1/18	Census
	Land Use	% Residential parcels	1/54	County land use data
		% Vacant parcels	1/54	County land use data
		% Industrial parcels	1/54	County land use data
	"Social Capital" Establishments	# Social capital establishments normalized by population	1/18	Dun and Bradstreet
	Retail Diversity	Number of unique business types	1/18	Dun and Bradstreet
	Regional Retail	% Businesses with more than 20 employees	1/18	Dun and Bradstreet
	Retail and Service Presence	# Retail establishments normalized by area	1/54	Dun and Bradstreet
		# Services establishments normalized by area	1/54	Dun and Bradstreet
		# Entertainment establishments normalized by area	1/54	Dun and Bradstreet

Clustering Method

In selecting the observations, each census tract in each of the four cities is treated as two separate instances, one for each year of available data (1990 and 2000). By doing so, we were able to type all neighborhoods across time and observe whether and how neighborhoods changed type between 1990 and 2000.

After experimenting with a variety of statistical techniques, the typology was then developed using hybrid hierarchical clustering.[13] This methodology was chosen because it combines some of the advantages of K-means clustering with the hierarchical structure that can be obtained by using hierarchical clustering. In other words, this method enabled us to identify stable broad neighborhood types as well as to "drill down" from very broad types to very detailed sub-clusters within each type. At the same time, this methodology enables us to look at neighborhood types "from the bottom up:" for any given census tract, the clustering can identify which individual tracts are most similar along the selected dimensions, which can be especially useful for the purposes of peer analysis for particular neighborhoods.

B. Table of Means

The table below provides a summary of the mean values of all the variables used in the clustering algorithm, as well as of select variables used for the profiling of each of the neighborhood types. The cells are color-coded as follows: light red indicates values below the overall mean, and light blue indicates values above the overall mean; dark red means very low (below the 20th percentile), and dark blue means very high (above the 80th percentile). The first two rows of the table also include the total number of tracts that fall in each type as well as the within-cluster variance. A higher score on this metric indicates that the cluster is less homogeneous.

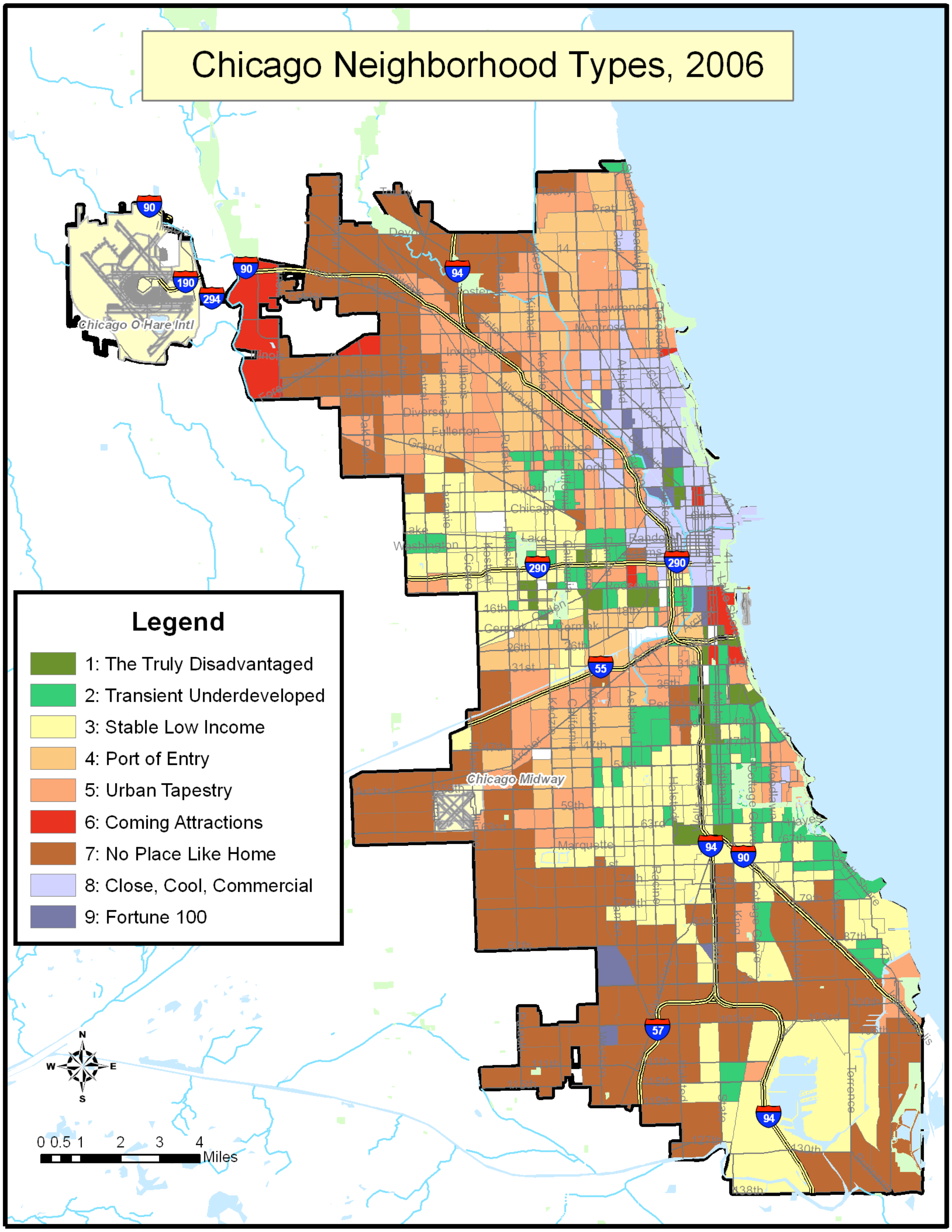
[13] Chipman, H. and Tibshirani, R. (2006) "Hybrid Hierarchical Clustering with Applications to Microarray Data", *Biostatistics*, Vol. 7, pp. 302-317.

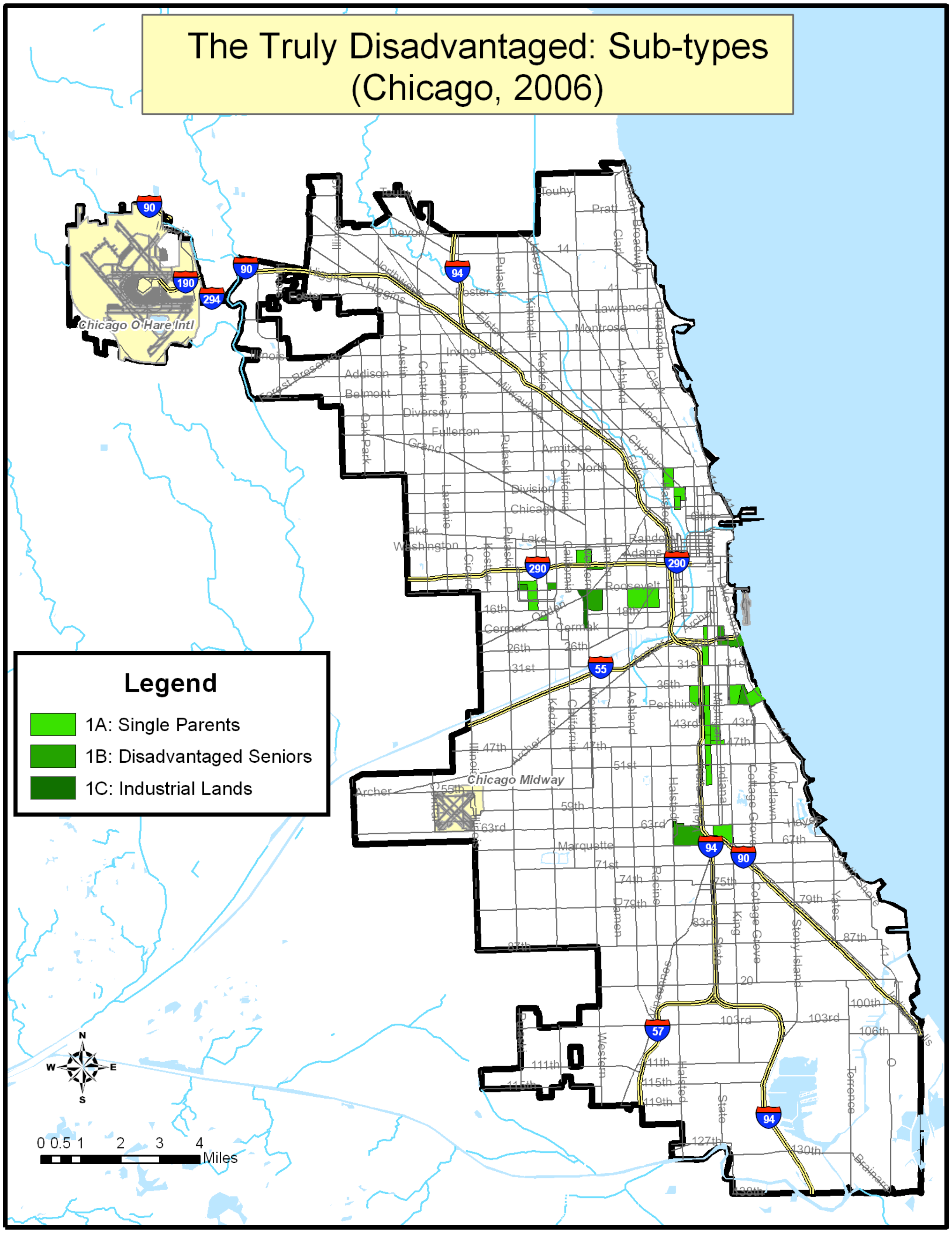
Cluster	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8	Type 9
Name	The Truly Disadvan-taged	Transient Under-Developed	Low Income Stable	Port of Entry	Urban Tapestry	Coming Attractions	No Place Like Home	Close, Cool, Commercial	Fortune 100
# Tract-Years	170	352	546	278	373	153	711	234	117
Within-Cluster Variance	2.4	1.18	0.73	0.76	0.67	1.05	0.76	1.6	2.29
Clustering Variable									
Median Household Income (in 2000 dollars)	9950	20900	23800	32200	37300	39900	45400	51700	100000
Income Diversity (1 - Herfindahl Index of Census Income Groupings)	0.512	0.808	0.842	0.891	0.901	0.905	0.908	0.11	0.16
% Age 0-18	0.397	0.312	0.343	0.311	0.254	0.159	0.251	0.096	0.229
% Age 19-34	0.237	0.283	0.232	0.318	0.313	0.438	0.24	0.479	0.183
% Age 35-64	0.25	0.301	0.319	0.298	0.33	0.322	0.367	0.335	0.446
% Age 65+	0.132	0.117	0.115	0.0833	0.114	0.0905	0.154	0.0995	0.154
% Single Parent Households	0.361	0.196	0.232	0.11	0.0917	0.0619	0.0811	0.0253	0.0346
% Foreign Born	0.0221	0.124	0.028	0.451	0.235	0.169	0.122	0.118	0.0702
% Moved in Less than 5 Years	0.526	0.603	0.417	0.601	0.553	0.776	0.387	0.726	0.433
% Moved in Over 10 Years	0.296	0.254	0.44	0.246	0.307	0.12	0.478	0.161	0.41
% Single Family Detached	0.0845	0.125	0.324	0.169	0.252	0.148	0.707	0.115	0.736
% Vacant Housing Units	0.212	0.167	0.126	0.0822	0.0737	0.105	0.048	0.0801	0.0449
% Home Owner	0.0855	0.178	0.364	0.288	0.397	0.215	0.687	0.291	0.766
Median Age of Housing Stock	38.4	45.1	51.2	49.5	51.2	18.8	42	46.8	33.8
Land Use: % Residential	0.337	0.581	0.702	0.723	0.787	0.759	0.885	0.729	0.839
Land Use: % Vacant	0.222	0.158	0.176	0.0713	0.0528	0.0877	0.066	0.0352	0.0966
Land Use: % Industrial	0.0665	0.0425	0.026	0.0333	0.0298	0.0189	0.0111	0.0294	0.017
Social Capital per person	0.0034	0.00245	0.0023	0.00109	0.00116	0.00162	0.00132	0.00558	0.00254
Retail Diversity (# Unique Retailer Types)	11	18.9	12.5	31.9	24.3	44.2	29.2	46.2	36.6
% Regional Business (greater than 20 employees)	0.366	0.672	0.288	1.39	0.908	1.45	0.672	2.35	0.807
Retail Concentration (per tract area)	3.02	3.75	3.07	4.48	3.86	3.84	3.16	5.05	3.28
Services Concentration (per tract area)	3.47	3.93	3.23	4.49	4.23	4.23	3.55	5.48	3.46
Entertainment Venues (per tract area)	1.9	2.76	1.87	3.53	3.16	2.95	2.22	4.63	2.13
Profile Variable (Year 2000 Values)									
Distance to CBD (normalized by farthest distance in each city)	0.171	0.264	0.354	0.306	0.351	0.43	0.552	0.197	0.411
% Race: White	0.0304	0.146	0.102	0.21	0.432	0.551	0.492	0.75	0.825
% Race: Black	0.924	0.643	0.819	0.081	0.133	0.197	0.297	0.0894	0.0889
% Race: Hispanic	0.0299	0.188	0.0693	0.602	0.346	0.158	0.166	0.0868	0.0586
% Unemployed	0.347	0.19	0.192	0.0932	0.0743	0.0523	0.0698	0.0523	0.0339

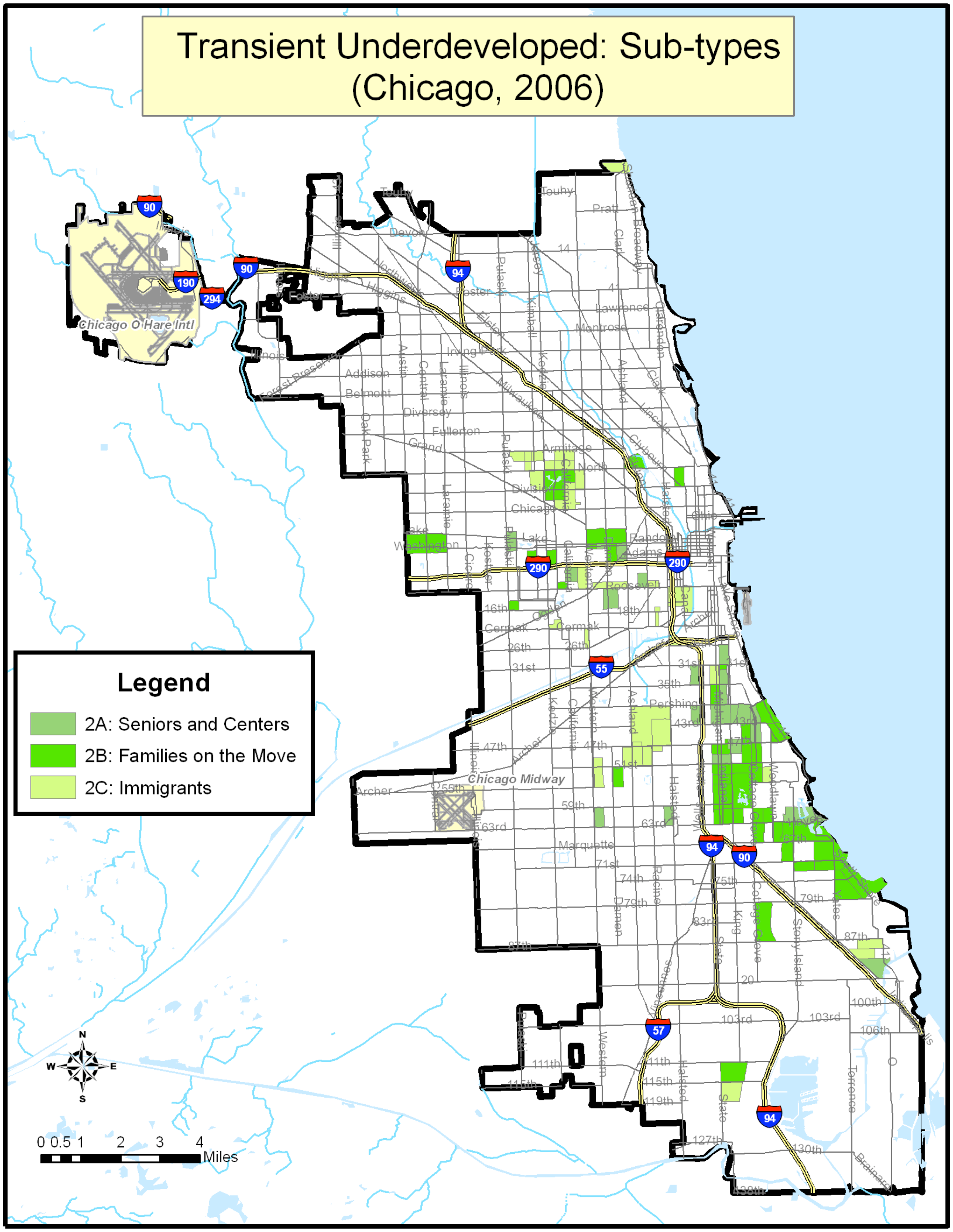
% No High School Diploma	0.487	0.408	0.376	0.474	0.283	0.138	0.226	0.0843	0.0359
% More than High School Diploma	0.224	0.344	0.325	0.319	0.496	0.704	0.516	0.821	0.878
% Occupation: Professional	0.161	0.324	0.258	0.261	0.413	0.53	0.402	0.67	0.708
% Occupation: Services	0.277	0.19	0.206	0.179	0.134	0.11	0.138	0.074	0.0468
% Occupation: Sales / Office	0.281	0.237	0.26	0.196	0.225	0.237	0.242	0.199	0.195
% Occupation: Construction	0.082	0.0719	0.0811	0.123	0.0752	0.0536	0.0833	0.0236	0.0158
% Occupation: Production/Transportation	0.198	0.175	0.195	0.238	0.151	0.0673	0.134	0.0327	0.0348
Credit Limit (in $K)	9.05	18.9	18.1	31.1	49	42.8	57	78.4	139
Balance to Credit Ratio	0.674	0.565	0.589	0.394	0.375	0.396	0.384	0.329	0.272
% Credit Lines Past Due	0.227	0.314	0.39	0.243	0.263	0.263	0.33	0.188	0.148
Crime Rate: Homicide	0.00086	0.000408	0.0004	0.000167	9.3E-05	0.00022	9.33E-05	0.000074	0.000129
Crime Rate: Violent	0.0785	0.045	0.0368	0.0234	0.016	0.0385	0.0163	0.0308	0.0326
Crime Rate: Property	0.393	0.283	0.205	0.197	0.163	0.215	0.14	0.35	0.319
HMDA Owner-Occ Median Income of Borrower (in $K)	57.8	56	40.4	54.9	70.7	68.2	56	99.4	145
HMDA Non-Owner-Occ Median Income of Borrower (in $K)	116	85.4	64.1	80.4	110	116	93.3	167	154
HMDA % Owner-Occ	0.784	0.792	0.785	0.899	0.906	0.9	0.935	0.903	0.958
HMDA % Non-Owner-Occ Loan	0.216	0.208	0.215	0.101	0.0937	0.1	0.065	0.0966	0.0419
Land Use: Commercial	0.114	0.0847	0.044	0.0878	0.0596	0.16	0.0387	0.135	0.0428
Land Use: Mixed Use	0.0058	0.0114	0.0093	0.00874	0.00836	0.002	0.00265	0.0089	0.000826
# Foreclosures	1.69	5.02	14.4	5.26	4.25	3.33	16.2	1.56	2.73
# Forclosures (per number of housing units)	0.00361	0.00648	0.0163	0.00353	0.0034	0.00152	0.0106	0.000892	0.00226
Public Housing (per number of housing units)	0.745	0.112	0.0497	0.0167	0.0141	0.0115	0.00283	0.0506	0.0126
LIHTC Housing (per number of housing units)	0.0772	0.0593	0.0245	0.0241	0.0109	0.0344	0.00713	0.0123	0.00038
Median Value of Owner-Occupied Homes	94600	119000	79200	134000	174000	162000	137000	279000	349000

