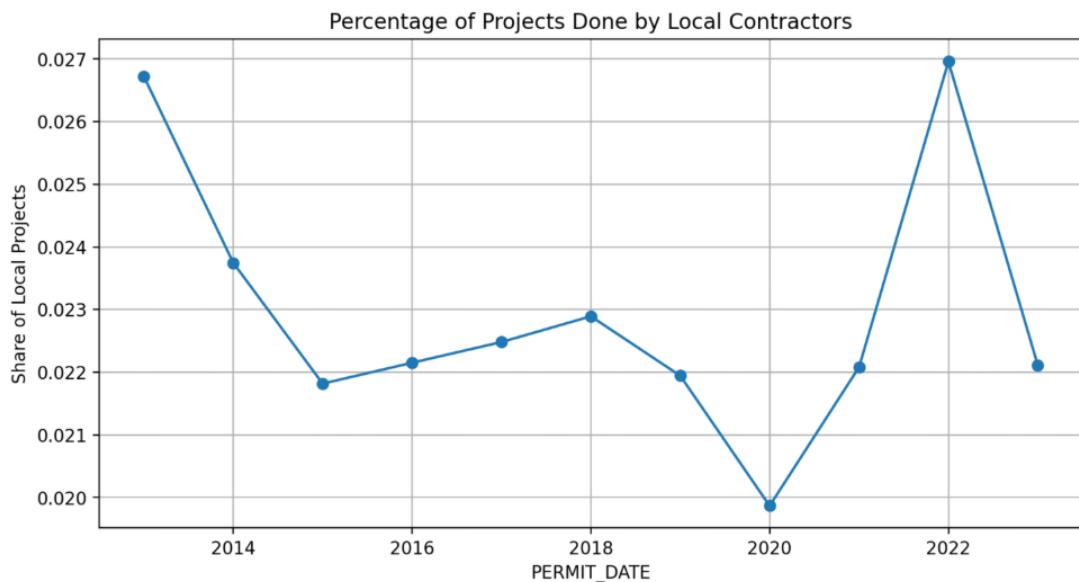


Assume we are **UrbanSC Fix**, a newly established General Contractor, facing a saturated and highly competitive construction market in Los Angeles. Instead of relying on intuition, we utilized public permit data to identify market gaps.

**First of all**, to determine if we should **focus on localization strategy**, we utilized zip code<sup>1</sup> data in both permit dataset and contractor dataset to analyze. The data reveals a shocking reality: **Less than 3%** of projects are performed by contractors within the same Zip Code. The trend line hovers between **0.020** and **0.027**. This means **97% of contractors** are traveling significant distances to work.



```
#1. Who's using local companies(same zip code means local)
contractor_permits["IS_LOCAL"] = (
    contractor_permits["PROJECT_ZIP"].fillna(0) ==
    contractor_permits["COMPANY_ZIP"].fillna(1)
)

#proportion
local_trends = contractor_permits.groupby(contractor_permits["PERMIT_DATE"].dt.year)[ "IS_LOCAL" ].mean()

#plot
plt.figure(figsize=(10, 5))
local_trends.plot(kind="line", marker="o")
plt.title("Percentage of Projects Done by Local Contractors")
plt.ylabel("Share of Local Projects")
plt.grid(True)
plt.show()
```

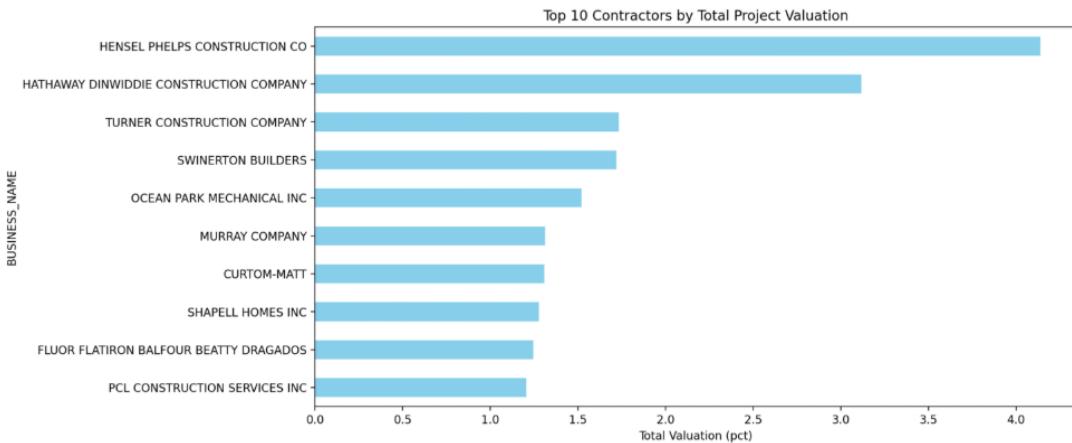
We initially thought sticking to our neighborhood was "standard practice." The data proves it is actually a **Blue Ocean Strategy**. Most competitors are **stuck in traffic, driving up costs and delaying timelines**. By strictly enforcing a "Local-Only" service radius, we could become the only contractor who can guarantee **"On-Site in 15 Minutes."** We aren't just "another local builder"; we are a logistical anomaly in a market of commuters. **We will market this as "Zero-Commute Efficiency"—passing the fuel and time savings directly to the customer.**

