ECON7890 Assignment 4 ? Kowloon Property Transactions

End-to-end notebook: import/clean the 28hse Kowloon transactions (Nov 2014?Nov 2020), merge macro data, explore, model price drivers, and summarize findings.

Tasks

- Import & clean the raw CSV, fix headers, parse numbers, handle missing values
- Merge with external macro indicators (World Bank unemployment & CPI)
- Exploratory data analysis with descriptive stats and visuals
- Train/evaluate multiple models to explain price per saleable sqft
- Summarize insights and next steps

In [9]:
```
import re
from pathlib import Path
from typing import Any, Dict, List

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import requests
import seaborn as sns
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder

%matplotlib inline

NOTEBOOK_DIR = Path(__file__).resolve().parent if '__file__' in globals() else Path
DATA_PATH = NOTEBOOK_DIR / 'hw.csv'
OUTPUT_DIR = NOTEBOOK_DIR / 'assignment4_outputs'
OUTPUT_DIR.mkdir(parents=True, exist_ok=True)
```

1) Load raw data

Read the provided `hw.csv` file and inspect the columns.

In [10]:
```
raw_df = pd.read_csv(DATA_PATH)
display(raw_df.head())
print(f"Rows: {len(raw_df):,}, Columns: {len(raw_df.columns)}")
raw_df.columns.tolist()
```

	date	withpre	id	rootid	fatherid	catid	catname	catfathername	
0	2020-11-27	1.0	683333	2	79	2058	Bel Air Heights	Diamond Hill	https://data.28hs
1	2020-11-27	1.0	683332	2	71	2712	Fa Yuen Plaza	Mong Kok	https://data.2
2	2020-11-27	1.0	683331	2	78	3094	Caldecott Hill	Yau Yat Tsuen	https://data.28ł
3	2020-11-27	NaN	683330	2	57	5035	Pang Ching Court	Wong Tai Sin	https://data.2
4	2020-11-27	1.0	683329	2	67	2564	Metro Harbour View	Tai Kok Tsui	https://data.28

5 rows × 35 columns

Rows: 80,000, Columns: 35

Out[10]:
```
['date',
 'withpre',
 'id',
 'rootid',
 'fatherid',
 'catid',
 'catname',
 'catfathername',
 'url_father',
 'url_cat',
 'source',
 'contract',
 'memo',
 'price',
 'price_value',
 'holddate',
 'winloss_flag',
 'winloss',
 'act_area',
 'area',
 'arearaw',
 'sq_price',
 'sq_price_value',
 'sq_actprice',
 'sq_actprice_value',
 'month',
 'day',
 'date_dm',
 'date_y',
 'block',
 'state',
 'floor',
 'room',
 'addr',
 'Unnamed: 34']
```

2) Cleaning helpers

The raw headers are cryptic and some fields embed units/HTML. Helper functions below parse numbers, percentages, and holding periods.

In [11]:
```python
def _parse_number(text: Any) -> float:
    # Extract first numeric value from a string; return NaN on failure.
    if pd.isna(text):
        return np.nan
    match = re.search(r"([0-9]*\.?[0-9]+)", str(text))
    if match:
        try:
            return float(match.group(1))
        except ValueError:
            return np.nan
    return np.nan
```

```
def _parse_percent(text: Any) -> float:
    # Convert percent strings (e.g., '413%') to decimal (4.13).
    if pd.isna(text):
        return np.nan
    text = str(text).replace('%', '').strip()
    if not text or text == '--':
        return np.nan
    try:
        return float(text) / 100.0
    except ValueError:
        return np.nan


def _parse_holding_years(text: Any) -> float:
    # Convert holding period text such as '16 years 251 days' into years.
    if pd.isna(text):
        return np.nan
    if text in ('--', '-1'):
        return np.nan
    text = str(text)
    years = _parse_number(text)
    days_match = re.search(r"([0-9]+)\s*day", text)
    days = float(days_match.group(1)) if days_match else 0.0
    if np.isnan(years):
        return days / 365.0 if days else np.nan
    return years + days / 365.0
```