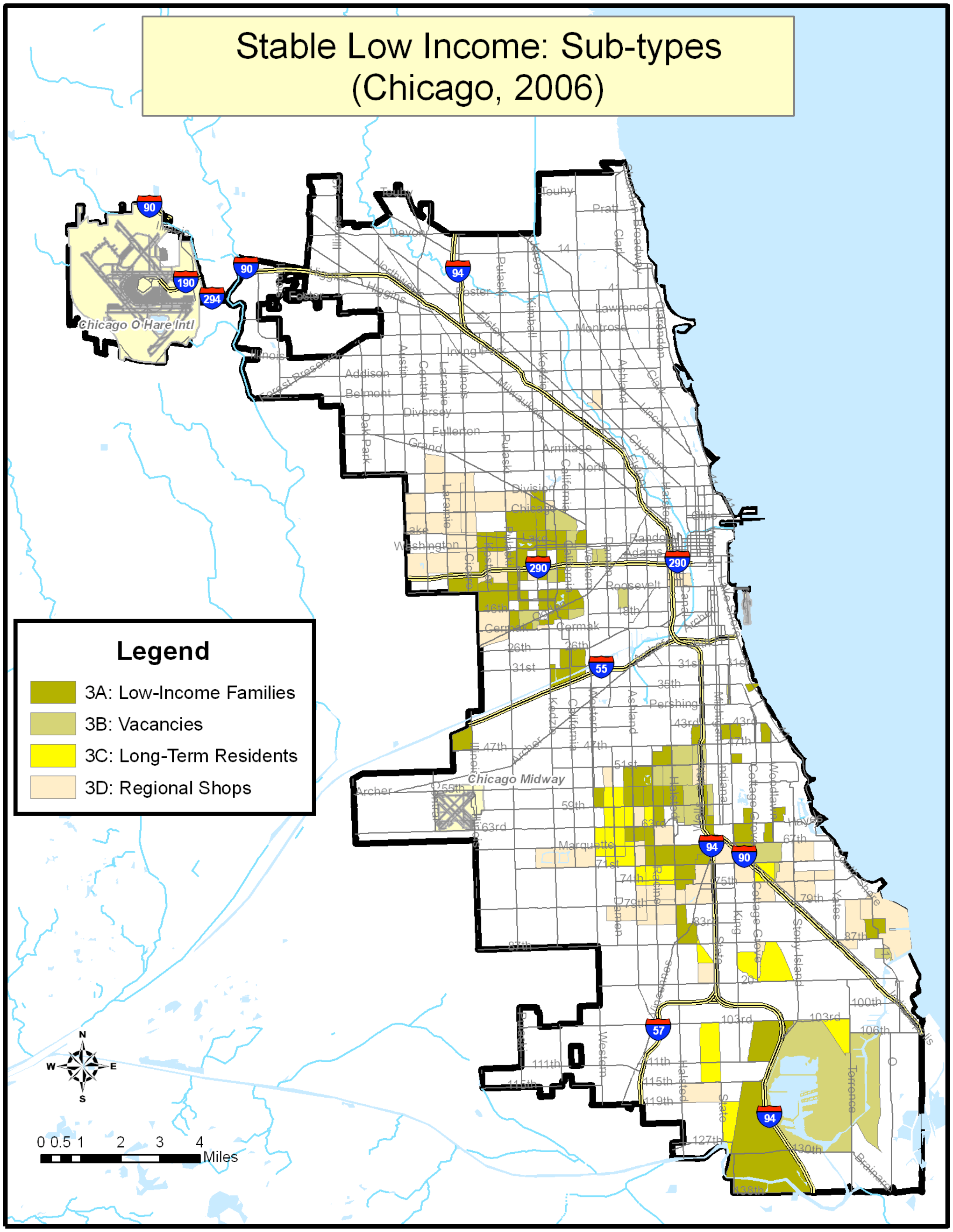
C. Maps

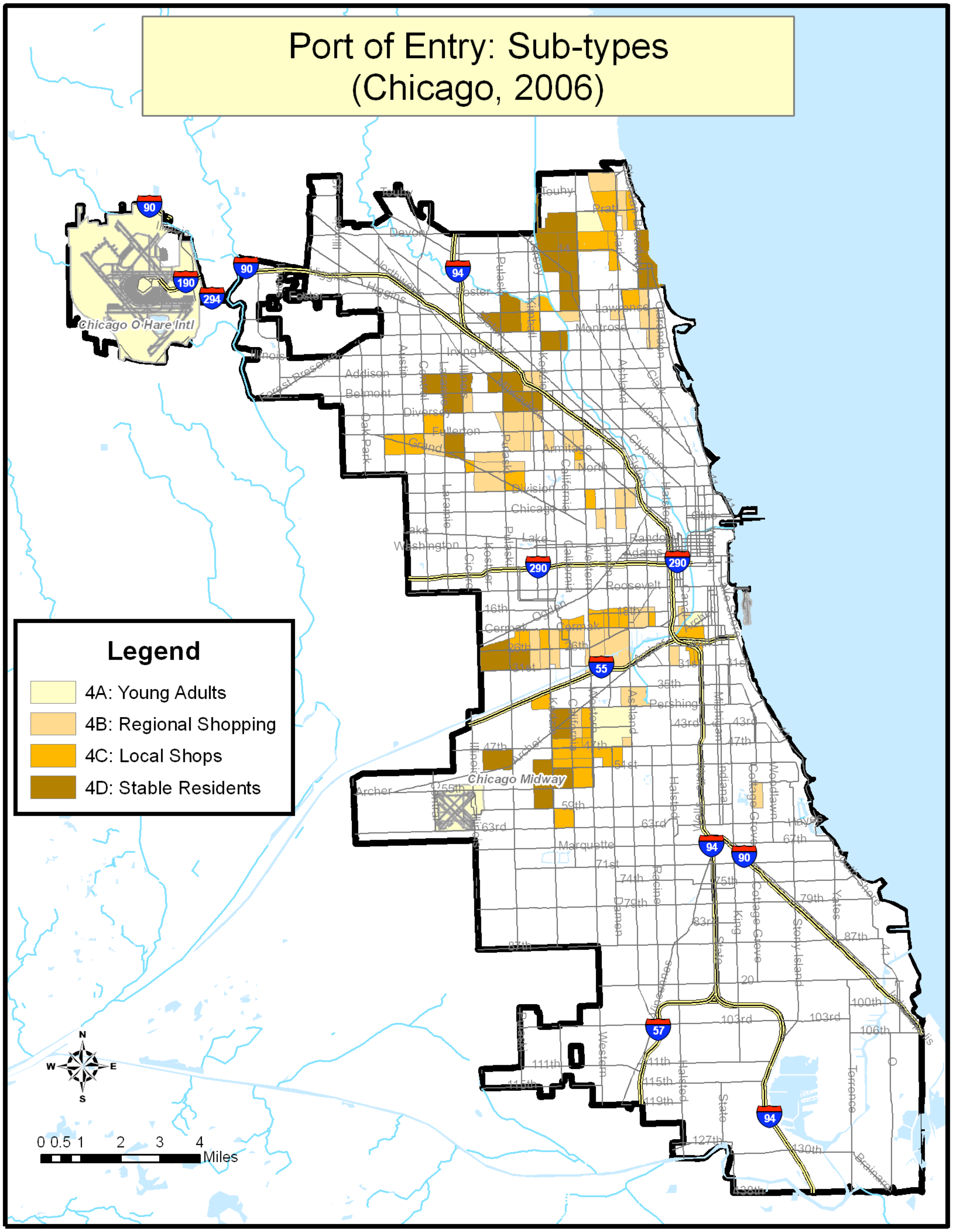
The maps below are arranged in alphabetical order by city. The maps are organized by type, from Type 1 to Type 9. Each city's individual type maps are preceded by the map showing all types in the city. Because not all types are present in all cities, only maps for types that are present are included for each city.

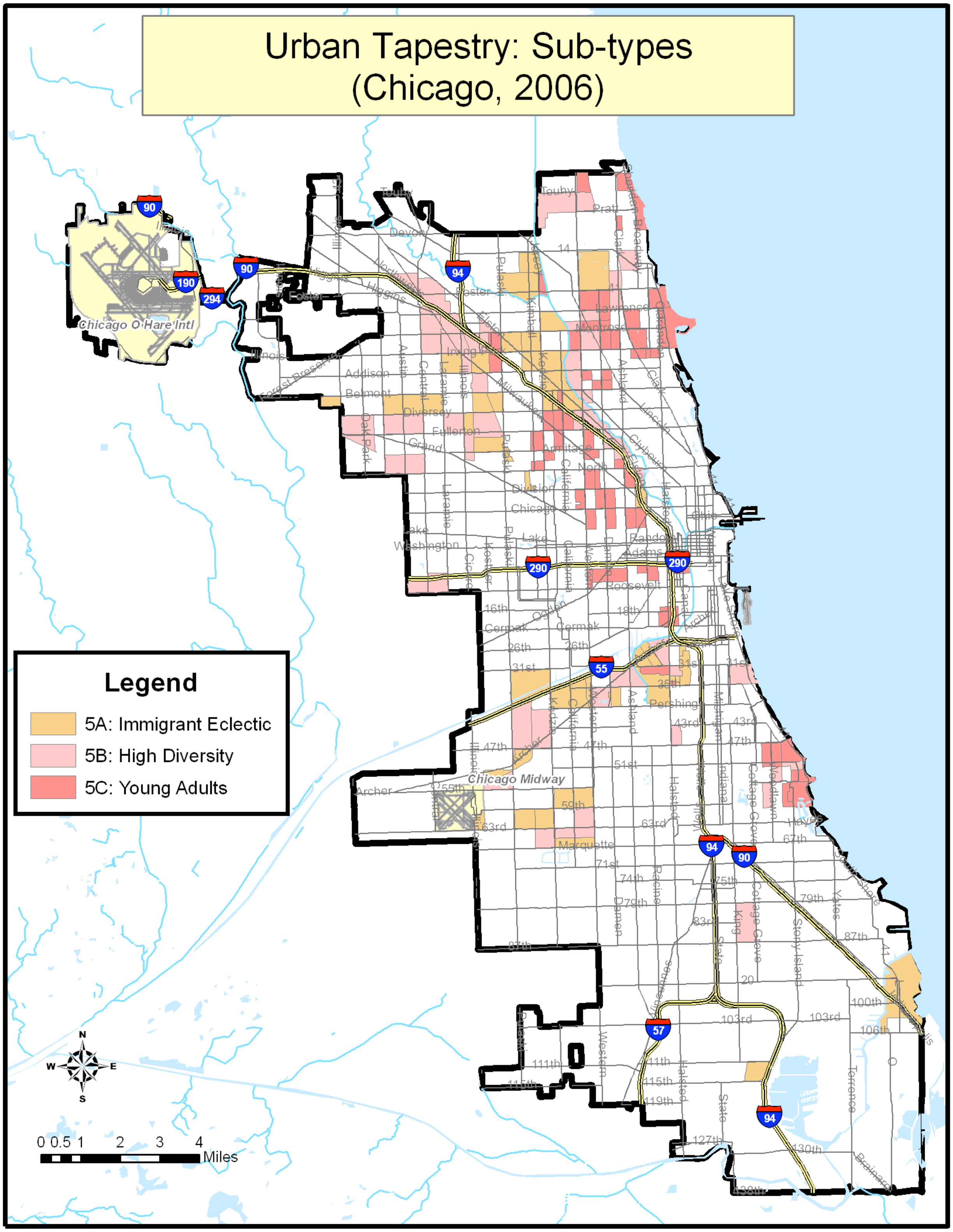

Chicago Neighborhood Types, 2006
Legend
1: The Truly Disadvantaged
2: Transient Underdeveloped
3: Stable Low Income
4: Port of Entry
5: Urban Tapestry
6: Coming Attractions
7: No Place Like Home
8: Close, Cool, Commercial
9: Fortune 100
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

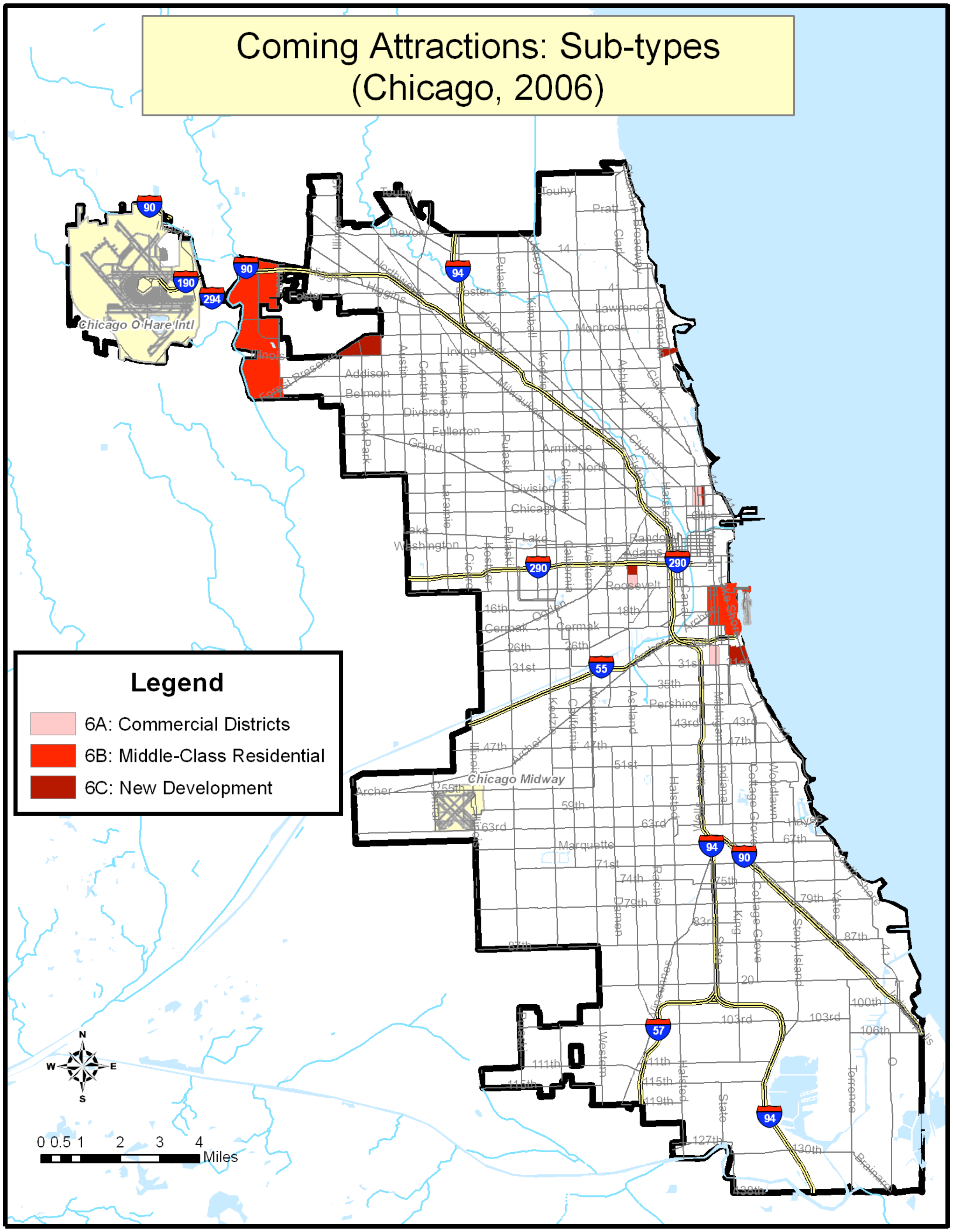

The Truly Disadvantaged: Sub-types
(Chicago, 2006)
Legend
1A: Single Parents
1B: Disadvantaged Seniors
1C: Industrial Lands
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

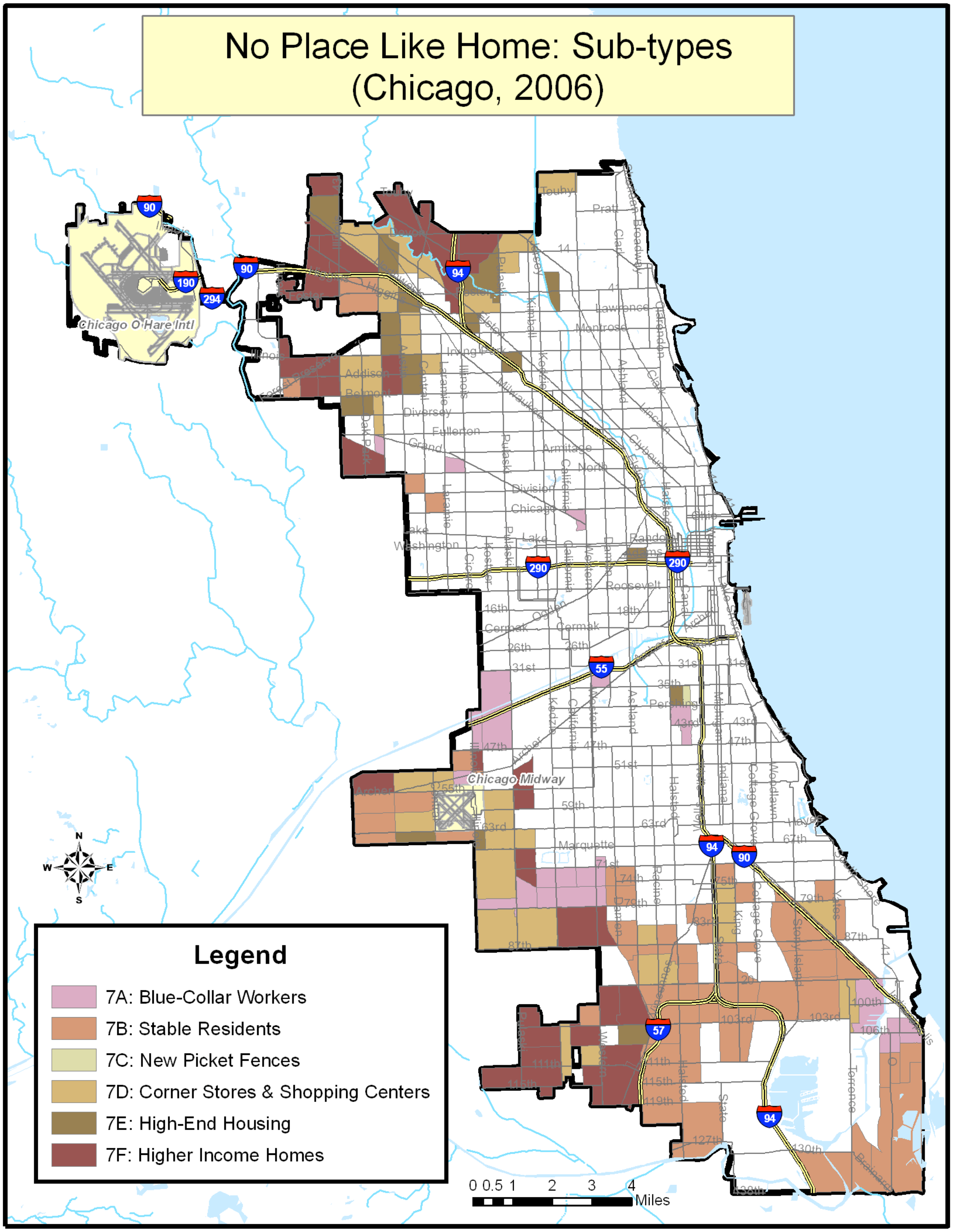

Transient Underdeveloped: Sub-types
(Chicago, 2006)
Legend
2A: Seniors and Centers
2B: Families on the Move
2C: Immigrants
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