**Then**, we turn to analyze our competitors. By computing the total project value that **Top 10** Contractors got, we found that the top players are massive commercial firms like **Hensel**

---

<sup>1</sup> Local project means zip code between permit records and contractors keeps the same

**Phelps (4%+)** and **Hathaway Dinwiddie**. These companies dominate the high-valuation projects.



#2. Are top companies gaining most of the revenue?

```
#Market share by company
total_market_value = contractor_permits["VALUATION"].sum()

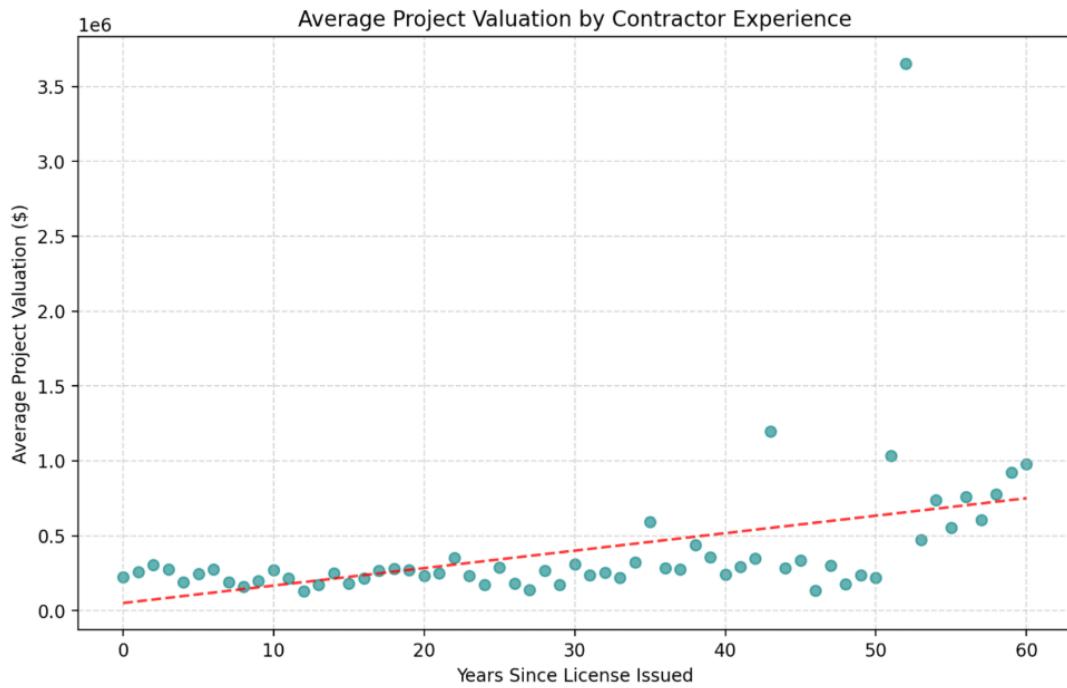
top_builders = (
    contractor_permits.groupby("BUSINESS_NAME")["VALUATION"]
    .sum()
    .sort_values(ascending=False)
    .head(10)
)

top_builders_mkt_share = (top_builders / total_market_value) * 100

#plot
plt.figure(figsize=(12, 6))
top_builders_mkt_share.sort_values().plot(kind="barh", color="skyblue")
plt.title("Top 10 Contractors by Total Project Valuation")
plt.xlabel("Total Valuation (pct)")
plt.show()
```

