The Datanators

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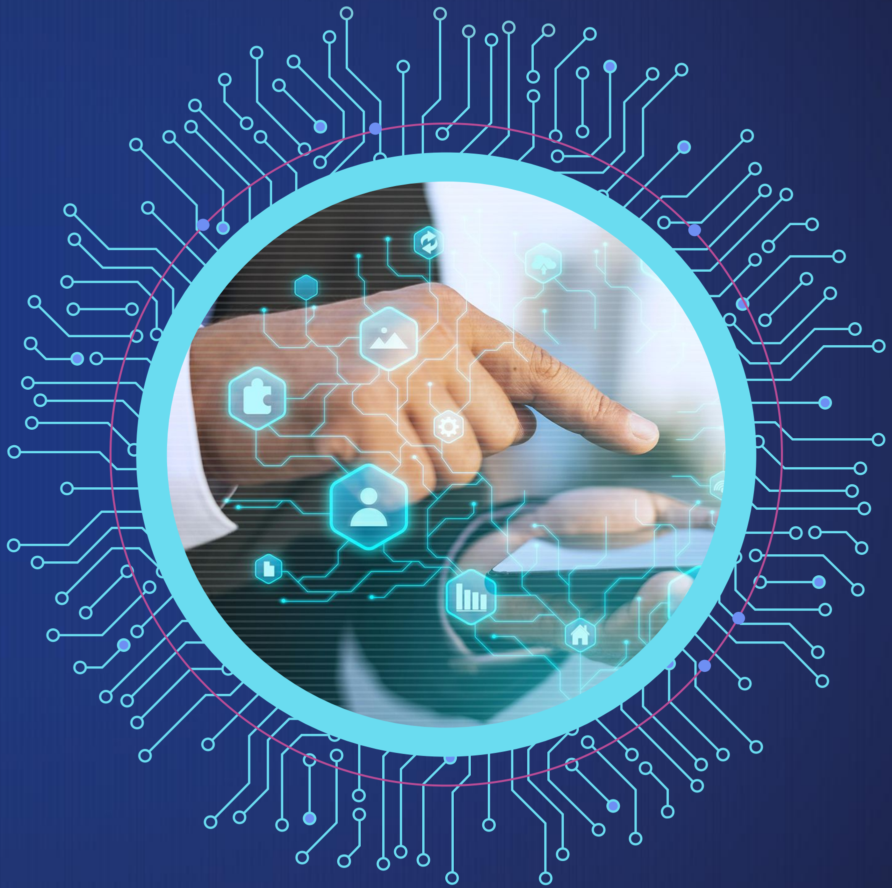
To inform Savills of notable trends or microtrends in the commercial real estate market that could be used to advise clients on where, when, whether and how to locate their offices.

—THE CHALLENGE

About us

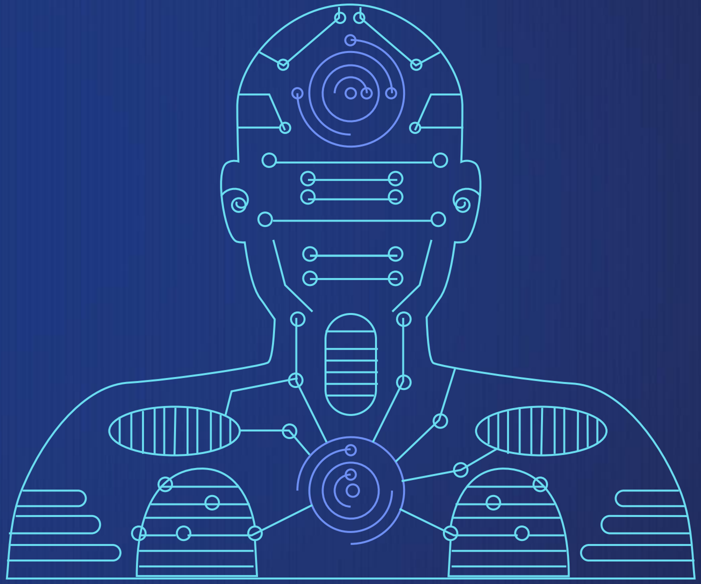
Savills is an international commercial real estate firm that helps businesses find a place to lease offices.