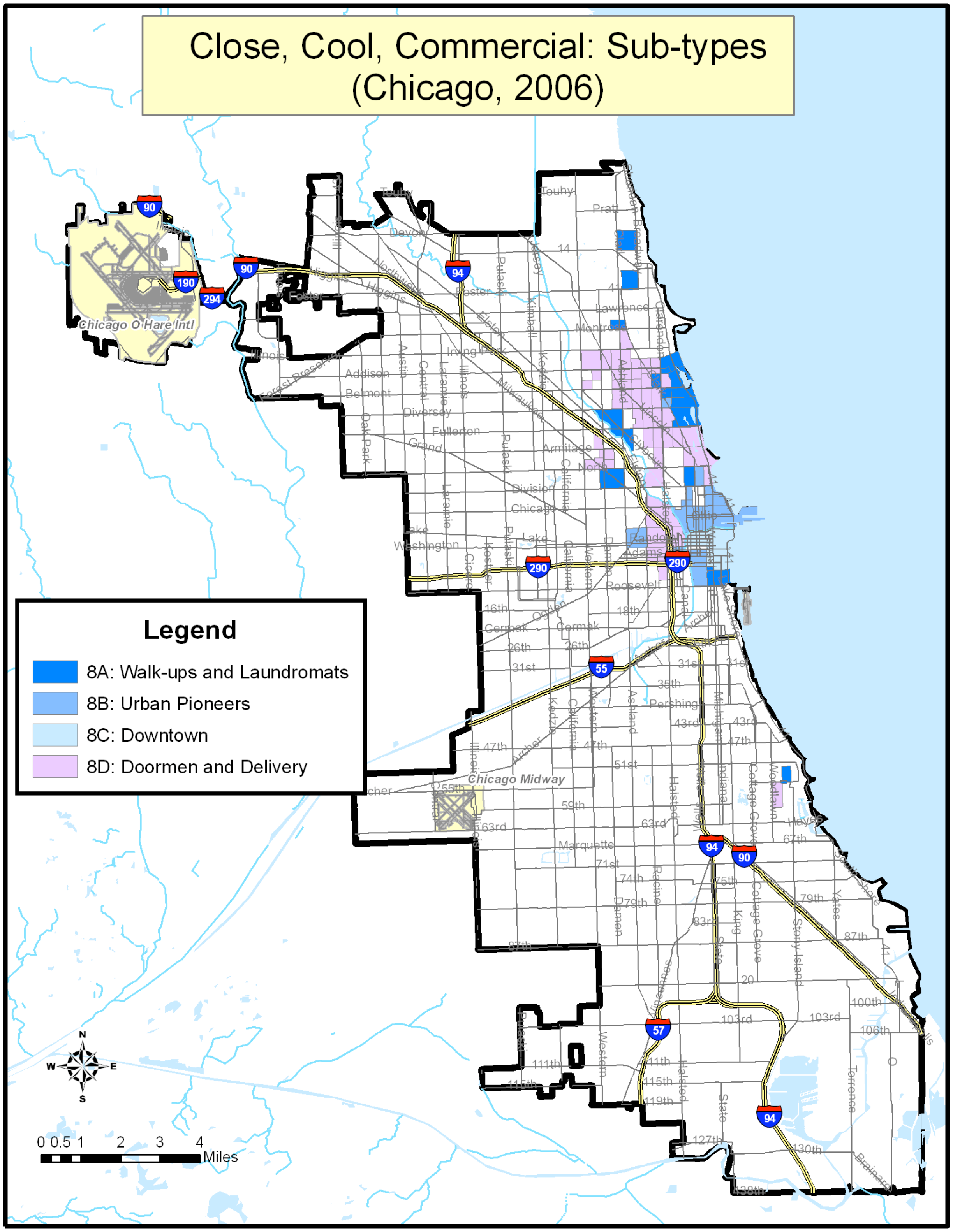

Stable Low Income: Sub-types
(Chicago, 2006)
Legend
3A: Low-Income Families
3B: Vacancies
3C: Long-Term Residents
3D: Regional Shops
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

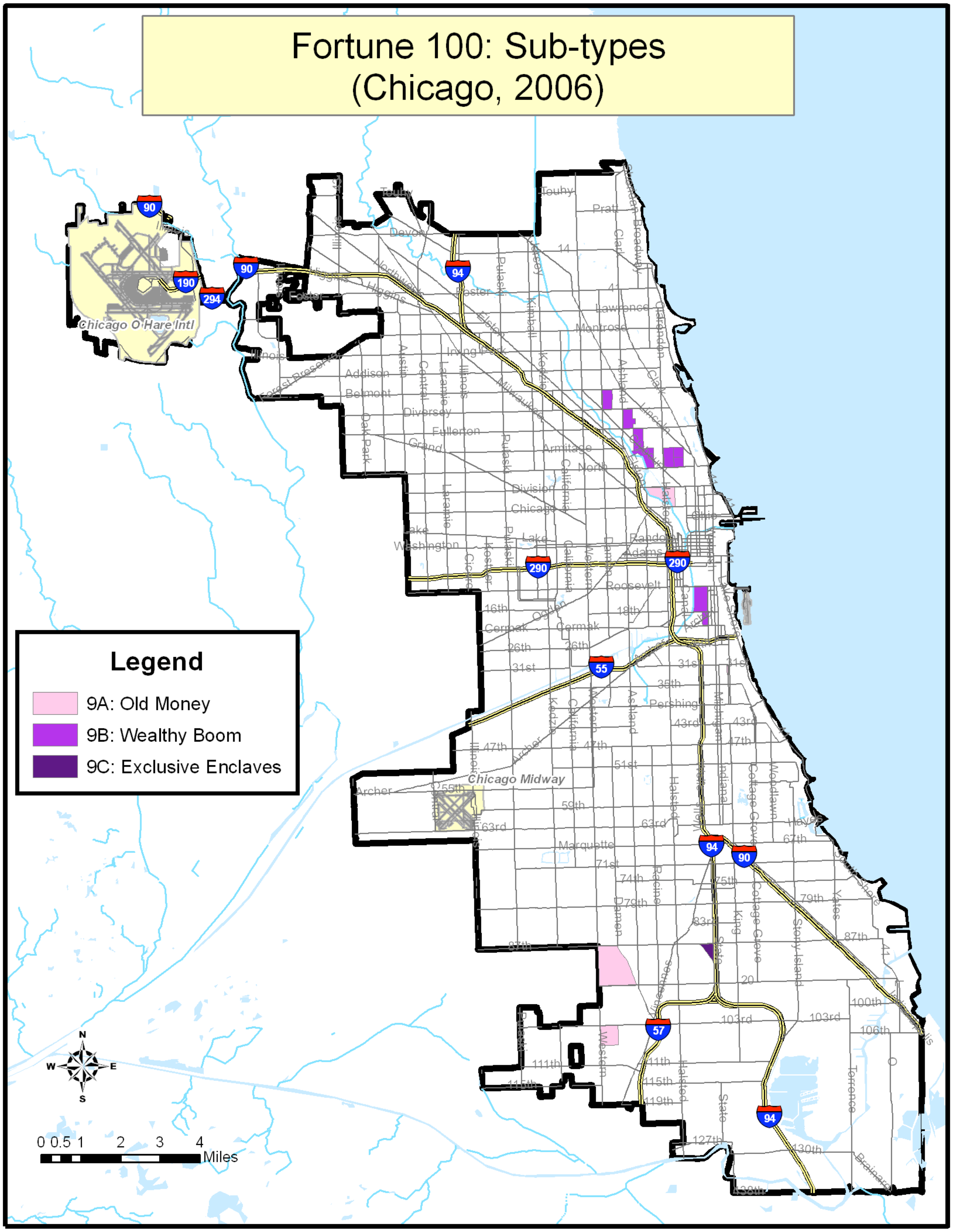

Port of Entry: Sub-types
(Chicago, 2006)
Legend
4A: Young Adults
4B: Regional Shopping
4C: Local Shops
4D: Stable Residents
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

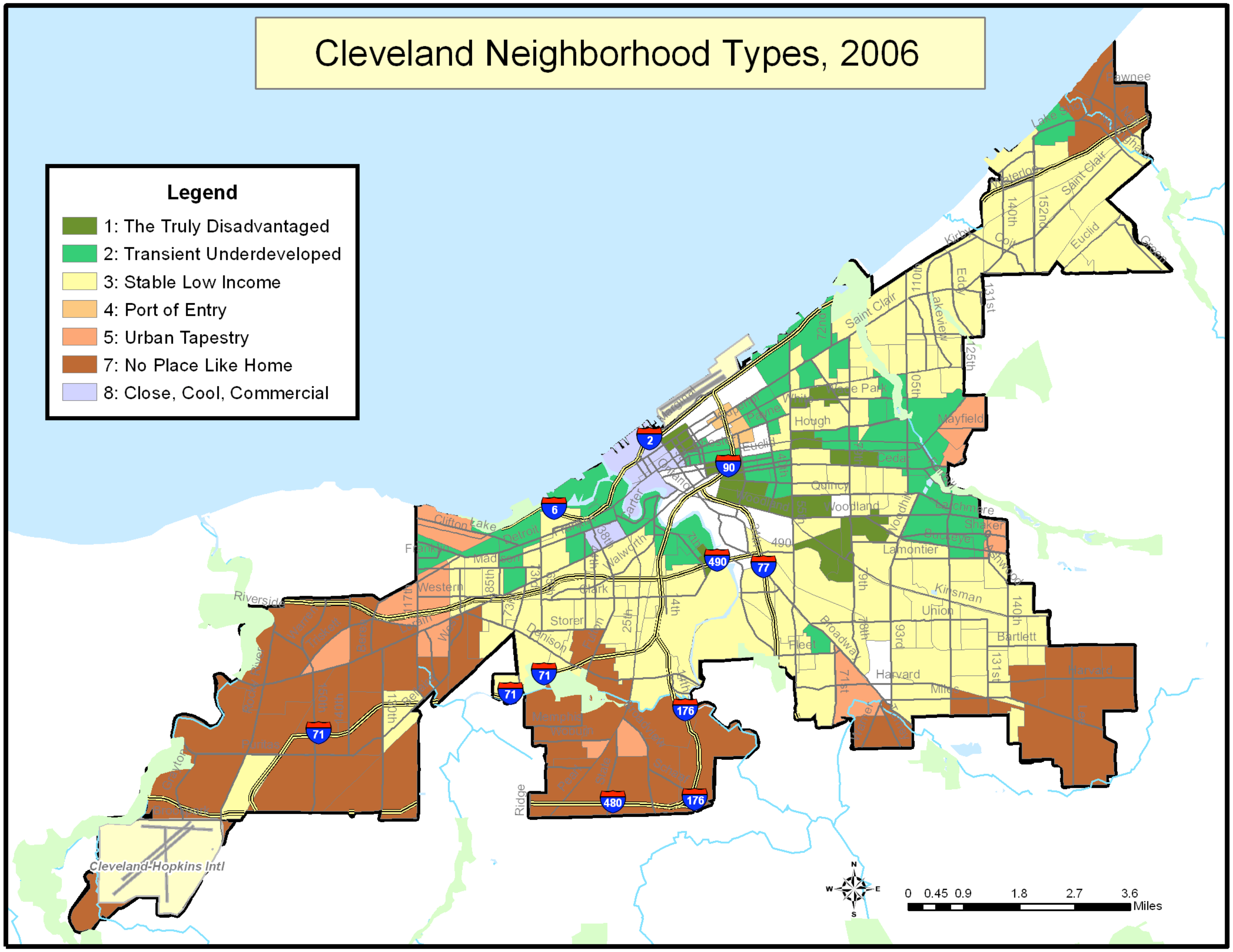

Urban Tapestry: Sub-types
(Chicago, 2006)
Legend
5A: Immigrant Eclectic
5B: High Diversity
5C: Young Adults
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

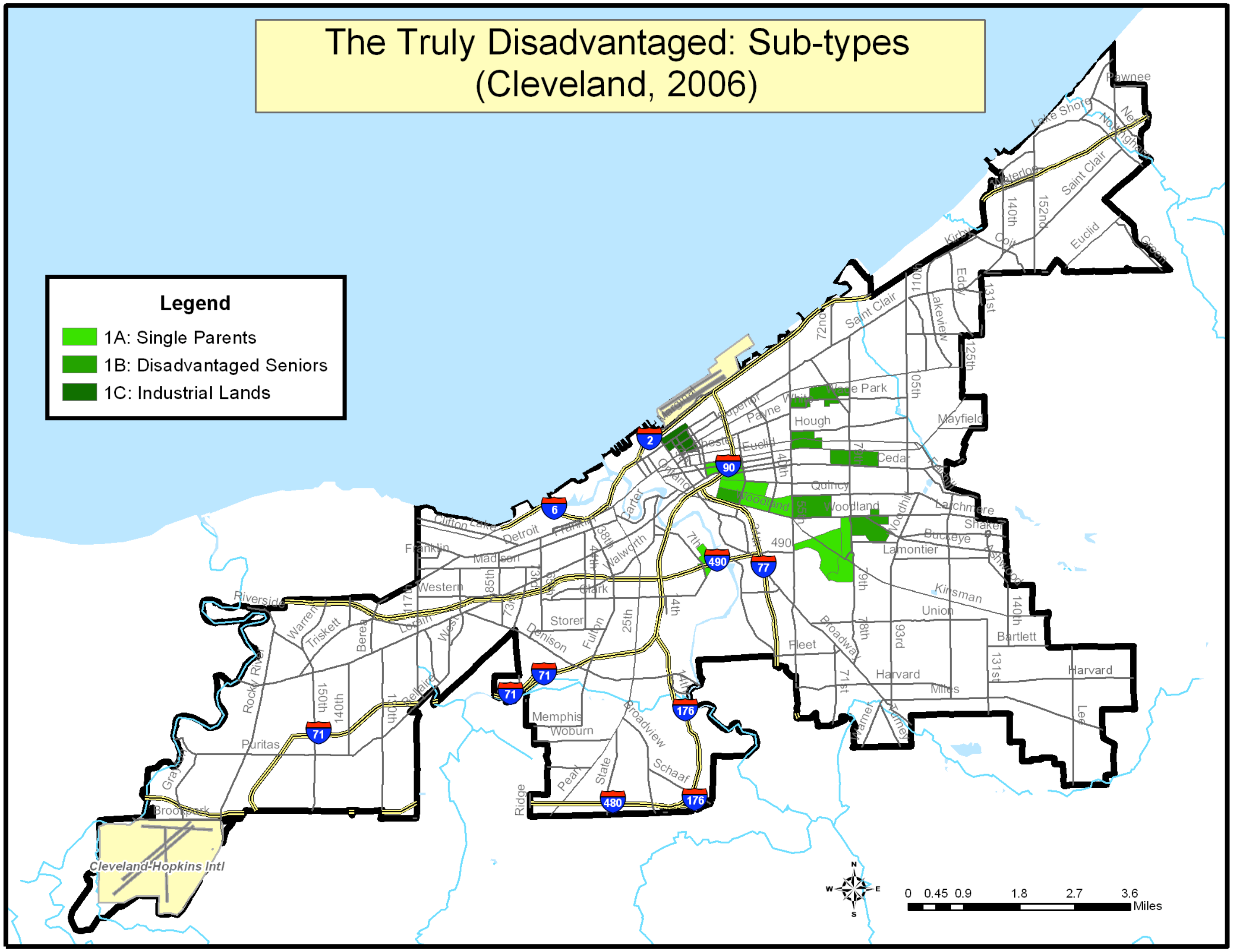

Coming Attractions: Sub-types
(Chicago, 2006)
Legend
6A: Commercial Districts
6B: Middle-Class Residential
6C: New Development
Chicago O'Hare Intl
Chicago Midway
N
W
E
S
0 0.5 1 2 3 4
Miles