Though we cannot compete on scale while these top 10 companies hold **nearly 20%** of the market value, **we will focus on the fragment of the market they ignore: individual homeowners (while they prefer to do skyscrapers and stadiums).**

This is not enough since we will not understand the market deeply only by the simple market share analysis. Thus we did another analysis exploring that "**Do established companies have larger project size?**". According to our analysis, the scatter plot shows a flat trend for **the first 10-20 years**. New companies (**License Age < 5**) typically handle projects valued around **\$250,000**. It takes **50+ years** of experience to consistently land **\$1M+** average valuations.



```
#3. Do established companies have larger project size

#convert establish date to datetime
contractor_permits["ESTABLISH_DATE"] = pd.to_datetime(contractor_permits["ESTABLISH_DATE"], errors="coerce")

#license age
contractor_permits["LICENSE_AGE"] = (
    contractor_permits["PERMIT_DATE"].dt.year - contractor_permits["ESTABLISH_DATE"].dt.year)

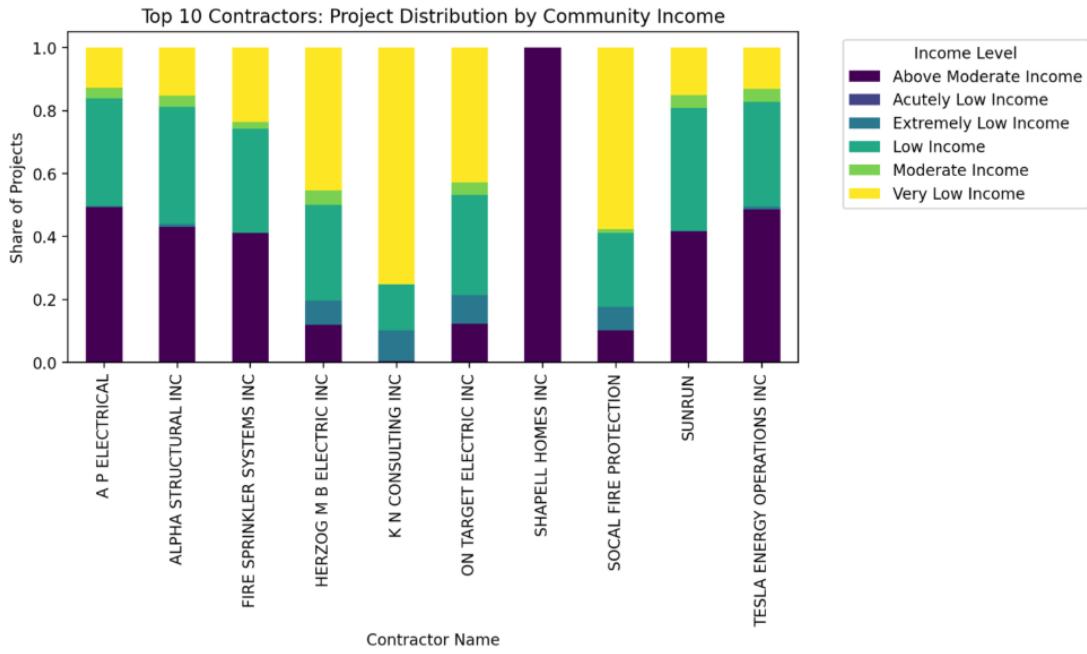
#filter negative and over-60-year values
valid_age = contractor_permits[
    (contractor_permits["LICENSE_AGE"] >= 0) &
    (contractor_permits["LICENSE_AGE"] <= 60)]

age_valuation = valid_age.groupby("LICENSE_AGE")["VALUATION"].mean()

#plot
plt.figure(figsize=(10, 6))
plt.scatter(age_valuation.index, age_valuation.values, color="teal", alpha=0.6)
#Trend line
z = np.polyfit(age_valuation.index, age_valuation.values, 1)
p = np.poly1d(z)
plt.plot(age_valuation.index, p(age_valuation.index), "r--", alpha=0.8)
plt.title("Average Project Valuation by Contractor Experience")
plt.xlabel("Years Since License Issued")
plt.ylabel("Average Project Valuation ($)")
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```

Since we are a startup, targeting luxury mansions (**\$1M+**) is statistically unrealistic and likely to fail. The strategy is we will target "**Mid-Scale Renovations**" (**\$50k - \$300k range**). This is the "sweet spot" for new entrants. **We will build our reputation here for the first 5 years before attempting to move up-market.**

Having regional and competitor analyses, we now need some target customer analysis. By connecting income data with top contractor data, we found that the market shows distinct polarization.