The Study Approach

Savills, seeking to stay ahead of the curve, analyzed leasing data, workforce mobility trends, and economic indicators across North America.

The Question Emerged: Do we really need ALL this Office Space?



OVERVIEW

01 Technical Tools Used

02 General Micro - Trends Observed

03 In - Depth Data Analysis with code snippets

04 Suggested Solutions

05 Future Forecast

TECHNICAL TOOLS USED

R

SQL

matplotlib

NumPy

SciPy

tidyverse

Power BI

02

GENERAL MICRO - TRENDS OBSERVED

KEY DATA POINTS

10%

Increase in leases for suburban office spaces, particularly in mixed-use developments that integrate work, retail, and residential zones.

30%

Year-over-year growth in demand for flexible workspaces in secondary markets, particularly among startups and tech firms.

WHAT WE FOUND

Flex-office spaces boomed

Coworking and serviced offices are now the go-to for businesses

Record-high office vacancies

Firms downsize as hybrid-work became the norm in urban centres

A Divergence in office demand

An unexpected trend...

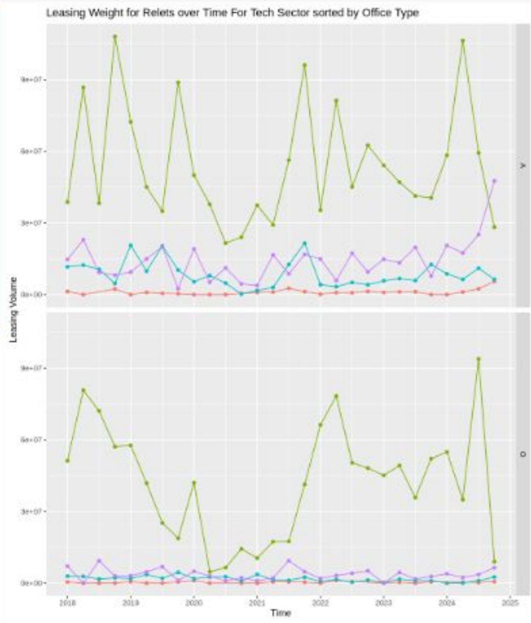
Office Space is changing

NOT needed in the traditional sense anymore

IN-DEPTH
DATA ANALYSIS


A PICTURE IS WORTH A THOUSAND WORDS.
PictureQuotes.com

The Effects of Remote Work on Leases and Rent Costs



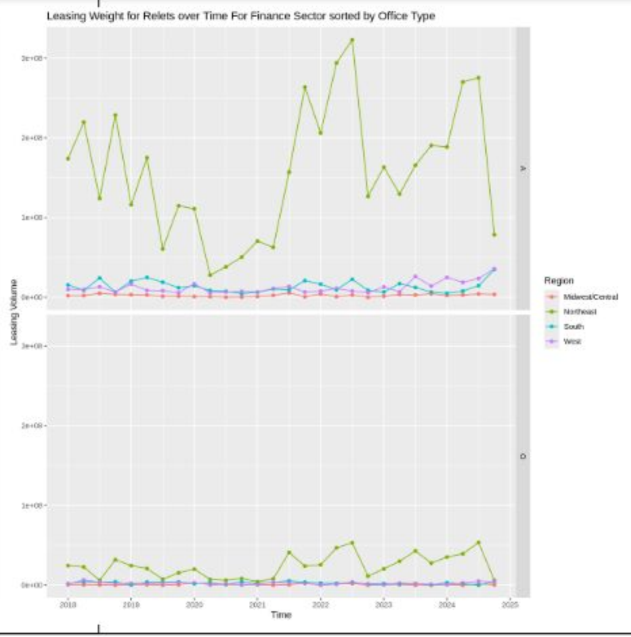
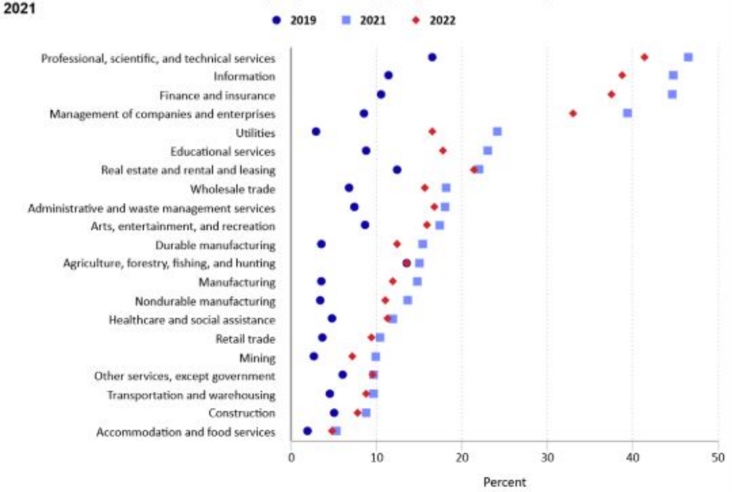