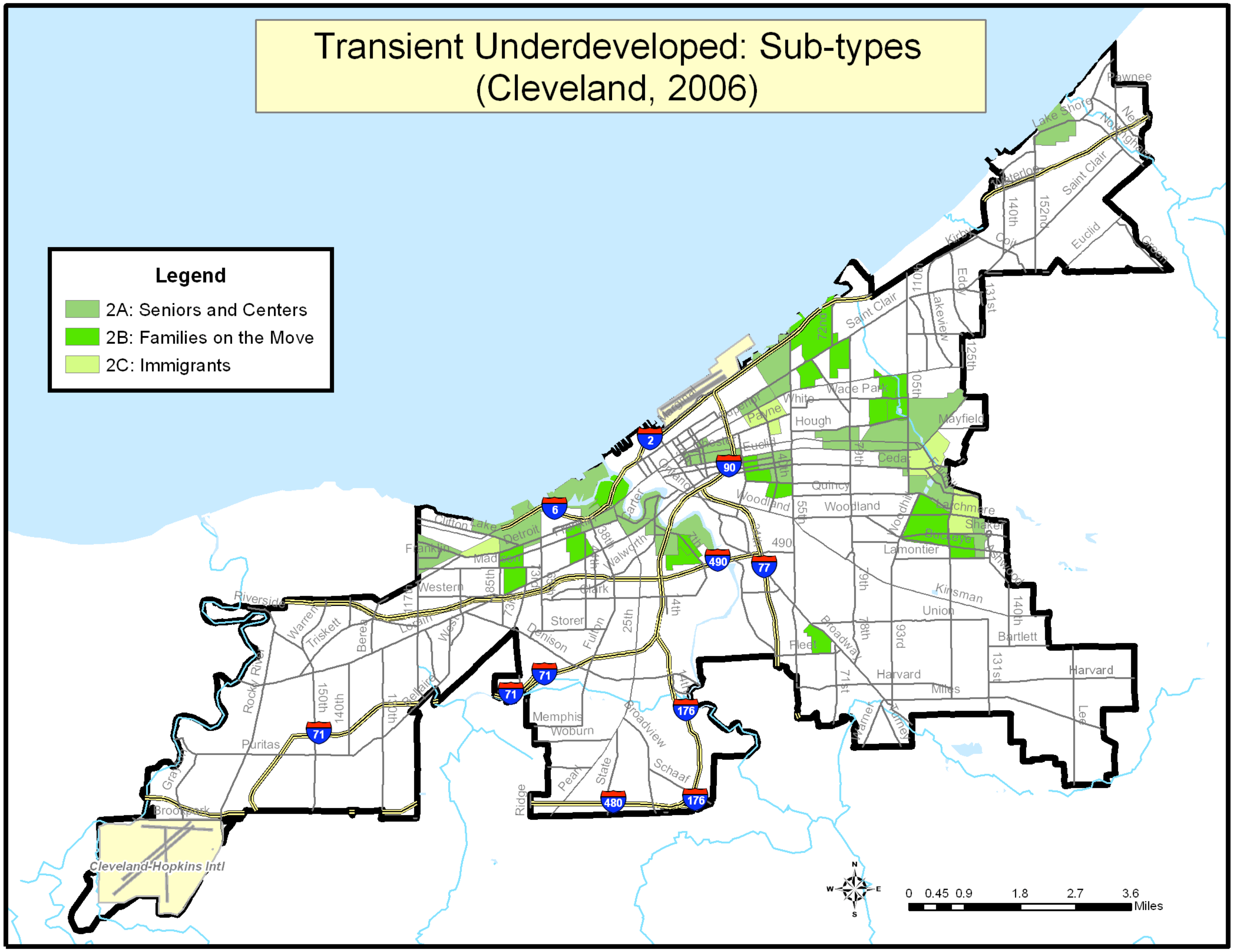

No Place Like Home: Sub-types
(Chicago, 2006)
Legend
7A: Blue-Collar Workers
7B: Stable Residents
7C: New Picket Fences
7D: Corner Stores & Shopping Centers
7E: High-End Housing
7F: Higher Income Homes
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

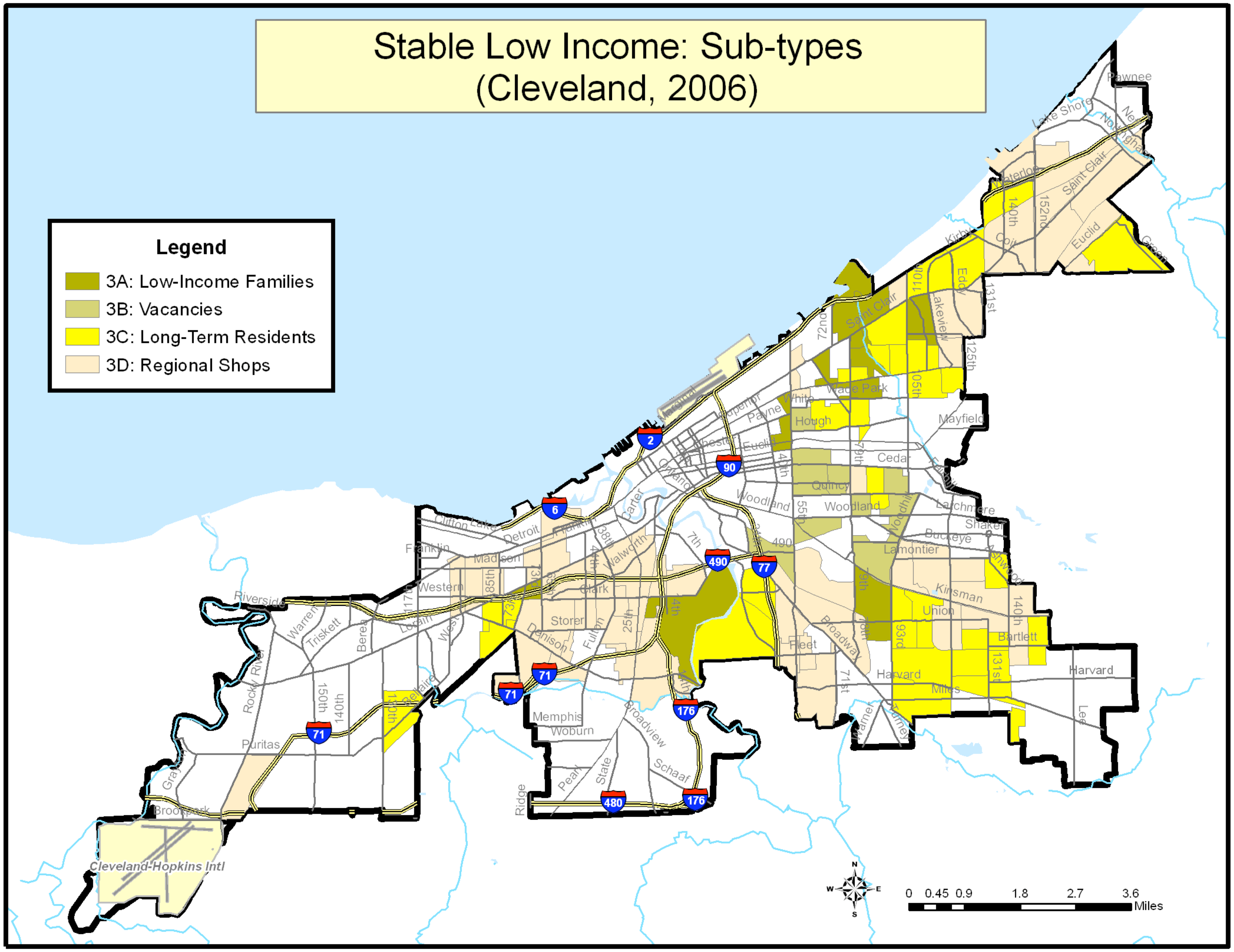

Close, Cool, Commercial: Sub-types
(Chicago, 2006)
Legend
8A: Walk-ups and Laundromats
8B: Urban Pioneers
8C: Downtown
8D: Doormen and Delivery
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

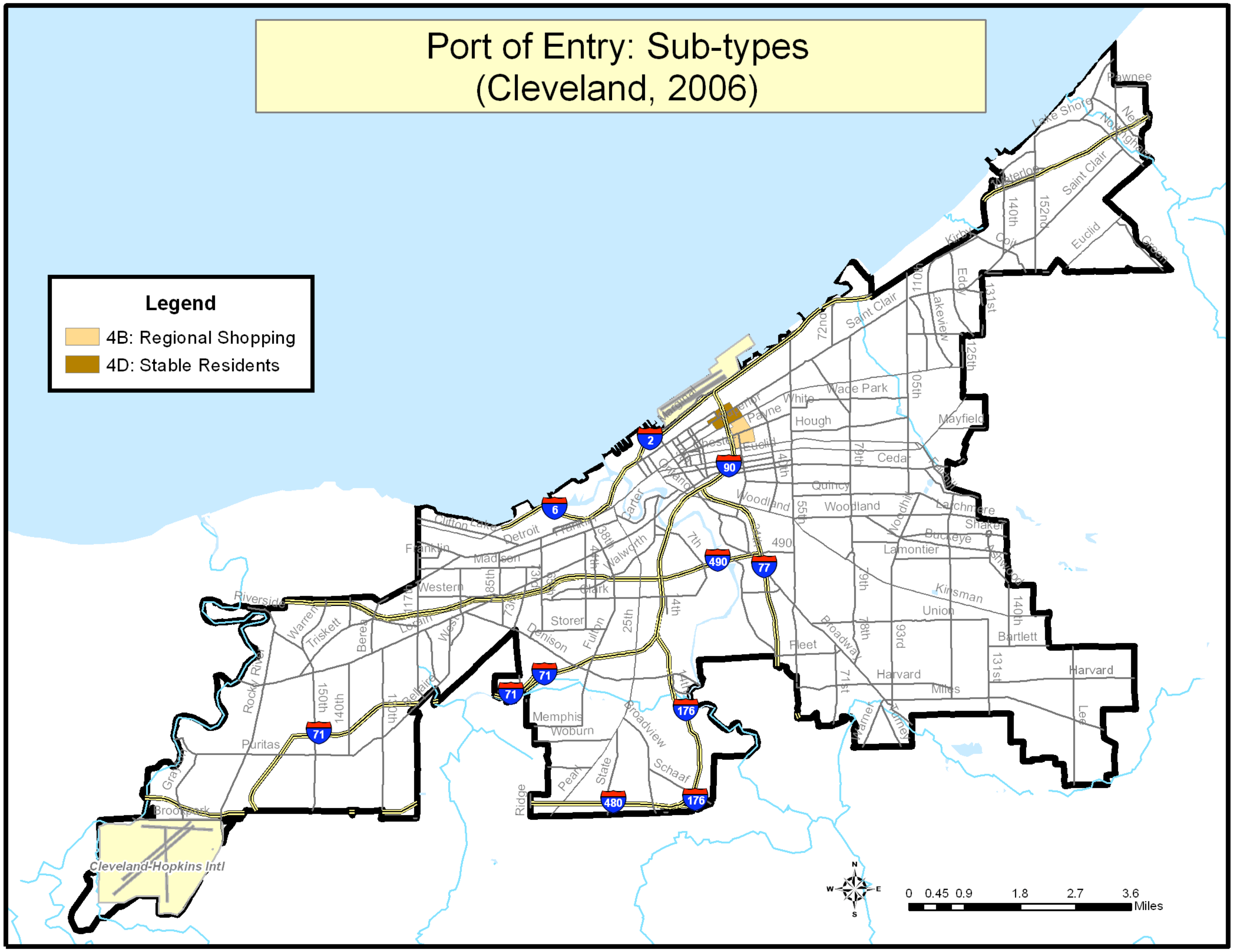

Fortune 100: Sub-types
(Chicago, 2006)
Legend
9A: Old Money
9B: Wealthy Boom
9C: Exclusive Enclaves
Chicago O'Hare Intl
Chicago Midway
0 0.5 1 2 3 4
Miles

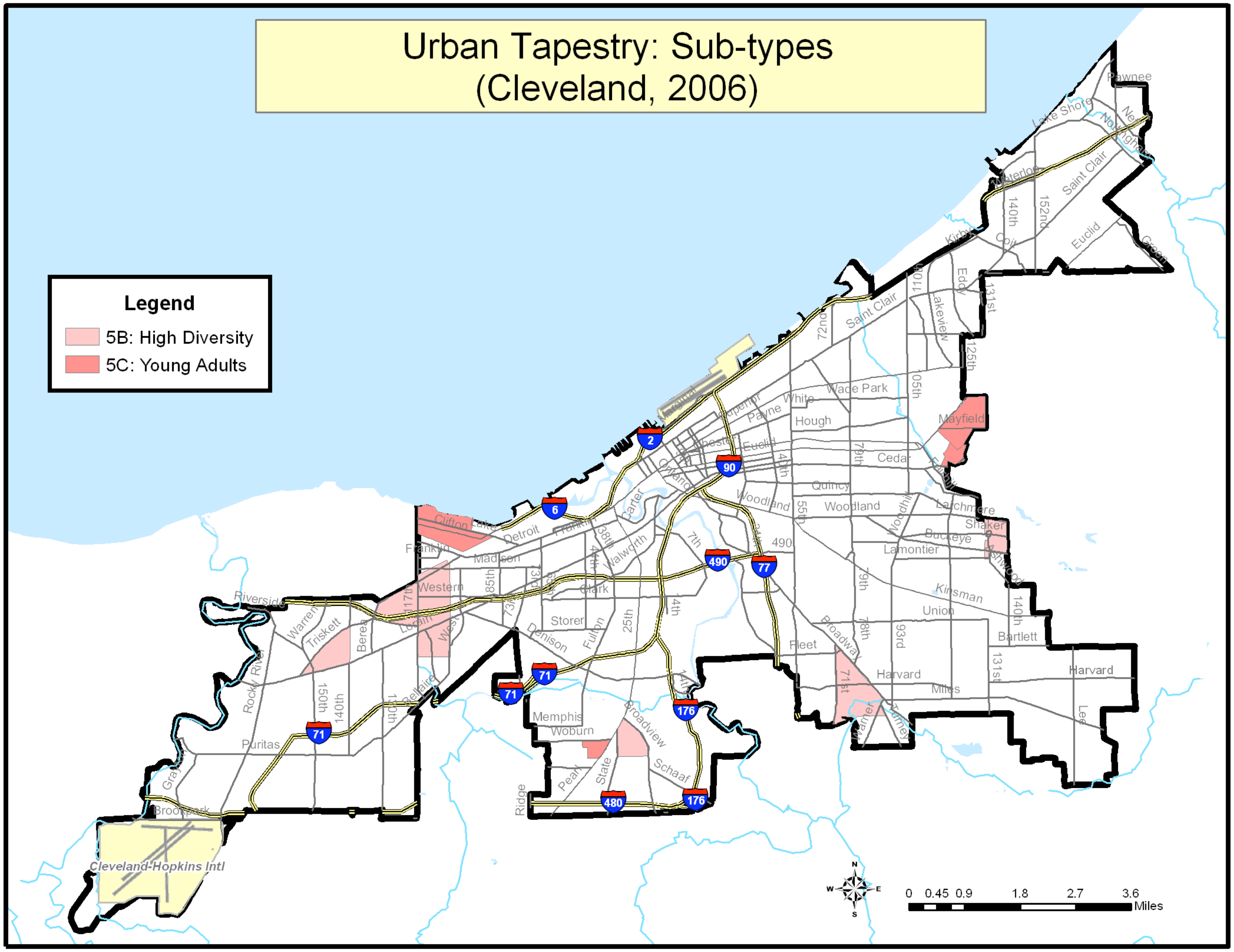

Cleveland Neighborhood Types, 2006
Legend
1: The Truly Disadvantaged
2: Transient Underdeveloped
3: Stable Low Income
4: Port of Entry
5: Urban Tapestry
7: No Place Like Home
8: Close, Cool, Commercial
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles

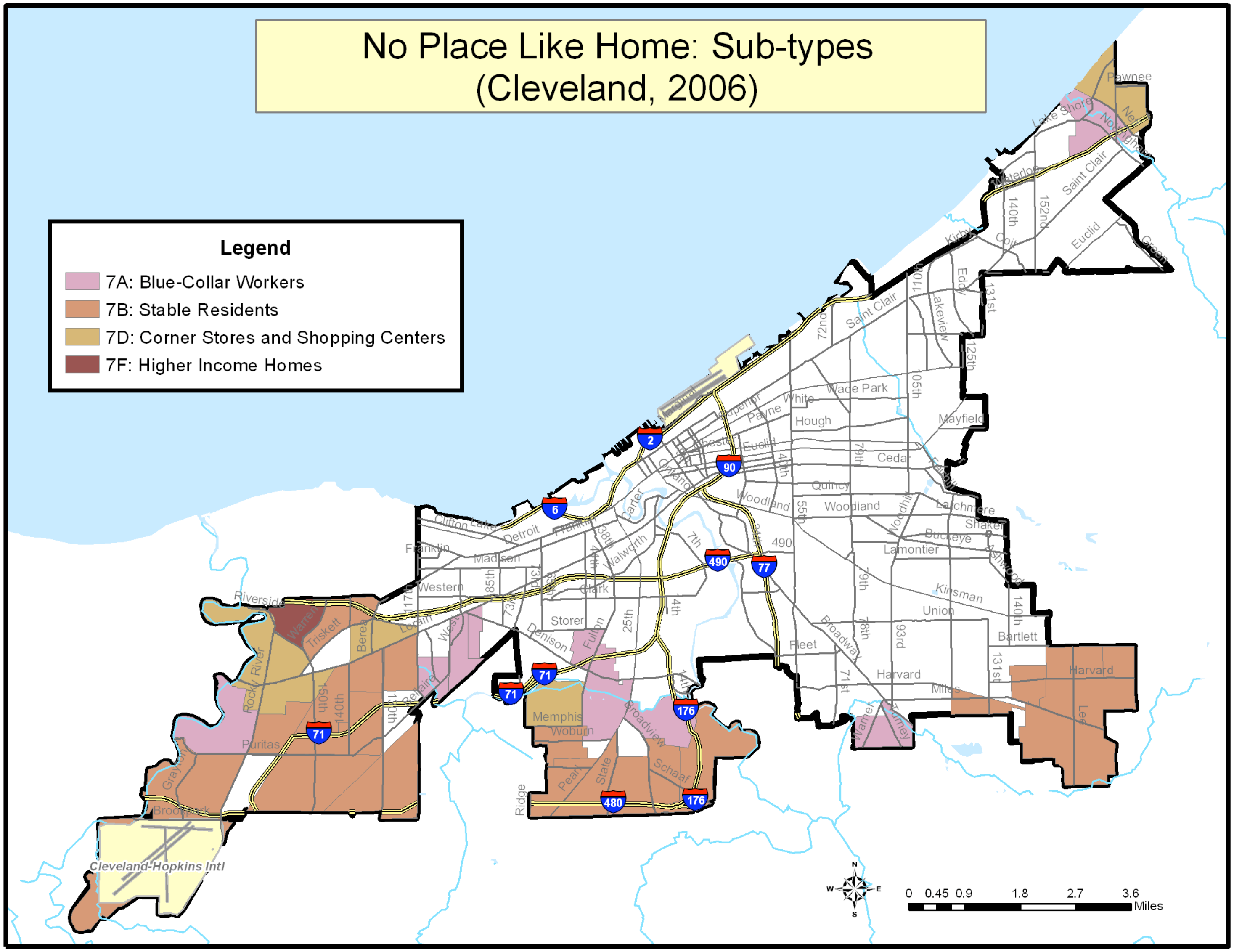

The Truly Disadvantaged: Sub-types
(Cleveland, 2006)
Legend
1A: Single Parents
1B: Disadvantaged Seniors
1C: Industrial Lands
Cleveland-Hopkins Intl
Hough
Cedar
Quincy
Woodland
Buckeye
Lamontier
Kinsman
Union
Harvard
Miles
Mayfield
Saint Clair
Superior
Payne
Euclid
Detroit
Madison
Franklin
Clifton
Western
Lorain
Storer
Denison
Fulton
Clark
Memphis
Woburn
Broadview
Schaaf
Pearl
State
Ridge
Puritas
Brookpark
Riverside
Warren
Triskett
Berea
Rocky River
Bartlett
Lee
Pawnee
Lake Shore
Waterloo
Euclid
Eddy
Coit
Kirby
Larchmere
Shaker
Fleet
Broadway
Union
Walworth
0 0.45 0.9 1.8 2.7 3.6
Miles