```
#4. Regional preference: Rich community vs Normal community
```

```
merged_census = contractor_permits.merge(
    census_tracts,
    left_on="CT",
    right_on="CENSUS_TRACT",
    how="inner"
)

#Top 10 busy companies
top_10_names = merged_census["BUSINESS_NAME"].value_counts().head(10).index.tolist()

subset = merged_census[merged_census["BUSINESS_NAME"].isin(top_10_names)]

#Crosstab
cross_tab = pd.crosstab(subset["BUSINESS_NAME"], subset["AMI_CATEGORY"], normalize="index")

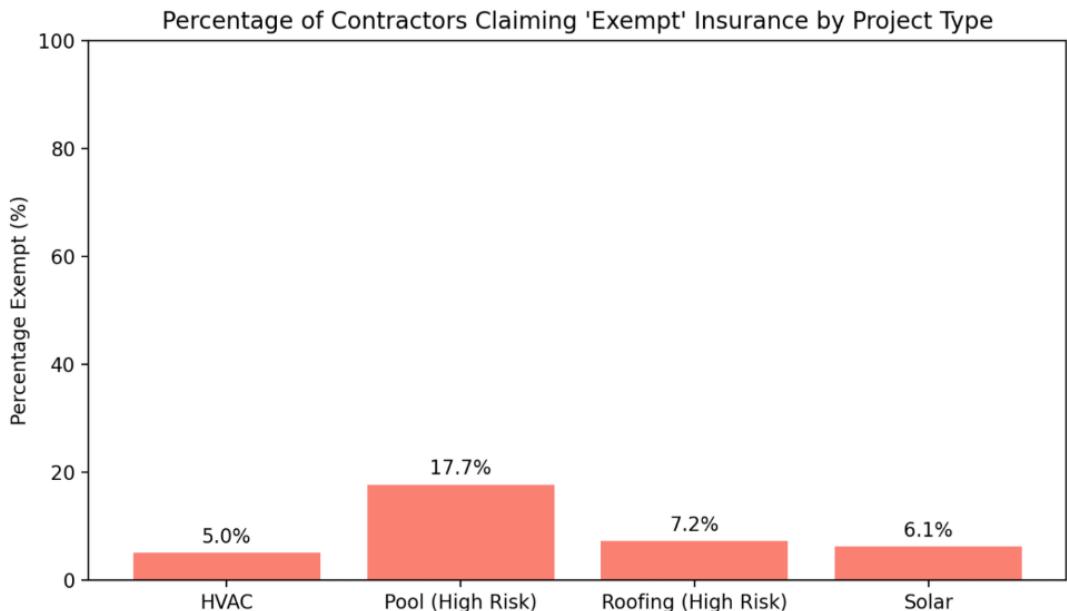
ax = cross_tab.plot(kind="bar", stacked=True, figsize=(10, 6), colormap="viridis")

plt.title("Top 10 Contractors: Project Distribution by Community Income")
plt.ylabel("Share of Projects")
plt.xlabel("Contractor Name")
plt.legend(title="Income Level", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

Companies like Shapell Homes Inc are **almost 100%** focused on "**Above Moderate Income**" customers. Meanwhile, companies like K N Consulting serve a mix of "**Very Low**" and "**Low**" income areas. In fact, The "**Above Moderate**" sector is crowded with specialists like Shapell. The "**Very Low**" sector often lacks budget. **BUT** the "**Moderate Income**" group are present but not dominated by any single monopoly. Therefore we could **identify our target audience**, which is **the Middle Class**—the neglected center. These clients are too small for Shapell but value quality more than the budget providers.