Chart 1. Percent of remote workers by major industry group, ranked from largest to smallest in 2021



Click legend items to change data display. Hover over chart to view data.
Source: U.S. Census Bureau, American Community Survey.

Suggested Solutions

OVERALL SOLUTIONS

Office Pooling

- Targeted for small start-ups to grow network and optimize resources

The “Hub n Spoke Model” - Flex Office Spaces

- Decentralized and dynamic with shorter, more flexible leases
- Aimed for SMBs & hybrid-first companies In high-growth areas

Industry-Specific Recommendations

Technology + Creative

- **<u>Decentralize:</u>** Firms in the Technology and Creative industries move out of crowded CBDs by expanding to suburbs with good public commute systems and high growth potential.
- **<u>Diversify:</u>** Companies in these sectors can diversify into smaller regional hubs with satellite offices in suburban markets like Austin, Nashville, and Denver, rather than one big centralised HQ.

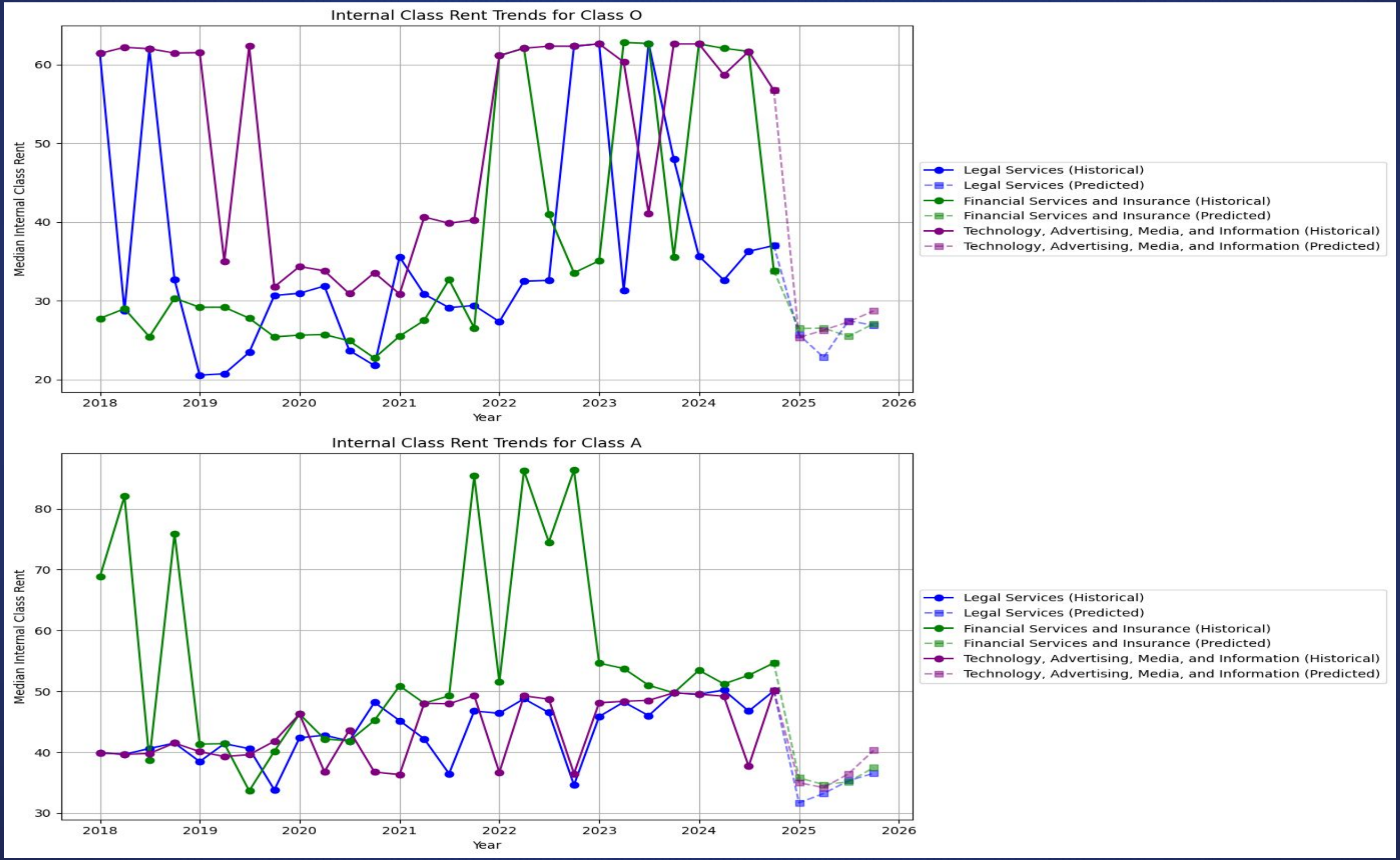
Finance + Legal

- **<u>Move to Higher Quality:</u>** Financial and legal & related industries, especially in the Northeast, that maintained physical offices sought Class A buildings with premium amenities, even at higher rents, leading to a polarization where lower-tier office spaces struggled with record vacancies. So, companies in these industries should move to high-octane CBDs with prime office locations for client-facing operations.