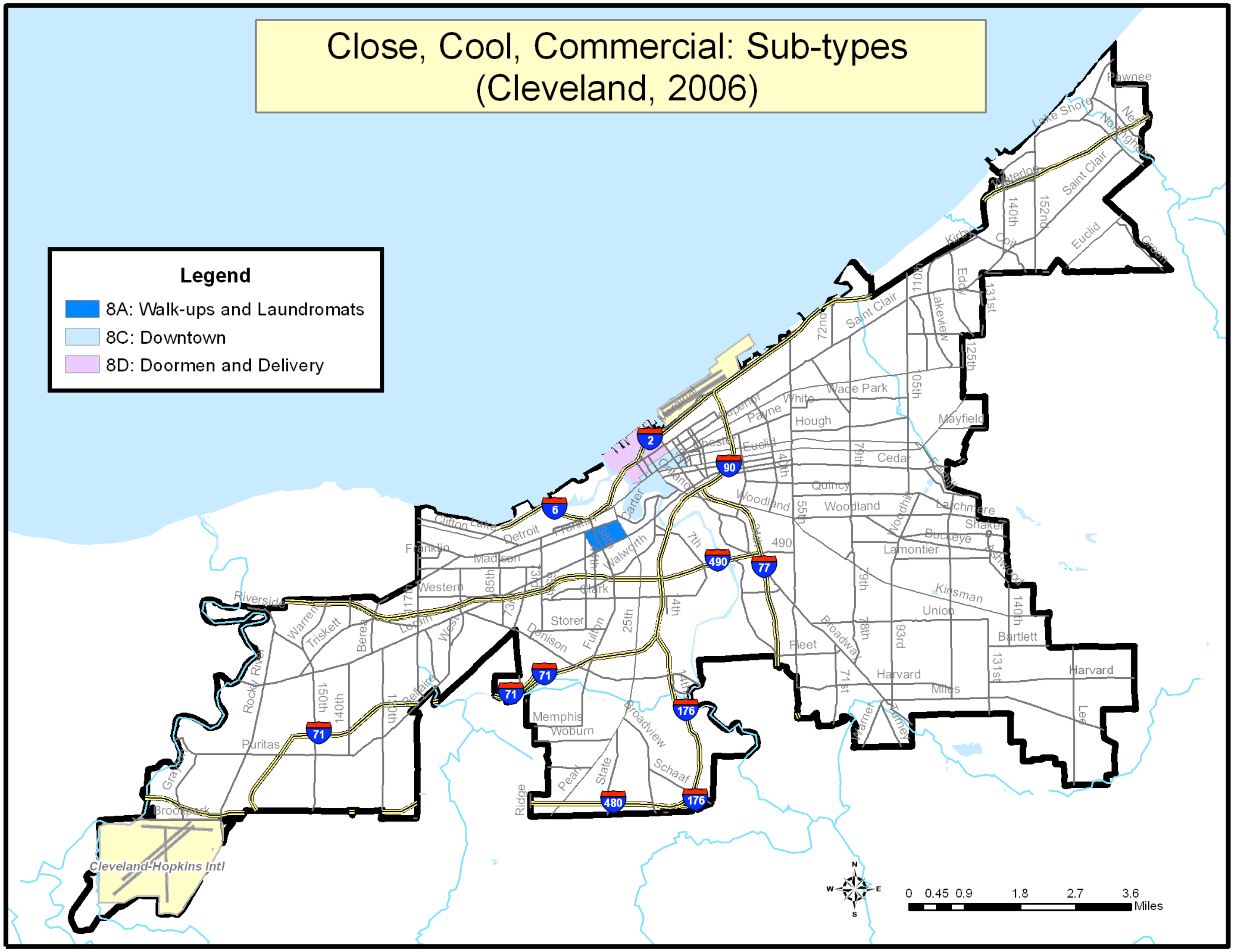

Transient Underdeveloped: Sub-types
(Cleveland, 2006)
Legend
2A: Seniors and Centers
2B: Families on the Move
2C: Immigrants
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles

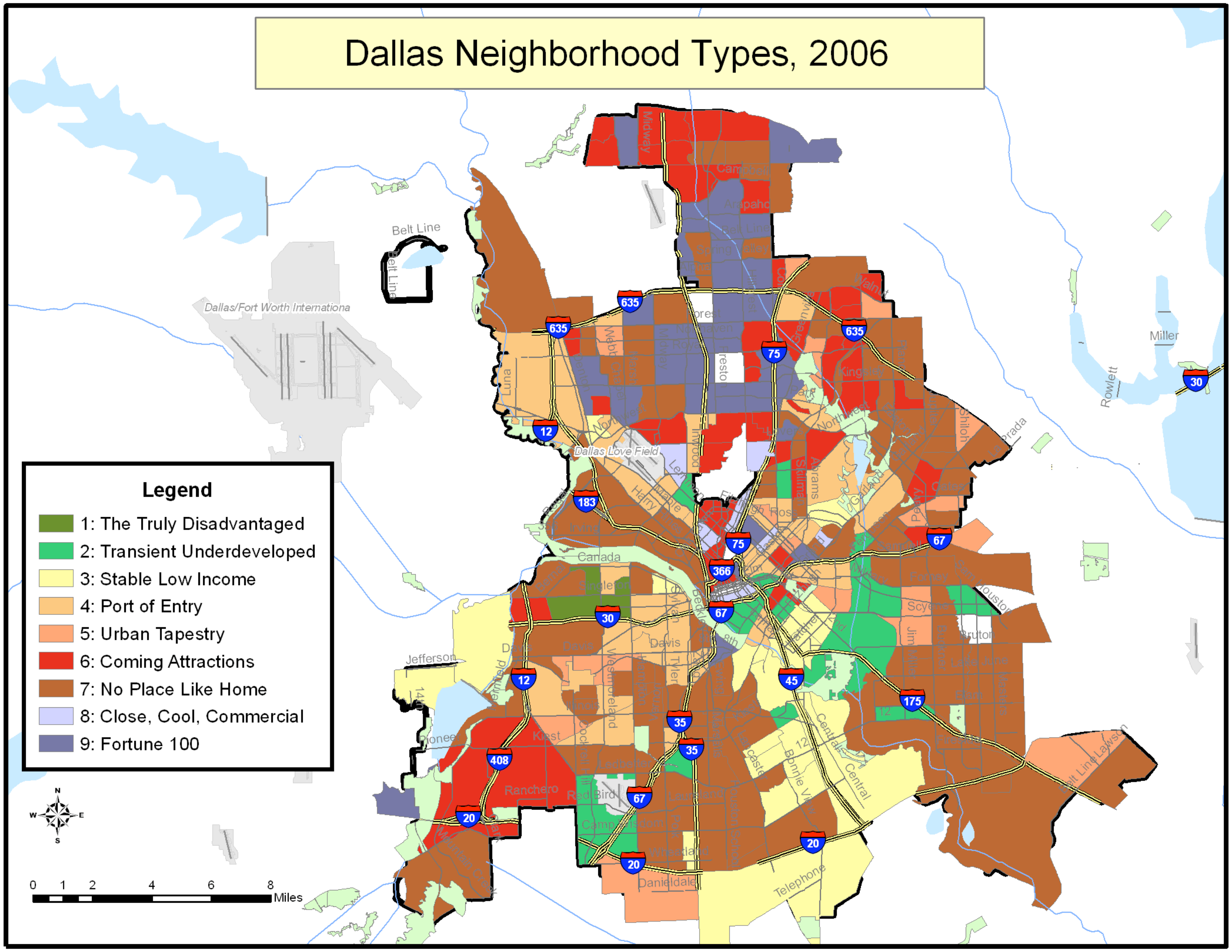

Stable Low Income: Sub-types
(Cleveland, 2006)
Legend
3A: Low-Income Families
3B: Vacancies
3C: Long-Term Residents
3D: Regional Shops
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles

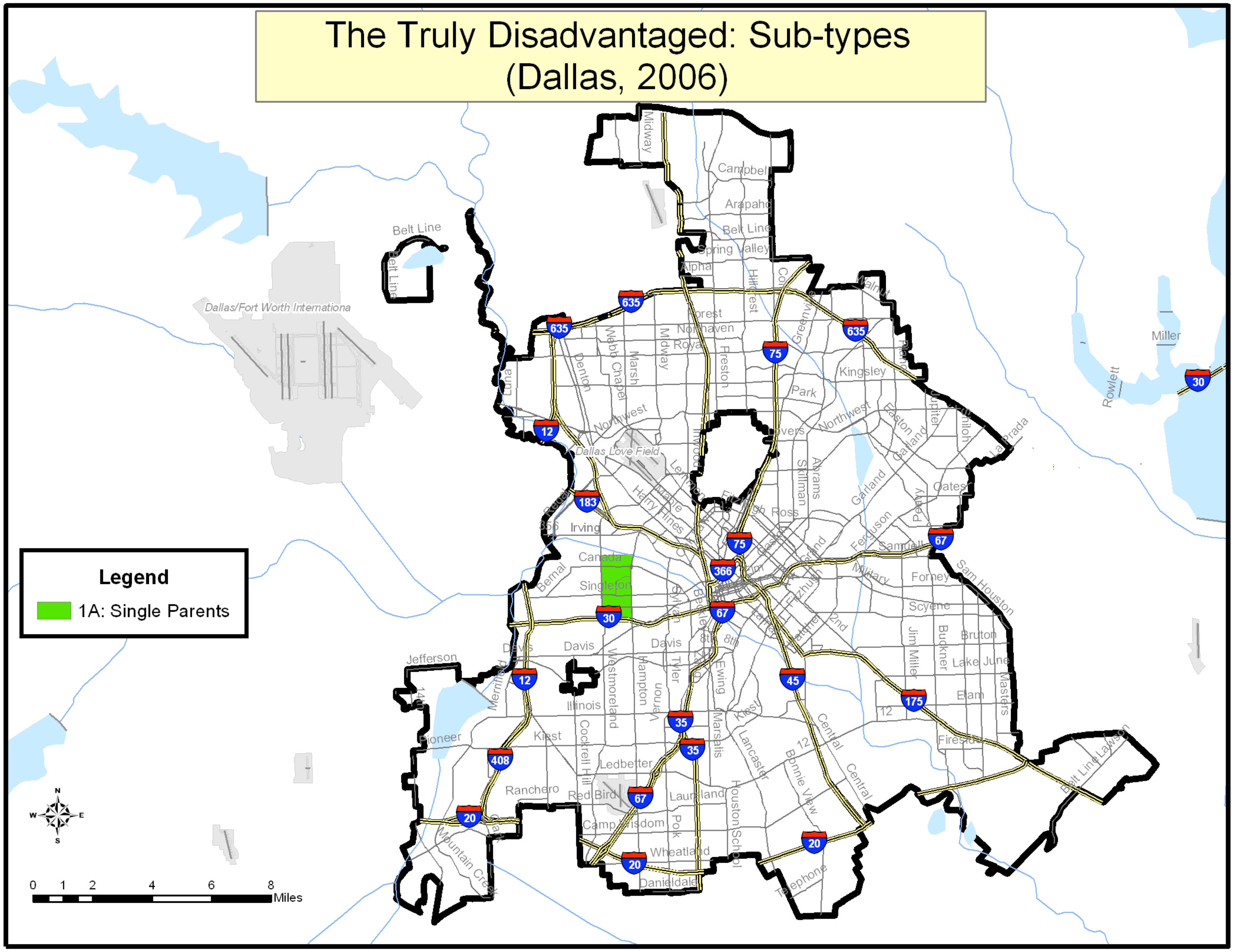

Port of Entry: Sub-types
(Cleveland, 2006)
Legend
4B: Regional Shopping
4D: Stable Residents
Cleveland-Hopkins Intl
Saint Clair
Wade Park
Hough
Mayfield
Woodland
Lamontier
Kinsman
Union
Bartlett
Harvard
Miles
Memphis
Woburn
Broadview
Schaar
Pearl
State
Ridge
Storer
Denison
Fulton
Western
Madison
Franklin
Detroit
Clifton
Riverside
Warren
Triskett
Berea
Puritas
Brookpark
Rocky River
Euclid
Lake Shore
Waterloo
Quincy
Fleet
Broadway
Lee
Eddy
Payne
0 0.45 0.9 1.8 2.7 3.6
Miles
N
S
E
W

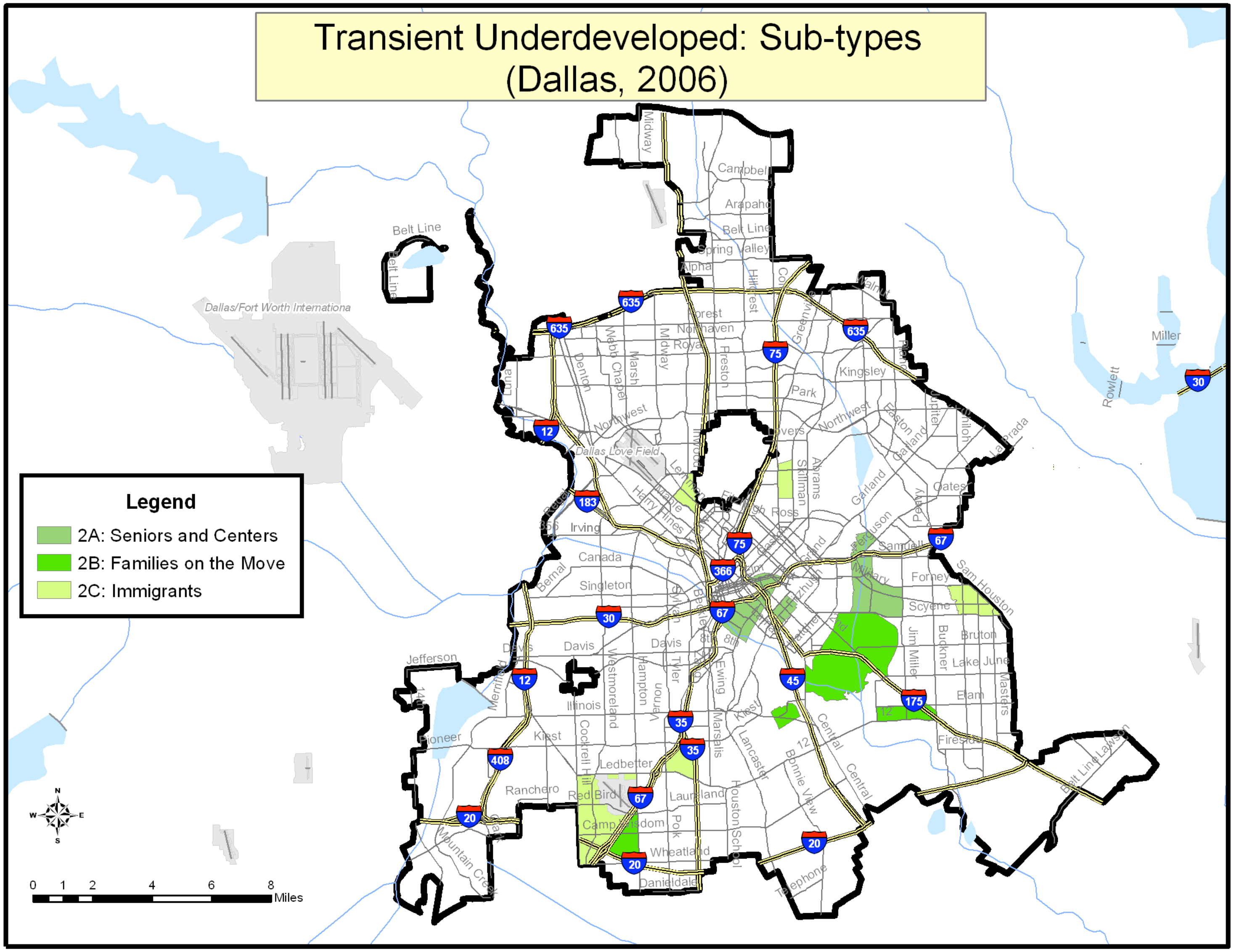

Urban Tapestry: Sub-types
(Cleveland, 2006)
Legend
5B: High Diversity
5C: Young Adults
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles


No Place Like Home: Sub-types
(Cleveland, 2006)
Legend
7A: Blue-Collar Workers
7B: Stable Residents
7D: Corner Stores and Shopping Centers
7F: Higher Income Homes
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles

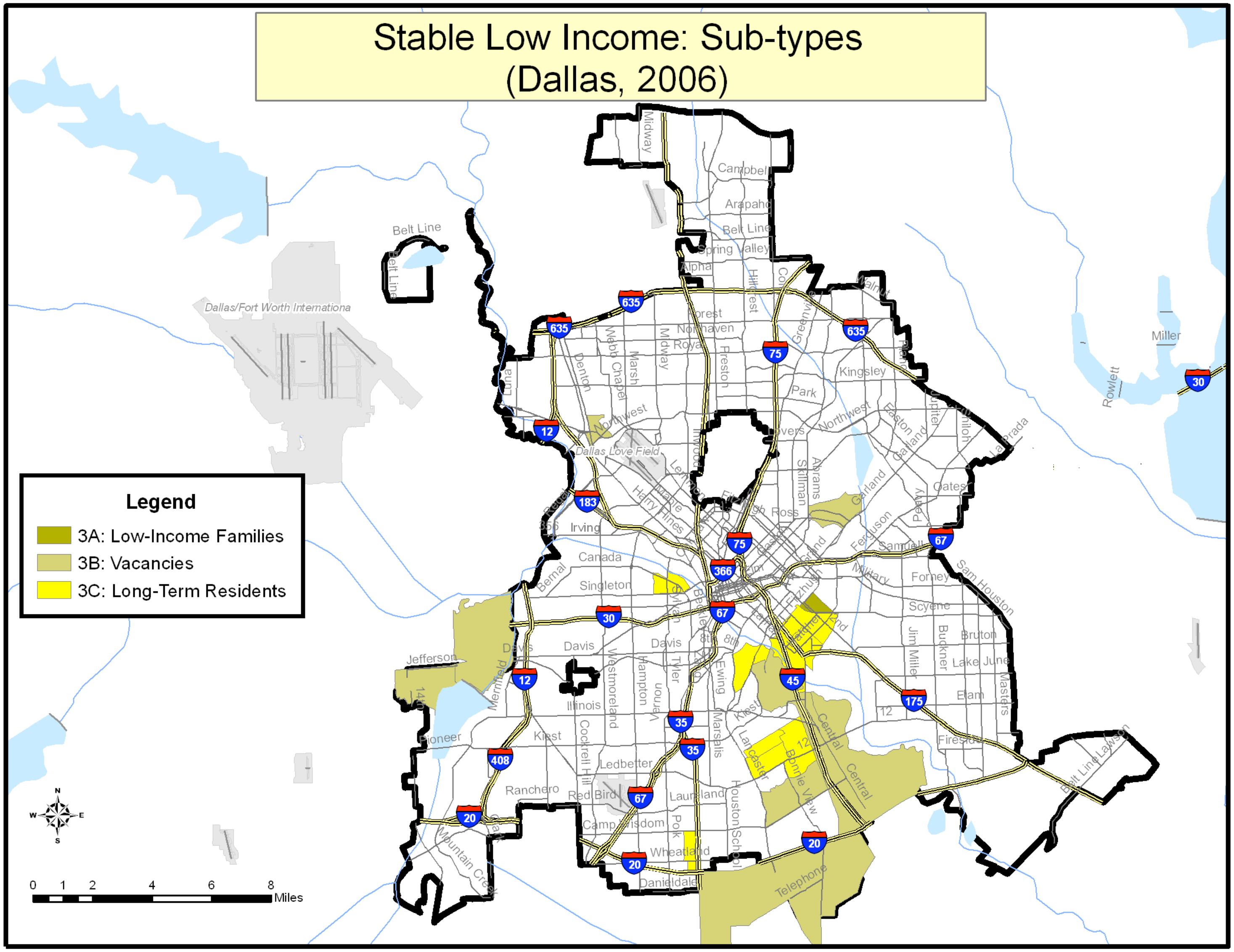

Close, Cool, Commercial: Sub-types
(Cleveland, 2006)
Legend
8A: Walk-ups and Laundromats
8C: Downtown
8D: Doormen and Delivery
Cleveland-Hopkins Intl
0 0.45 0.9 1.8 2.7 3.6
Miles