Above are a couple of basic market analysis, we still get time to go deeper and wider in the future. However, the workers' insurance coverage data seems to be a little bit important—it's about compliance. **According to our market experience, the cost of employee insurance**

is nonnegligible, which may lead to cost saving and compliance risk. By classifying the types of project, we found that the **exempt rate of insurance varies from project type**.



```
#5. Compliance: did some of companies really paid for worker injury insurance

#identify the risk level of project
def simple_category(desc):
    d = str(desc).lower()
    if "roof" in d: return "Roofing (High Risk)"
    if "pool" in d: return "Pool (High Risk)"
    if "hvac" in d: return "HVAC"
    if "solar" in d: return "Solar"
    return "Other"

contractor_permits["Project_Type"] = contractor_permits["AI_DESCRIPTION"].apply(simple_category)
plot_data = contractor_permits[contractor_permits["Project_Type"] != "Other"].copy()

#
exempt_rates = plot_data.groupby("Project_Type")["WORKERS_COMP_COVERAGE_TYPE"].apply(
    lambda x: (x == "Exempt").mean() * 100
)

#plot
plt.figure(figsize=(9, 5))
bars = plt.bar(exempt_rates.index, exempt_rates.values, color="salmon")
plt.bar_label(bars, fmt='%.1f%%', padding=3)
plt.title("Percentage of Contractors Claiming 'Exempt' Insurance by Project Type")
plt.ylabel("Percentage Exempt (%)")
plt.ylim(0, 100)
plt.show()
```

As we can see, while Roofing (7.2%), Solar (6.1%), and HVAC (5.0%) have high compliance rates, **Swimming Pools stand out with a 17.7% Exempt rate.** This is significantly higher than other high-risk<sup>2</sup> categories, demonstrating that **some contractors may avoid insurance illegally to save cost.** Knowing that, when bidding for pool projects, we will simply show this chart to the client and say "Mr. Client, almost 1 in 5 pool contractors in LA claim they have no employees to avoid insurance. If you hire them and an accident happens, **YOU** are liable. **We are part of the safe 80%.**" That's to say **in HVAC and Roofing, we compete on service (because everyone is safe). In Pools, we compete on Risk Mitigation.** This is a proper

---

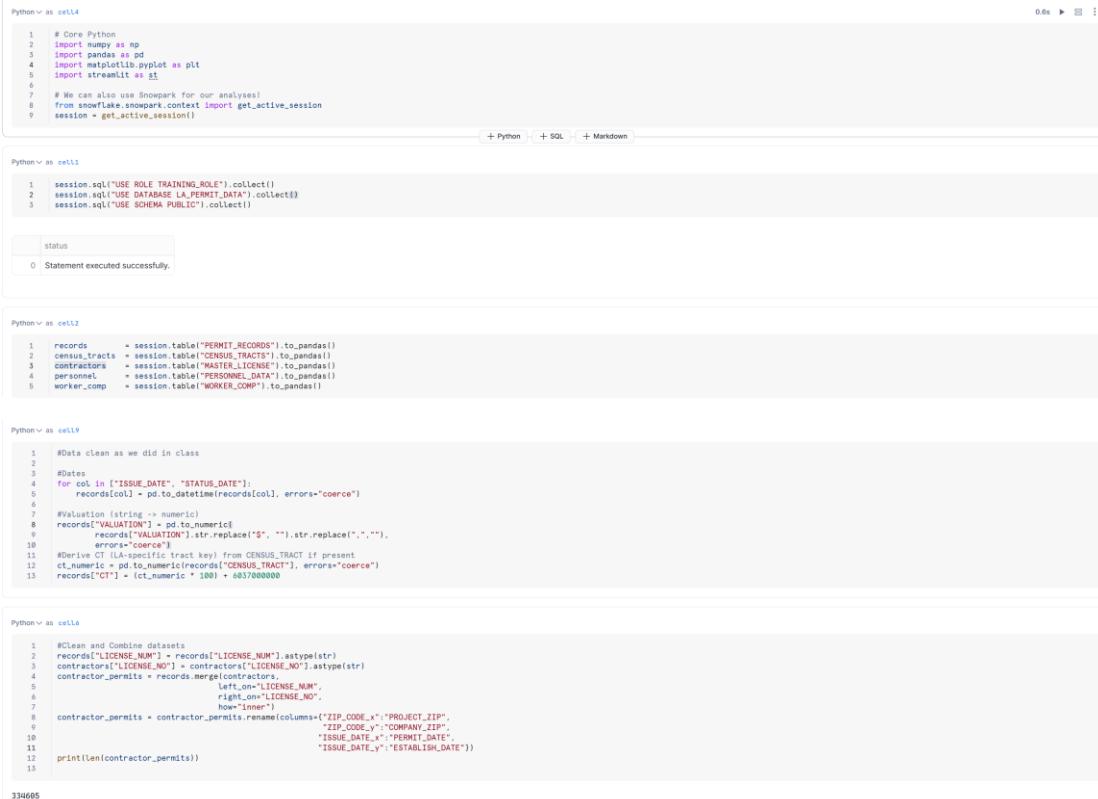
<sup>2</sup> High risk means this type of project needs a large number of workers, which may lead to illegal insurance cost saving

differentiation strategy.