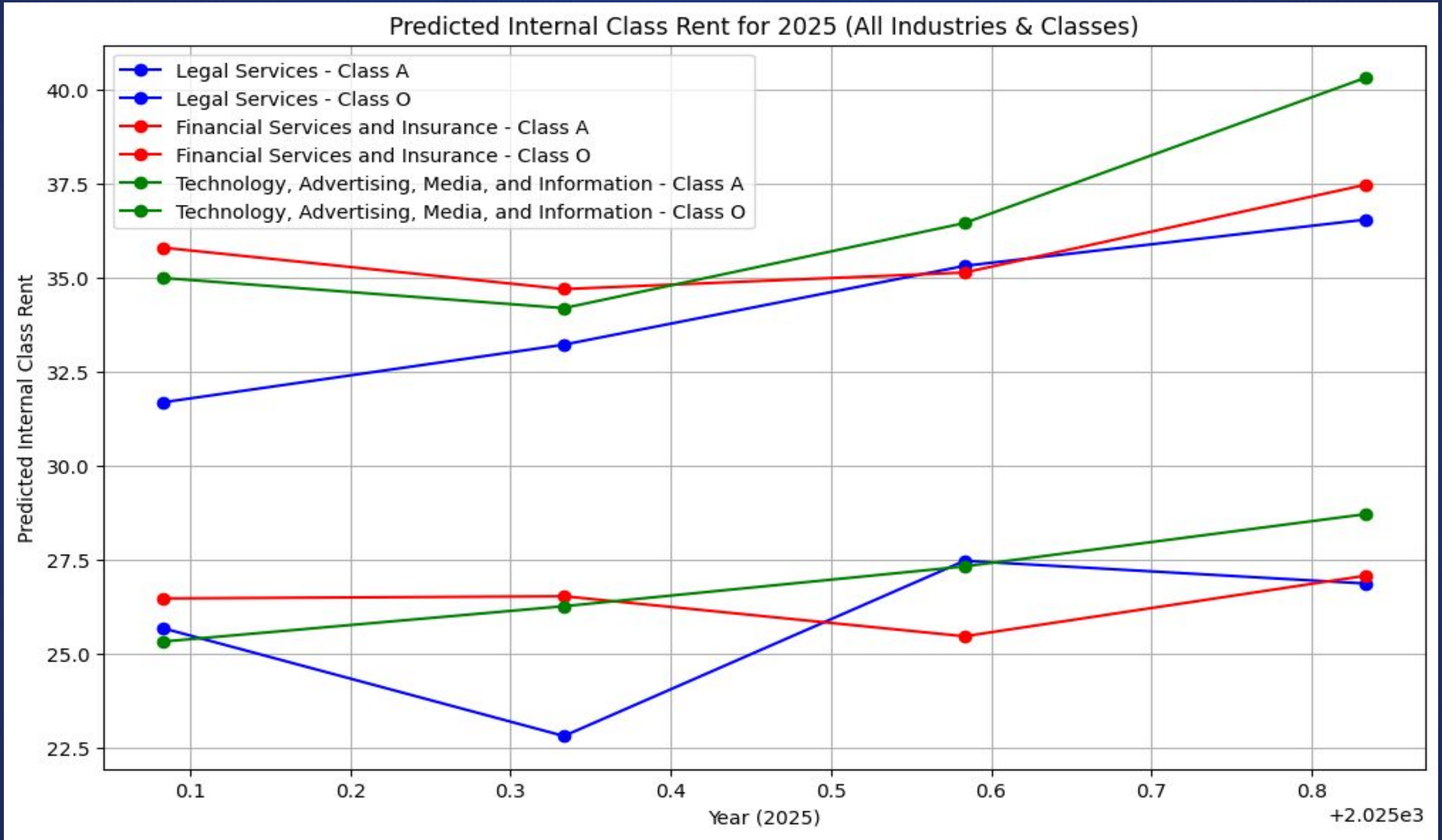
05

OUR FUTURE FORECAST

Predicted Class Trends (O & A)



Predicted Internal Class Rent



Thank You for Listening!

Do you have any questions?

Appendix (Code Snippets)

Random Forest

```
# Filter data for 2018-2024
df = df[(df['year'] >= 2018) & (df['year'] <= 2024)]

# Map quarters to starting months
quarter_to_month = {'Q1': '01', 'Q2': '04', 'Q3': '07', 'Q4': '10'}
df['month'] = df['quarter'].map(quarter_to_month)

# Create a valid datetime column
df['date_signed'] = pd.to_datetime(df['year'].astype(str) + '-' + df['month'] + '-01')

# Extract numerical features from date_signed
df['year_signed'] = df['date_signed'].dt.year
df['month_signed'] = df['date_signed'].dt.month

# Define industries to focus on
industries_of_interest = [
    "Legal Services",
    "Financial Services and Insurance",
    "Technology, Advertising, Media, and Information"
]

df = df[df['internal_industry'].isin(industries_of_interest)]  # Filter industries
```

Continued...

```
# Handle categorical variables with One-Hot Encoding
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
categorical_features = df[["region", "internal_industry", "internal_class"]].astype(str)
categorical_encoded = encoder.fit_transform(categorical_features)

# Convert categorical encoding into DataFrame
encoded_df = pd.DataFrame(categorical_encoded, columns=encoder.get_feature_names_out())

# Combine encoded features with numerical features
df_final = pd.concat([encoded_df, df[['year_signed', 'month_signed', target]].reset_index(drop=True)], axis=1)

# Define features (X) and target (y)
X = df_final.drop(columns=[target])
y = df_final[target]

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Continued...

```
# Train Random Forest Model
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Predictions and evaluation
y_pred = rf.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f"RMSE: {rmse}")

# Forecast future rent for 2025 (one year)
forecast_year = 2025
months = [1, 4, 7, 10]  # Quarterly predictions
```

Some R Code...

```
options(repr.plot.width=10, repr.plot.height=10)
ggplot(leases_only_relets, aes(x = chronological_order, y = total_leasing, colour = region)) +
geom_point() +
geom_line() +
facet_grid(rows = vars(internal_class)) +
labs(x = "Time", y = "Leasing Volume", colour = "Region") +
ggtitle("Leasing Volume for Relets over Time For Tech Sector sorted by Office Type and Region") +
scale_x_continuous(breaks = c(2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025))
```