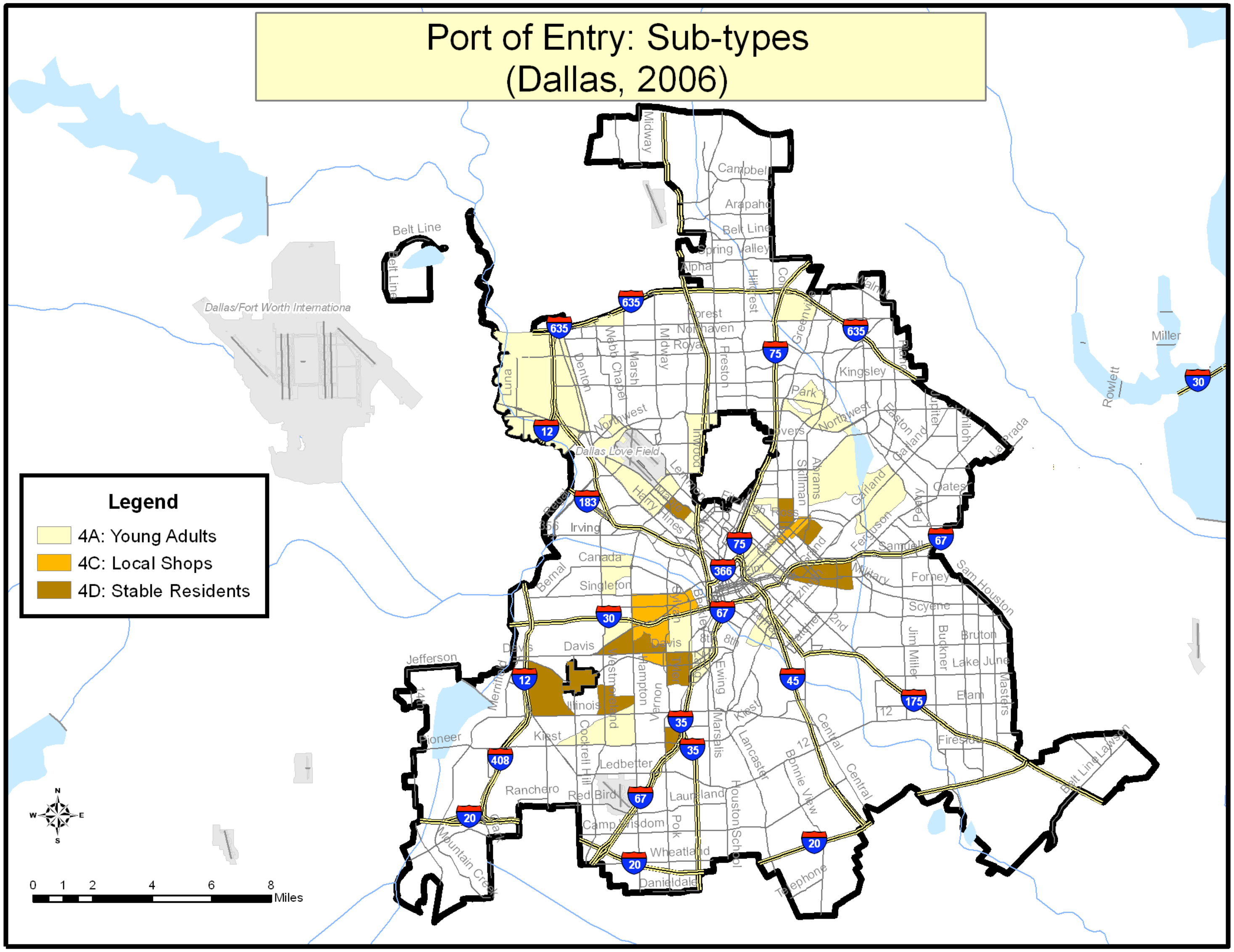

Dallas Neighborhood Types, 2006
Legend
1: The Truly Disadvantaged
2: Transient Underdeveloped
3: Stable Low Income
4: Port of Entry
5: Urban Tapestry
6: Coming Attractions
7: No Place Like Home
8: Close, Cool, Commercial
9: Fortune 100
Dallas/Fort Worth International
Dallas Love Field
0 1 2 4 6 8
Miles

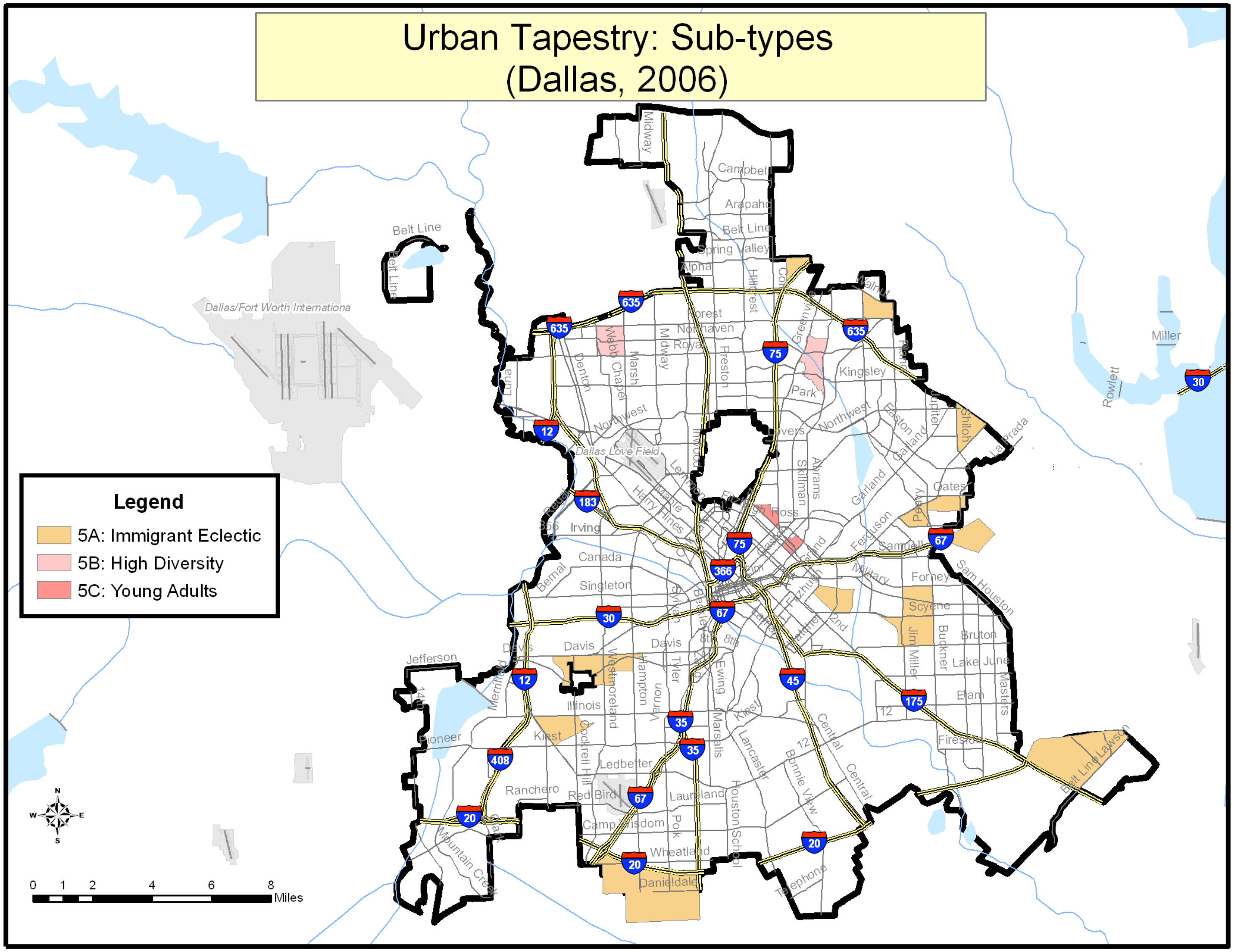

The Truly Disadvantaged: Sub-types
(Dallas, 2006)
Legend
1A: Single Parents
0 1 2 4 6 8
Miles

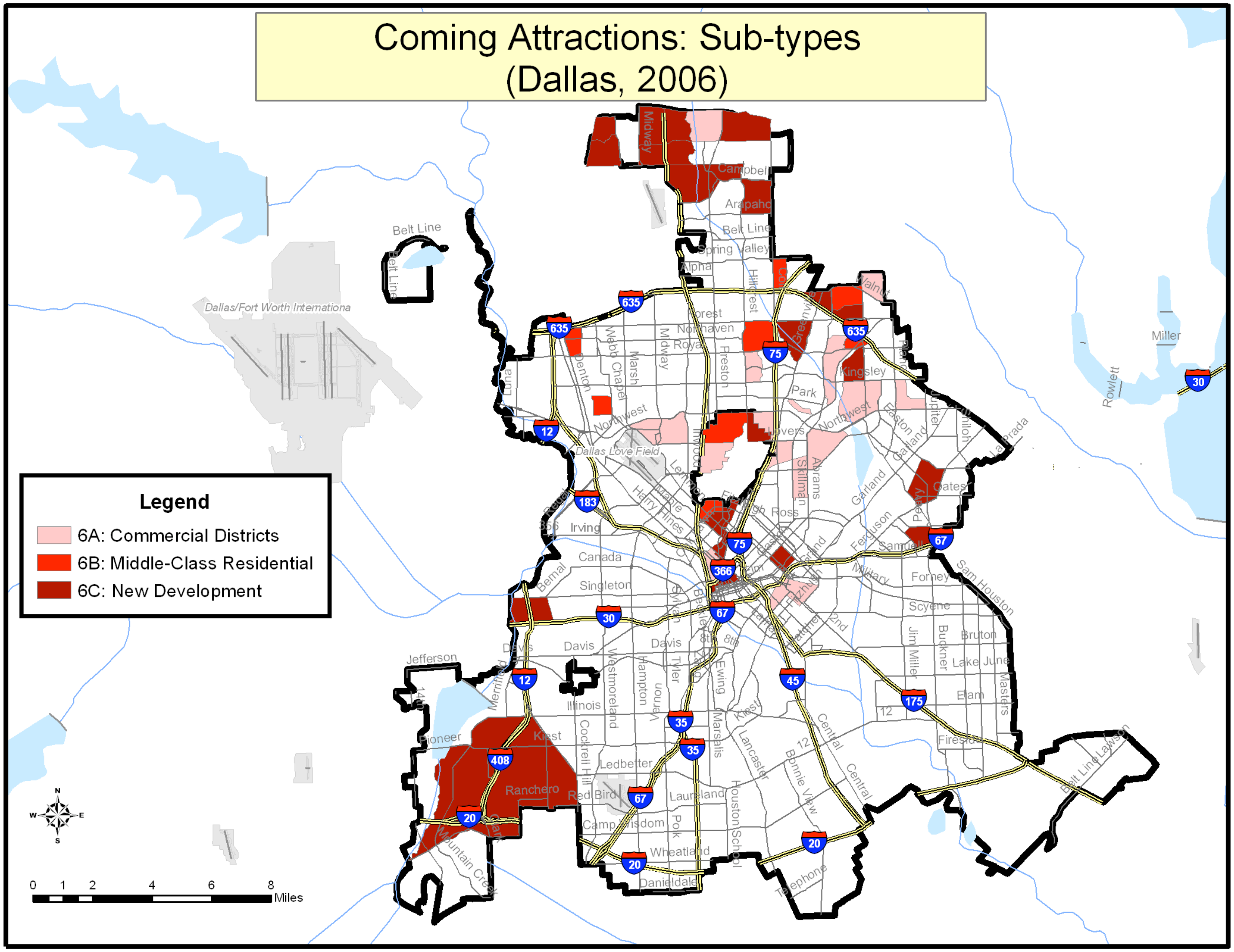


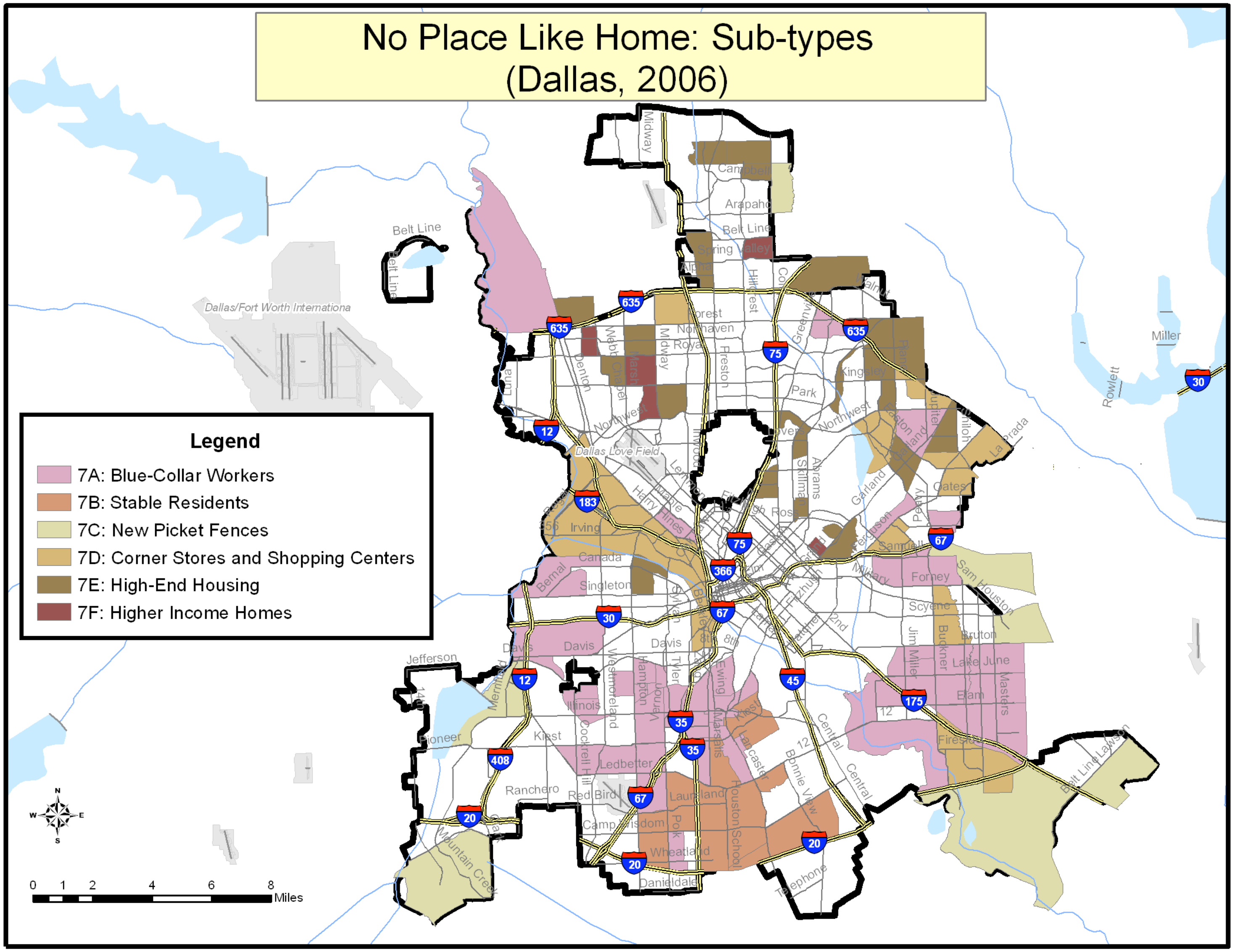
Transient Underdeveloped: Sub-types
(Dallas, 2006)
Legend
2A: Seniors and Centers
2B: Families on the Move
2C: Immigrants
0 1 2 4 6 8
Miles
Dallas/Fort Worth International
Dallas Love Field
Belt Line
Jefferson
Irving
Canada
Singleton
Davis
Illinois
Kiest
Ledbetter
Ranchero
Red Bird
Laureland
Wheatland
Danieldale
Campbell
Arapaho
Spring Valley
Northaven
Royal
Kingsley
Park
Northwest
Ross
Samuell
Forney
Scyene
Bruton
Elam
Miller
Rowlett