In conclusion, by respecting the data, UrbanSC Fix avoids the trap of competing with commercial giants or expecting unrealistic project valuations. We will operate as a hyper-local logistical specialist for the middle-class residential market, using the industry's widespread non-compliance in pool construction as a powerful tool to win trust and contracts.

---

Below are code for data preparing and cleaning, and streamlit as well.



The screenshot shows a Jupyter Notebook interface with five code cells. The first cell contains imports for Python, including numpy, pandas, matplotlib, and streamlit. It also includes a comment about using Snowpark for analyses and a call to get\_active\_session(). The second cell uses session.sql() to collect three tables: PERMIT\_RECORDS, CENSUS\_TRACTS, and PERSONNEL\_DATA. The third cell defines variables for records, census\_tracts, contractors, personnel, and worker\_comp, each being a pandas DataFrame. The fourth cell contains data cleaning logic, including handling dates and numeric values, and derives a CT value from the CENSUS\_TRACT table. The fifth cell performs a merge operation between contractor and contractor\_permits DataFrames based on LICENSE\_NO, resulting in 334685 rows.

```
Python in cell1
1 # Core Python
2 import numpy as np
3 import pandas as pd
4 import matplotlib.pyplot as plt
5 import streamlit as st
6
7 # We can also use Snowpark for our analyses!
8 from snowflake.snowpark.context import get_active_session
9 session = get_active_session()

Python in cell2
1 session.sql("USE ROLE TRAINING_ROLE").collect()
2 session.sql("USE DATABASE LA_PERMIT_DATA").collect()
3 session.sql("USE SCHEMA PUBLIC").collect()

Python in cell3
status
0 Statement executed successfully.

Python in cell4
records = session.table("PERMIT_RECORDS").to_pandas()
census_tracts = session.table("CENSUS_TRACTS").to_pandas()
contractors = session.table("LA_PERMIT_LICENSE").to_pandas()
personnel = session.table("PERSONNEL_DATA").to_pandas()
worker_comp = session.table("WORKER_COMP").to_pandas()

Python in cell5
#Data clean as we did in class
#Dates
for col in ["ISSUE_DATE", "STATUS_DATE"]:
    records[col] = pd.to_datetime(records[col], errors="coerce")
#Valuation (string -> numeric)
records["VALUATION"] = pd.to_numeric(
    records["VALUATION"].str.replace("$", "").str.replace(",",""),
    errors="coerce")
#Derive CT (LA-specific tract key) from CENSUS_TRACT if present
ct_numeric = pd.to_numeric(records["CENSUS_TRACT"], errors="coerce")
records["CT"] = (ct_numeric * 100) + 6837000000

Python in cell6
#Clean and Combine datasets
records["LICENSE_NUM"] = records["LICENSE_NUM"].astype(str)
contractors["LICENSE_NO"] = contractors["LICENSE_NO"].astype(str)
contractor_permits = records.merge(contractors,
    left_on="LICENSE_NUM",
    right_on="LICENSE_NO",
    how="inner")
contractor_permits = contractor_permits.rename(columns={
    "ZIP_CODE_X": "PROJECT_ZIP",
    "ZIP_CODE_Y": "COMPANY_ZIP",
    "ISSUE_DATE_X": "PERMIT_DATE",
    "ISSUE_DATE_Y": "ESTABLISH_DATE"})
print(len(contractor_permits))

334685
```

Streamlit:

Streamlit App: HIPPO 2025-11-19 9:48pm

**Filters**  
Issue Year Range: 2023 - 2023  
Search Contractor Name:

## UrbanSC Fix: Market Intelligence Dashboard

Total Permits: 334,605 Total Valuation: \$58765.1 M Avg Local Project Rate: 2.30%

Local Trends | Market Share | Compliance Risk

### Top 10 Contractors by Valuation

Contractor	Valuation (%)
CYPRUS KIP	~1.2
FLUENT	~1.2
SOLAR CITY INC.	~3.0
SOUTHERN GEN.	~3.5
SOUTHERN GEN.	~1.2
TESLA ENERGY	~1.2

Y-axis: Market Share (%)