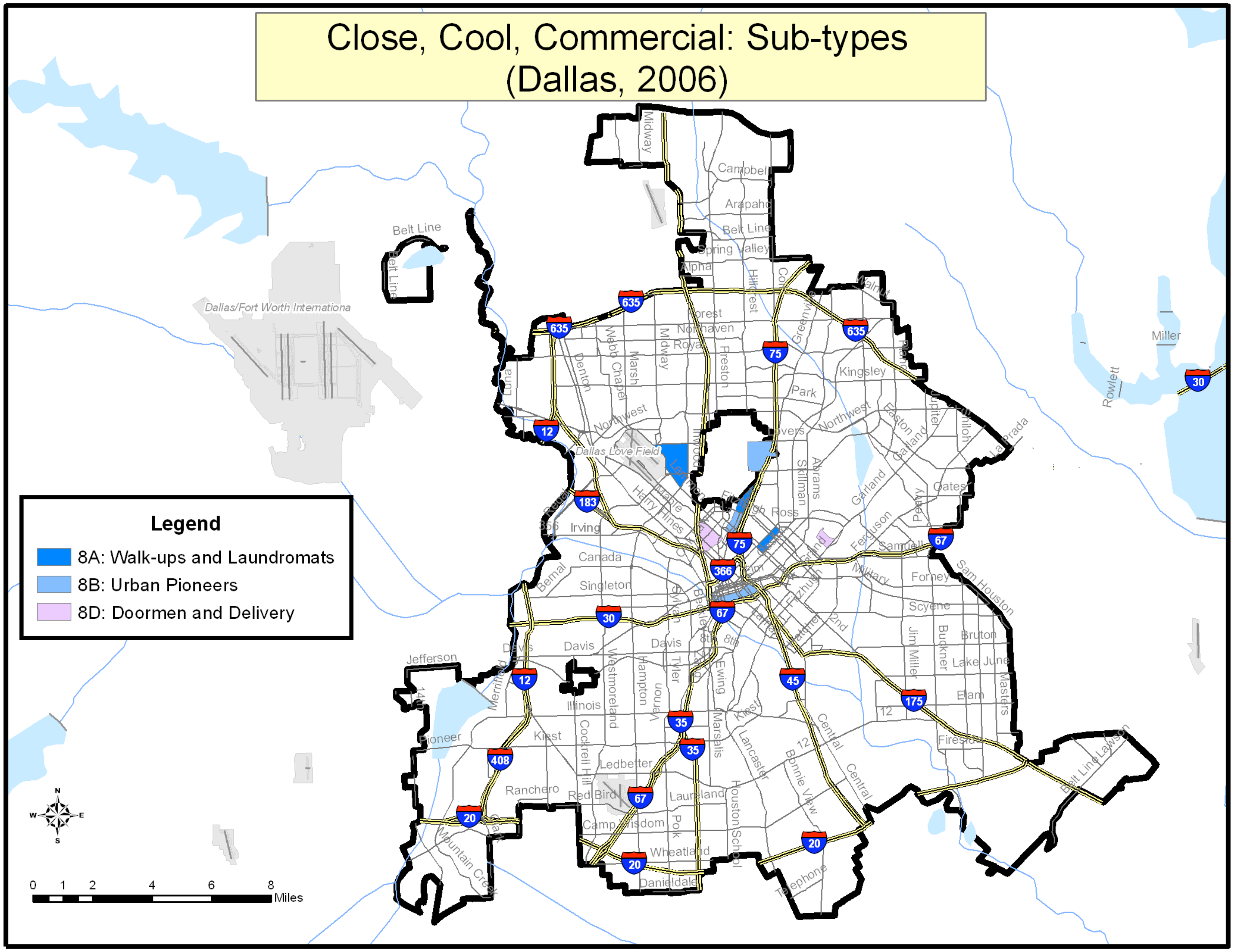

Stable Low Income: Sub-types
(Dallas, 2006)
Legend
3A: Low-Income Families
3B: Vacancies
3C: Long-Term Residents
0 1 2 4 6 8
Miles
N
S
E
W
Dallas/Fort Worth Internationa
Dallas Love Field
Belt Line
Campbell
Arapaho
Spring Valley
Northaven
Royal
Kingsley
Park
Northwest
Irving
Canada
Singleton
Davis
Jefferson
Illinois
Kiest
Ledbetter
Ranchero
Red Bird
Camp Wisdom
Wheatland
Danieldale
Laureland
Telephone
Forney
Scyene
Bruton
Elam
Military
Sam Houston
Central
Bonnie View
Lancaster
Westmoreland
Hampton
Cockrell Hill
Mountain Creek
Pioneer
Miller
Rowlett
Gaston
Garland
Samuell
Ferguson
Buckner
Jim Miller
Masters
Lake June
Fireside
Midway
Preston
Hillcrest
Greenville
Abrams
Skillman
Marsh
Webb Chapel
Denton
Luna
Harry Hines
Marsalis
Ewing
Tyler
Vernon
Merrifield
Houston School
Polk
Oates
Shiloh
Jupiter
La Prada
Belt Line Lawson
635
75
12
183
366
67
30
45
175
35
408
20

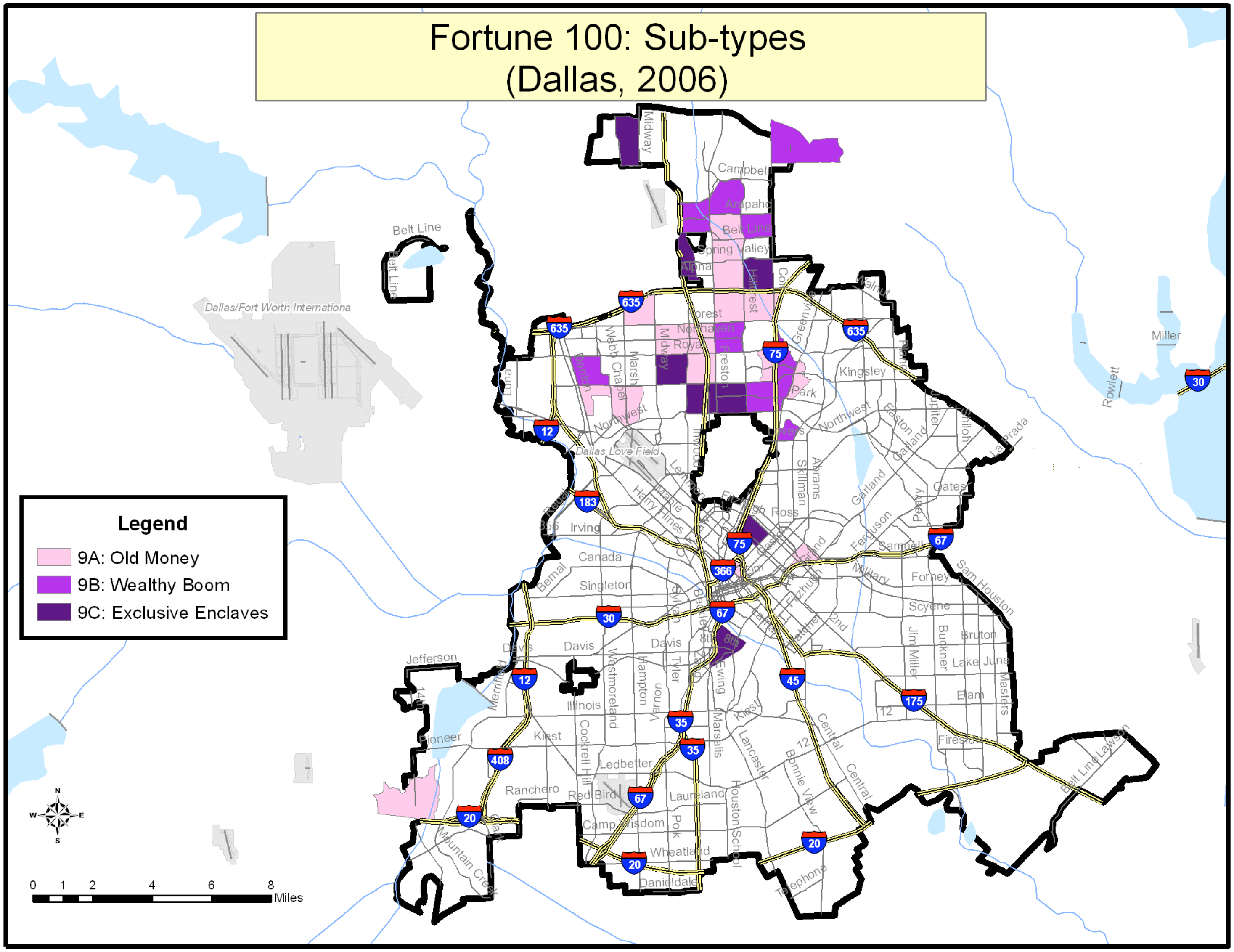

Port of Entry: Sub-types
(Dallas, 2006)
Legend
4A: Young Adults
4C: Local Shops
4D: Stable Residents
0 1 2 4 6 8 Miles
Dallas/Fort Worth International
Dallas Love Field
Irving
Belt Line

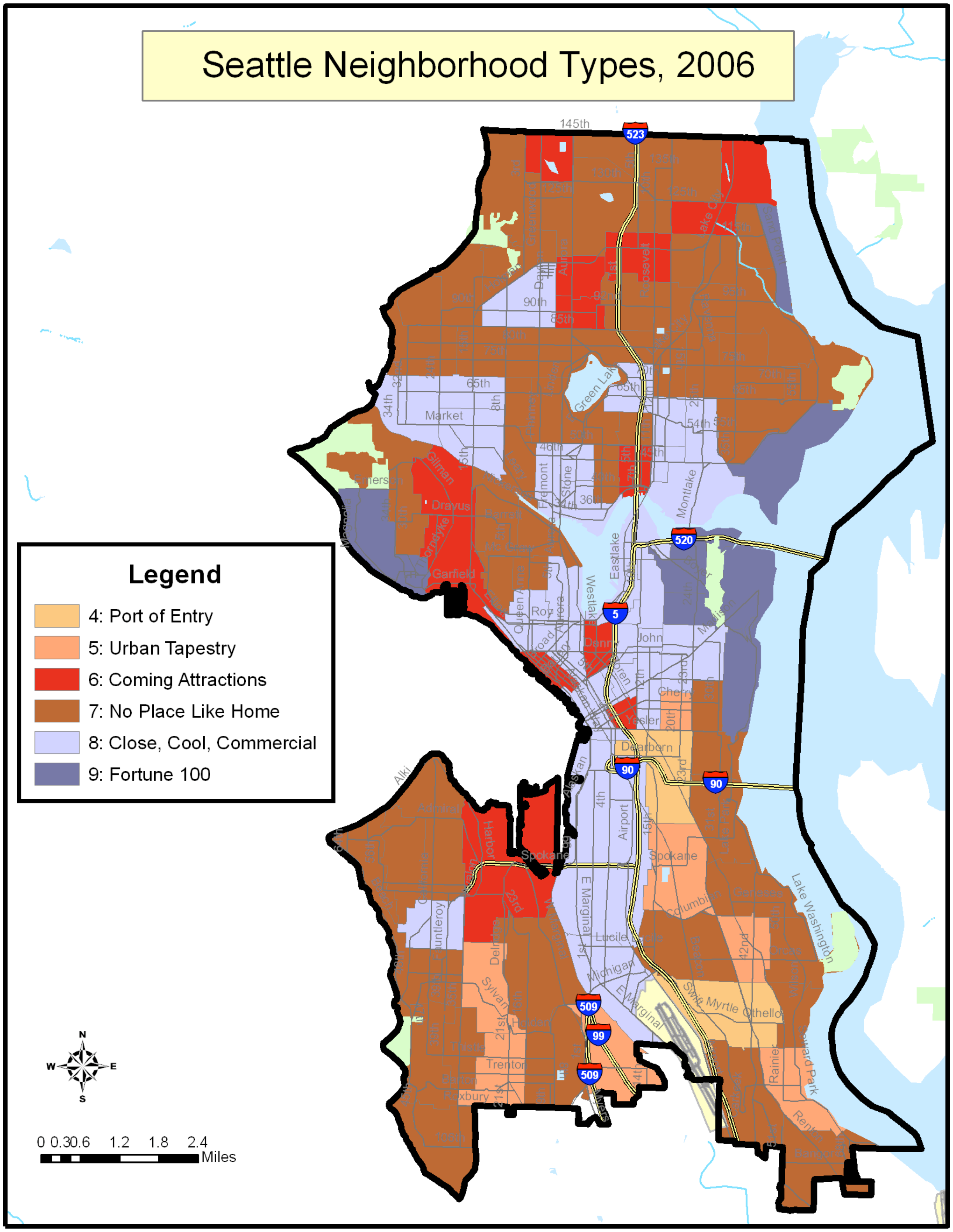

Urban Tapestry: Sub-types
(Dallas, 2006)
Legend
5A: Immigrant Eclectic
5B: High Diversity
5C: Young Adults
0 1 2 4 6 8 Miles

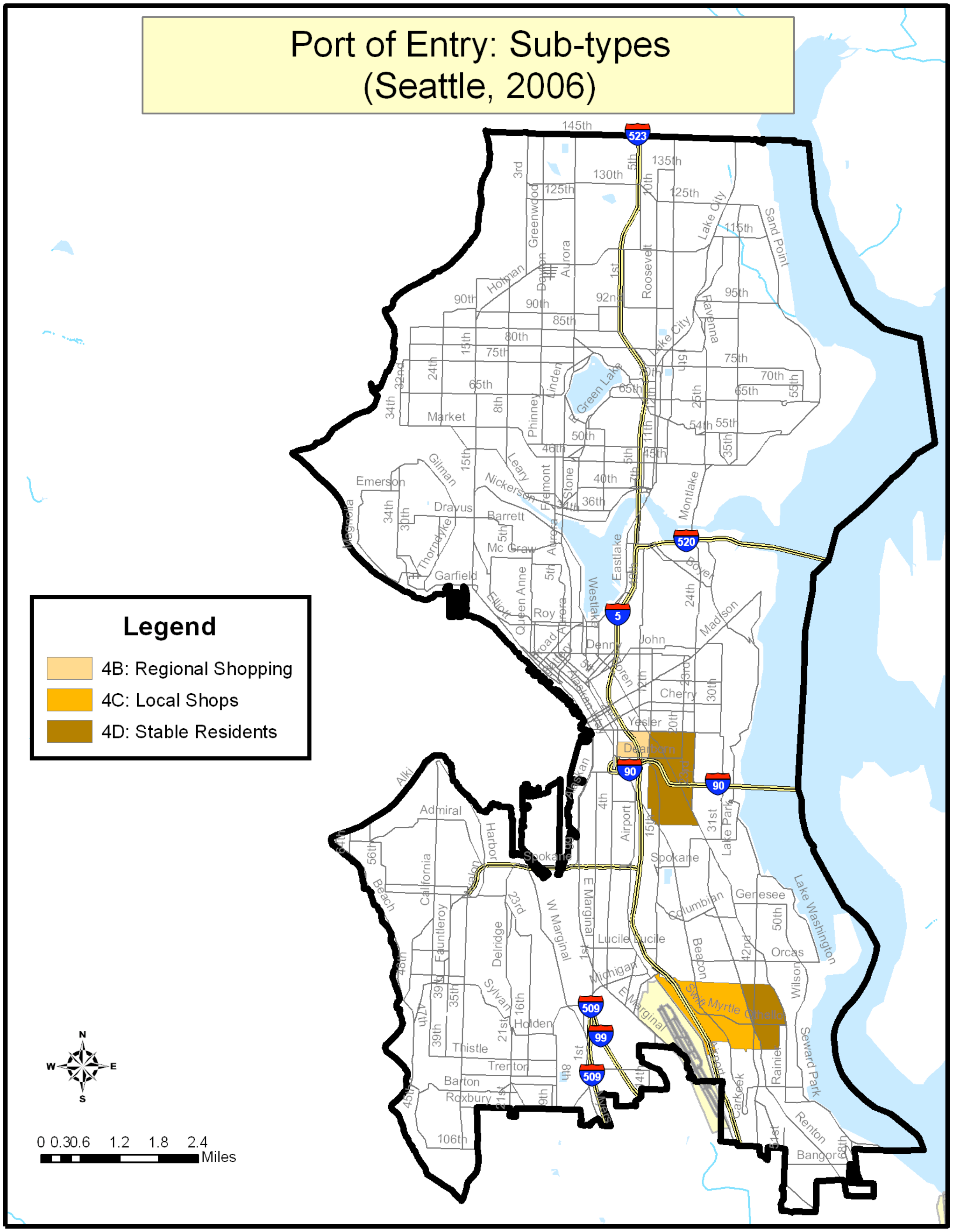

Coming Attractions: Sub-types
(Dallas, 2006)
Legend
6A: Commercial Districts
6B: Middle-Class Residential
6C: New Development
0 1 2 4 6 8
Miles
Dallas/Fort Worth Internationa
Dallas Love Field

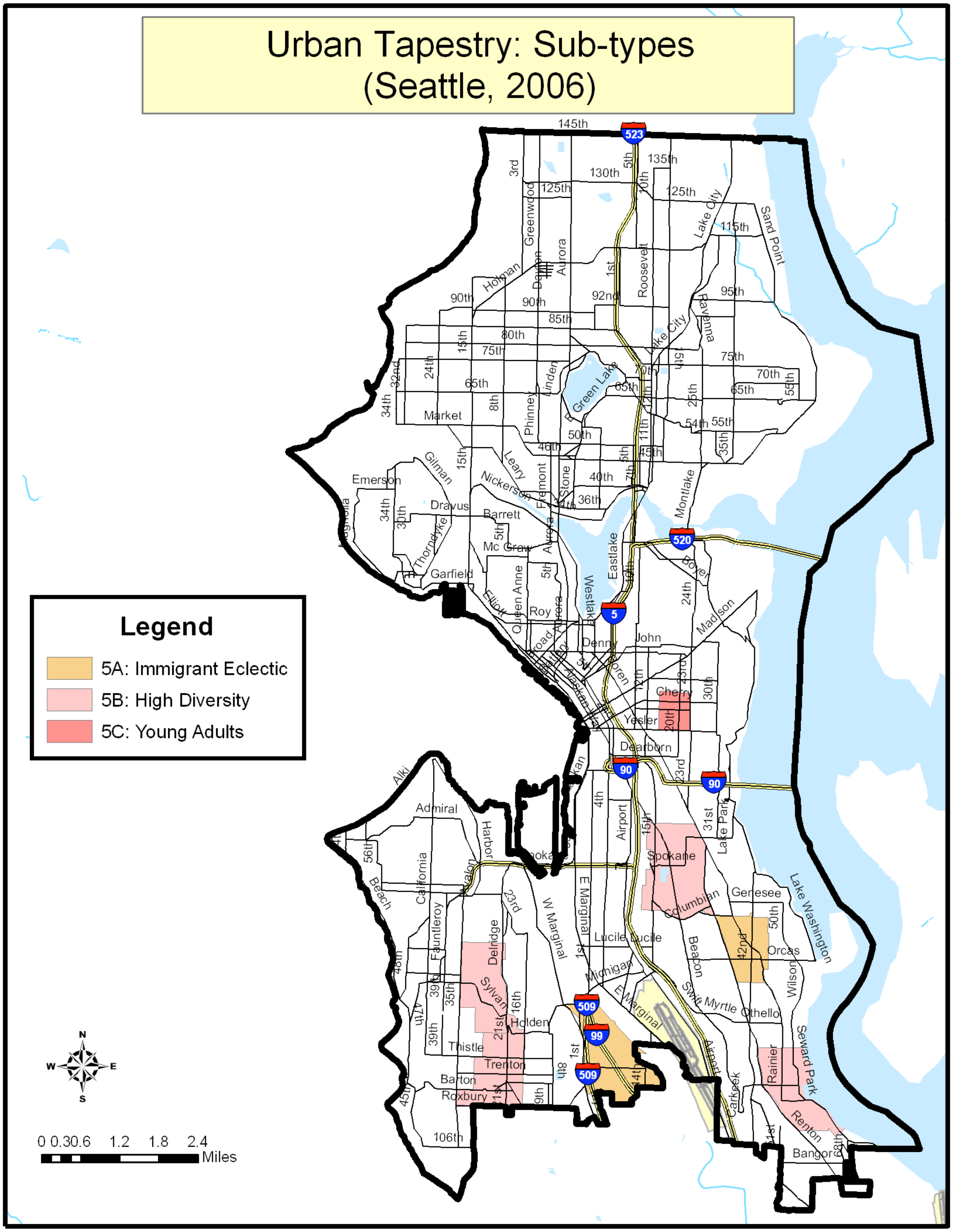

No Place Like Home: Sub-types
(Dallas, 2006)
Legend
7A: Blue-Collar Workers
7B: Stable Residents
7C: New Picket Fences
7D: Corner Stores and Shopping Centers
7E: High-End Housing
7F: Higher Income Homes
0 1 2 4 6 8
Miles
Dallas/Fort Worth Internationa
Dallas Love Field
Belt Line
Miller
Rowlett
Jefferson
Forney
Davis
Irving
Canada
Singleton
Ledbetter
Kiest
Ranchero
Red Bird
Camp Wisdom
Wheatland
Danieldale
Telephone
Lake June
Elam
Scyene
Bruton
Military
Northwest
Northaven
Royal
Park
Kingsley
Arapaho
Campbell
Spring Valley
Forest
La Prada
Gates
Samuell
Sam Houston
Fireside
Pioneer
Mountain Creek
Laureland
Polk
Houston School
Bonnie View
Central
Lancaster
Westmoreland
Hampton
Cockrell Hill
Tyler
Midway
Preston
Hillcrest
Skillman
Abrams
Garland
Jim Miller
Buckner
Masters
Denton
Harry Hines
Luna
Bernal
Illinois

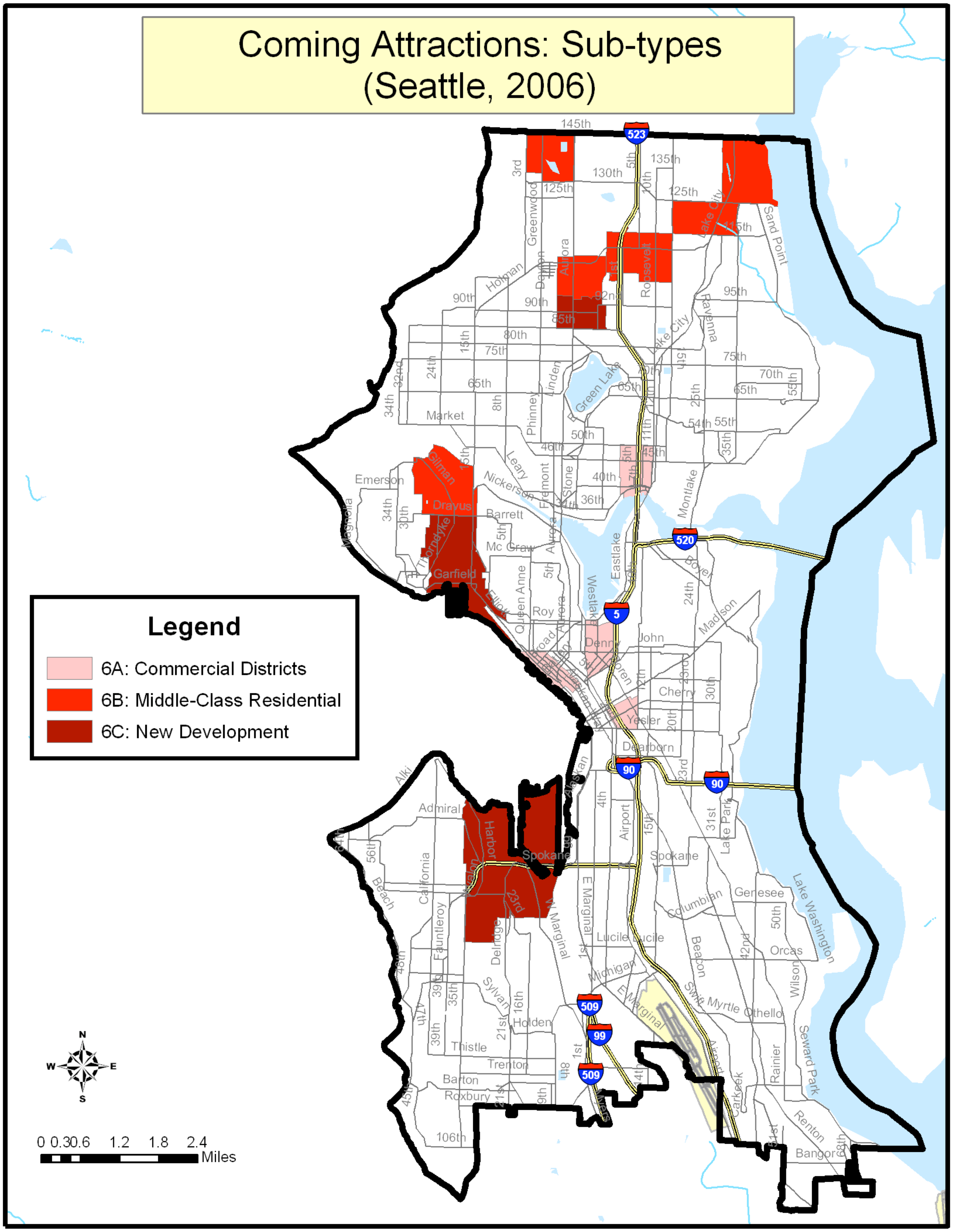

Close, Cool, Commercial: Sub-types
(Dallas, 2006)
Legend
8A: Walk-ups and Laundromats
8B: Urban Pioneers
8D: Doormen and Delivery
0 1 2 4 6 8 Miles

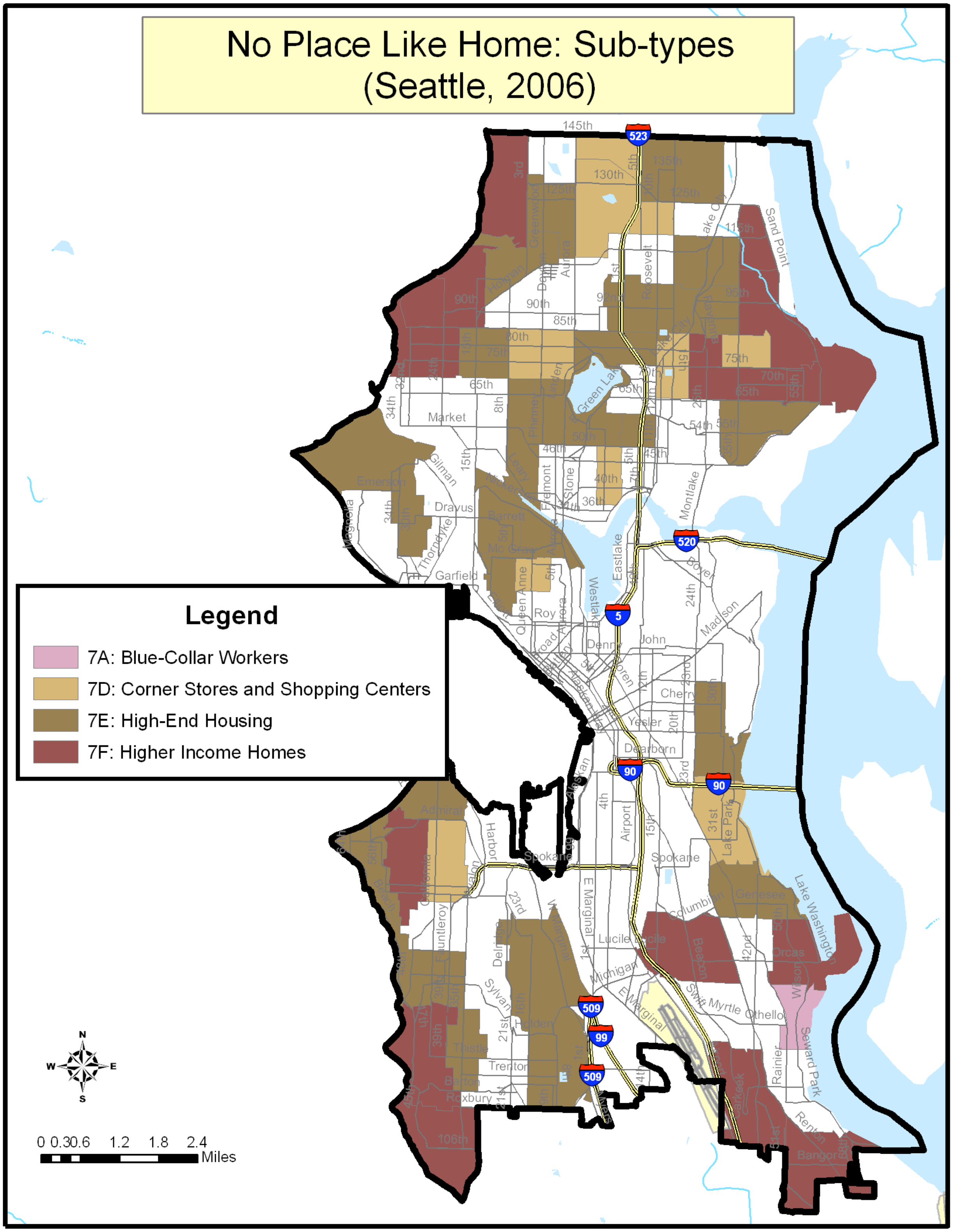

Fortune 100: Sub-types
(Dallas, 2006)
Legend
9A: Old Money
9B: Wealthy Boom
9C: Exclusive Enclaves
0 1 2 4 6 8
Miles

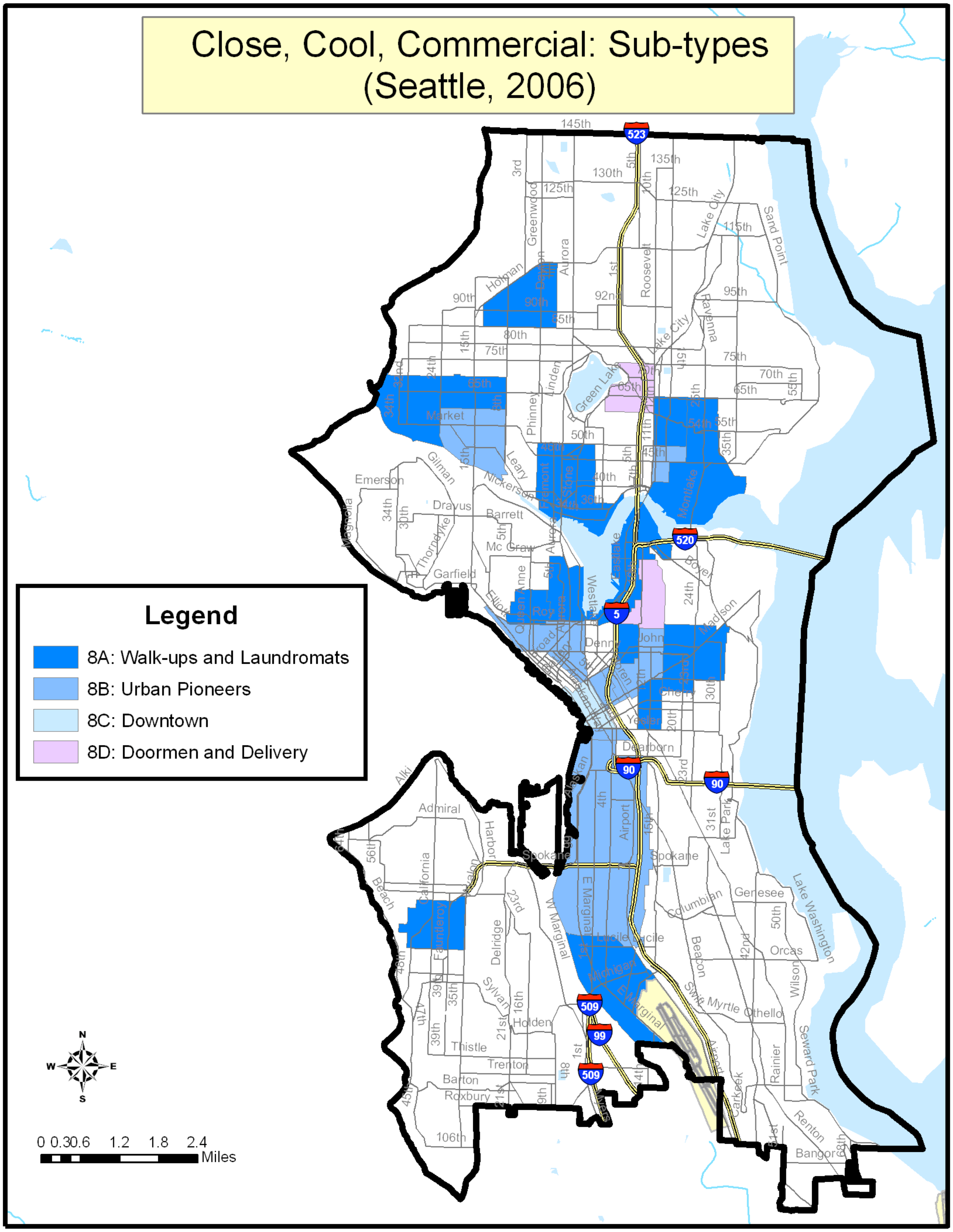

Seattle Neighborhood Types, 2006
Legend
4: Port of Entry
5: Urban Tapestry
6: Coming Attractions
7: No Place Like Home
8: Close, Cool, Commercial
9: Fortune 100
N
W
E
S
0 0.30.6 1.2 1.8 2.4
Miles
Lake Washington

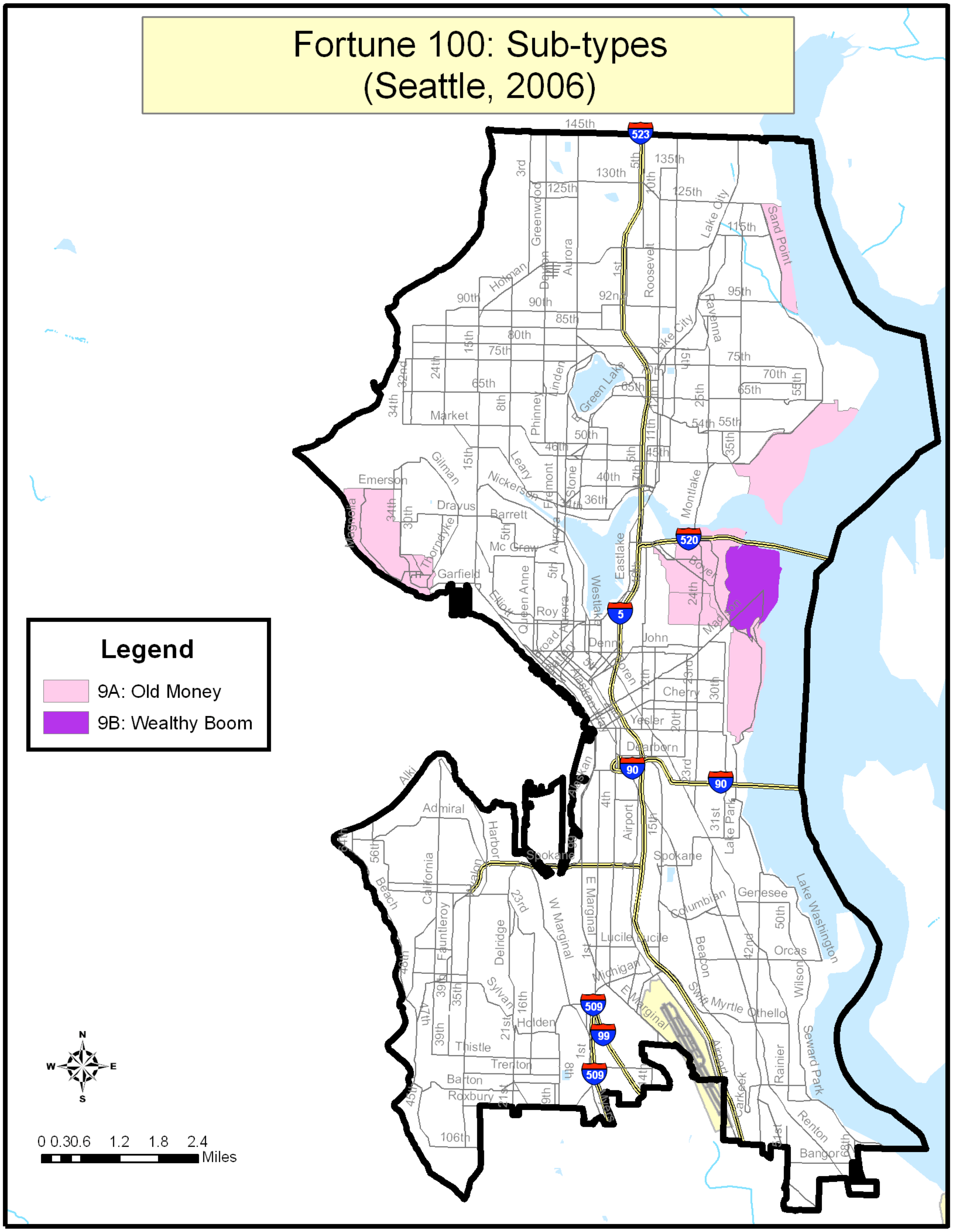

Port of Entry: Sub-types
(Seattle, 2006)
Legend
4B: Regional Shopping
4C: Local Shops
4D: Stable Residents
N
W
E
S
0 0.3 0.6 1.2 1.8 2.4
Miles


Urban Tapestry: Sub-types
(Seattle, 2006)
Legend
5A: Immigrant Eclectic
5B: High Diversity
5C: Young Adults
N
W
E
S
0 0.30.6 1.2 1.8 2.4
Miles


Coming Attractions: Sub-types
(Seattle, 2006)
Legend
6A: Commercial Districts
6B: Middle-Class Residential
6C: New Development
N
W
E
S
0 0.3 0.6 1.2 1.8 2.4
Miles


No Place Like Home: Sub-types
(Seattle, 2006)
Legend
7A: Blue-Collar Workers
7D: Corner Stores and Shopping Centers
7E: High-End Housing
7F: Higher Income Homes
0 0.3 0.6 1.2 1.8 2.4
Miles
N
S
E
W
145th
130th
125th
90th
85th
80th
75th
70th
65th
Market
46th
45th
40th
36th
Emerson
Dravus
Garfield
Roy
Denny
John
Cherry
Yesler
Dearborn
Spokane
Admiral
Lucile
Michigan
Myrtle
Othello
Trenton
Roxbury
106th
Sand Point
Lake Washington
Seward Park
Montlake
Eastlake
Westlake
Roosevelt
Madison
Rainier
Airport
E Marginal
Fauntleroy
Harbor
523
520
5
90
99
509


Close, Cool, Commercial: Sub-types
(Seattle, 2006)
Legend
8A: Walk-ups and Laundromats
8B: Urban Pioneers
8C: Downtown
8D: Doormen and Delivery
0 0.3 0.6 1.2 1.8 2.4
Miles


Fortune 100: Sub-types
(Seattle, 2006)
Legend
9A: Old Money
9B: Wealthy Boom
0 0.30.6 1.2 1.8 2.4
Miles