### Detailed Data View

PCIS_PERMIT_NUM	ISSUE_DATE	ISSUE_YEAR	PROJECT_ZIP	AI_DESCRIPTION	VALUATION	LICENSE_NUM	CONTRACTOR_BUSINESSNAME	LICENSE_NO	BUSINESS_NAME	
0	13041-20000-33076	2013-11-26 00:00:00	2013	91326	photovoltaic system installation; transformerless system; 3.8 kilowatt ac ss	None	901196	A W S ELECTRICAL & SOLAR INC	901196	A W S ELECTRICAL SERVICES
1	13041-10000-14434	2013-11-26 00:00:00	2013	90007	solar panel installation; roof mounted; electrical interconnect; main panel u	None	888104	SOLARCITY CORPORATION	888104	TESLA ENERGY OPERATIONS INC
2	13019-10000-01351	2013-11-26 00:00:00	2013	90011	demolition; single family dwelling; detached garage;	\$500	693797	CYPRUS KIP	693797	CYPRUS KIP
3	12018-10000-23480	2013-11-26 00:00:00	2013	90028	defered submit; metal ceiling system installation; lobby renovation	\$01	445804	HOWARD BUILDING CORPORATION	445804	HOWARD BUILDING CORPORATION
4	13044-20000-07838	2013-11-26 00:00:00	2013	91601	installation of hvac systems; mixed use building; 5 story	None	471428	CERTIFIED SERVICE	471428	CERTIFIED SERVICE
5	13019-10000-02932	2013-11-26 00:00:00	2013	91405	demolition; building removal; site clearing; lot clearing	32133	668511	UNLIMITED ENVIRONMENTAL INC	668511	UNLIMITED ENVIRONMENTAL INC
6	13041-10000-26491	2013-11-26 00:00:00	2013	91324	install photovoltaic system; install roof mounting system; connect to electr	None	888104	SOLARCITY CORPORATION	888104	TESLA ENERGY OPERATIONS INC

```

1 # Import python packages
2 import streamlit as st
3 import pandas as pd
4 import numpy as np
5 from snowflake.snowpark.context import get_active_session
6
7 # --- Page Configuration ---
8 st.set_page_config(layout="wide", page_title="UrbanFix LA Dashboard")
9 st.title("UrbanSC Fix: Market Intelligence Dashboard")
10
11 # Get current Snowflake session
12 session = get_active_session()
13
14 @st.cache_data
15 def obtain_data():
16     # 1. Fetch Permit Records
17     permits = session.sql("""
18         SELECT pcis_permit_num, issue_date, year(issue_date) as issue_year,
19             zip_code as project_zip, ai_description, valuation, license_num,
20             contractor_business_name
21         FROM la_permit_data.public.permit_records
22     """).to_pandas()
23
24     # 2. Data Cleaning
25     # Convert dates
26     permits['ISSUE_DATE'] = pd.to_datetime(permits['ISSUE_DATE'])
27     # Clean valuation (remove $ and ,) and convert to numeric
28     permits['VALUATION'] = pd.to_numeric(
29         permits['VALUATION'].astype(str).str.replace(r'[$,]', '', regex=True),
30         errors='coerce'
31     )
32     # Ensure join keys are strings
33     permits['LICENSE_NUM'] = permits['LICENSE_NUM'].astype(str)
34
35     # 3. Fetch Master License Data
36     # NOTE: Fetching 'workers_comp_coverage_type' directly from here (no separate join needed)
37     licenses = session.sql("""
38         SELECT license_no, business_name, zip_code as company_zip, workers_comp_coverage_type
39         FROM la_permit_data.public.master_license
40         WHERE license_no IN (SELECT DISTINCT license_num FROM la_permit_data.public.permit_records)
41     """).to_pandas()
42     licenses['LICENSE_NO'] = licenses['LICENSE_NO'].astype(str)
43
44     # 4. Merge Tables
45     # Inner join to match permits with contractor details
46     df_merged = permits.merge(
47         licenses,
48         left_on="LICENSE_NUM",
49         right_on="LICENSE_NO",
50         how="inner"
51     )
52
53     # 5. Feature Engineering: Local vs Non-Local
54     # Compare Project Zip with Company Zip
55     df_merged['IS_LOCAL'] = (
56         df_merged['PROJECT_ZIP'].fillna(0) == df_merged['COMPANY_ZIP'].fillna(1)
57     )
58
59     return df_merged
60
61 # Load Data
62 df_main = obtain_data()
63
64 # --- Sidebar Filters ---
65 st.sidebar.header('Filters')

```

```

66
67 # 1. Year Slider Filter
68 if not df_main.empty:
69     date0 = int(df_main['ISSUE_YEAR'].min())
70     date1 = int(df_main['ISSUE_YEAR'].max())
71     min_year, max_year = st.sidebar.slider('Issue Year Range', date0, date1, value=(date0, date1))
72 else:
73     min_year, max_year = 2013, 2024
74
75 # 2. Contractor Name Search
76 contractor_search = st.sidebar.text_input('Search Contractor Name:')
77
78 # Function to apply filters
79 @st.cache_data
80 def filter_data(df, min_y, max_y, search_term):
81     # Filter by Year
82     filtered = df[df['ISSUE_YEAR'].between(min_y, max_y)]
83
84     # Filter by Name (if provided)
85     if search_term:
86         filtered = filtered[filtered['BUSINESS_NAME'].str.contains(search_term, case=False, na=False)]
87
88     return filtered
89
90 # Apply the filters
91 df = filter_data(df_main, min_year, max_year, contractor_search)
92
93 # --- Main Metrics Section ---
94 col1, col2, col3 = st.columns(3)
95 with col1:
96     st.metric('Total Permits', f'{len(df)}')
97 with col2:
98     # Display in Millions
99     st.metric('Total Valuation', f'${df["VALUATION"].sum() / 1e6:.1f} M')
100 with col3:
101     # Calculate percentage of local projects
102     local_rate = df['IS_LOCAL'].mean() * 100
103     st.metric('Avg Local Project Rate', f'{local_rate:.2f}%')
104
105 st.divider()
106
107 # --- Charts Section (Native Streamlit Charts) ---
108 tab1, tab2, tab3 = st.tabs(["📍 Local Trends", "📈 Market Share", "⚠️ Compliance Risk"])
109
110 # Chart 1: Localization Trends (Line Chart)
111 with tab1:
112     st.subheader("Contractor Localization Trends")
113     # Group by year and calculate mean of boolean IS_LOCAL
114     local_trends = df.groupby('ISSUE_YEAR')[['IS_LOCAL']].mean()
115     st.line_chart(local_trends)
116     st.caption("Y-axis: Share of projects done by local contractors (0.02 = 2%)")
117
118 # Chart 2: Market Share (Bar Chart)
119 with tab2:
120     st.subheader("Top 10 Contractors by Valuation")
121     total_val = df['VALUATION'].sum()
122
123     if total_val > 0:
124         # Get Top 10 by Valuation Sum
125         top_builders = df.groupby("BUSINESS_NAME")["VALUATION"].sum().sort_values(ascending=False).head(10)
126         # Convert to percentage
127
127         top_pct = (top_builders / total_val) * 100
128         st.bar_chart(top_pct)
129         st.caption("Y-axis: Market Share (%)")
130     else:
131         st.info("No valuation data available.")
132
133 # Chart 3: Compliance Risk (Bar Chart)
134 with tab3:
135     st.subheader("Insurance Exempt Rates by Project Type")
136
137     # Helper function to categorize project types based on description
138     def get_category(desc):
139         d = str(desc).lower()
140         if "roof" in d: return "Roofing (High Risk)"
141         if "pool" in d: return "Pool (High Risk)"
142         if "hvac" in d: return "HVAC"
143         if "solar" in d: return "Solar"
144         return "Other"
145
146     # Create a copy to avoid SettingWithCopyWarning
147     risk_df = df.copy()
148     risk_df["Category"] = risk_df["AI_DESCRIPTION"].apply(get_category)
149     plot_data = risk_df[risk_df["Category"] != "Other"]
150
151     wc_col = "WORKERS_COMP_COVERAGE_TYPE"
152
153     if wc_col in plot_data.columns and not plot_data.empty:
154         # Calculate percentage of 'Exempt' status
155         exempt_rates = plot_data.groupby("Category")[wc_col].apply(lambda x: (x == "Exempt").mean() * 100)
156         st.bar_chart(exempt_rates)
157         st.caption("Y-axis: Percentage of contractors claiming 'Exempt' status (%)")
158     else:
159         st.info("No insurance data available in the current selection.")
160
161 # --- Detailed Data Table ---
162 st.subheader('Detailed Data View')
163 st.dataframe(df.head(100), use_container_width=True)

```