3) Clean transactions

- Drop unnamed columns
- Rename to readable headers
- Parse dates, numbers, areas, floor, holding period, win/loss
- Remove bad rows and duplicates

In [12]:
```
def clean_transactions(df: pd.DataFrame) -> pd.DataFrame:
    df = df.copy()

    df = df.drop(columns=[c for c in df.columns if c.startswith('Unnamed')], errors
    rename_map: Dict[str, str] = {
        'withpre': 'pre_sale_flag',
        'catname': 'estate',
        'catfathername': 'district',
        'price': 'price_label',
        'price_value': 'price_hkd',
        'holddate': 'holding_period_text',
        'winloss': 'winloss_pct',
        'act_area': 'saleable_area',
        'area': 'gross_area',
        'arearaw': 'gross_area_raw',
        'sq_price': 'sq_price_label',
        'sq_price_value': 'price_per_gross_sf',
        'sq_actprice': 'sq_actprice_label',
        'sq_actprice_value': 'price_per_saleable_sf',
```

```
        'date_y': 'year_text',
        'state': 'building',
        'addr': 'address',
    }
    df = df.rename(columns=rename_map)

    df['date'] = pd.to_datetime(df['date'], errors='coerce')
    df['year'] = df['date'].dt.year
    df['month'] = df['date'].dt.month
    df['pre_sale_flag'] = df['pre_sale_flag'].fillna(0).astype(int)
    df['price_hkd'] = pd.to_numeric(df['price_hkd'], errors='coerce')
    df['price_per_gross_sf'] = pd.to_numeric(df['price_per_gross_sf'], errors='coer
    df['price_per_saleable_sf'] = pd.to_numeric(df['price_per_saleable_sf'], errors

    df['saleable_area'] = df['saleable_area'].apply(_parse_number)
    df['gross_area'] = df['gross_area'].apply(_parse_number)
    gross_series = df['gross_area_raw'] if 'gross_area_raw' in df.columns else pd.S
    df['gross_area_raw'] = pd.to_numeric(gross_series, errors='coerce')

    df['floor_num'] = df['floor'].apply(_parse_number)
    df['holding_period_years'] = df['holding_period_text'].apply(_parse_holding_yea
    df['winloss_pct'] = df['winloss_pct'].apply(_parse_percent)

    df['price_per_saleable_sf'] = df['price_per_saleable_sf'].fillna(
        df['price_hkd'] / df['saleable_area']
    )

    df = df.dropna(subset=['date', 'price_hkd', 'saleable_area', 'price_per_saleabl
    df = df[(df['saleable_area'] > 0) & (df['price_hkd'] > 0) & (df['price_per_sale

    df['estate'] = df['estate'].astype(str).str.strip()
    df['district'] = df['district'].astype(str).str.strip()
    df['building'] = df['building'].astype(str).str.strip()

    if 'id' in df.columns:
        df = df.drop_duplicates(subset=['id'])

    return df


cleaned_df = clean_transactions(raw_df)
display(cleaned_df.head())
print(f"Cleaned rows: {len(cleaned_df):,}")
cleaned_df.to_csv(OUTPUT_DIR / 'cleaned_transactions.csv', index=False)
```

	date	pre_sale_flag	id	rootid	fatherid	catid	estate	district	
0	2020-11-27	1	683333	2	79	2058	Bel Air Heights	Diamond Hill	https://data.28hse
1	2020-11-27	1	683332	2	71	2712	Fa Yuen Plaza	Mong Kok	https://data.28
2	2020-11-27	1	683331	2	78	3094	Caldecott Hill	Yau Yat Tsuen	https://data.28h
4	2020-11-27	1	683329	2	67	2564	Metro Harbour View	Tai Kok Tsui	https://data.28h
5	2020-11-27	1	683328	2	65	2521	Nob Hill	Mei Foo	https://data.28h

5 rows × 37 columns

```
Cleaned rows: 38,257
```

4) Macro data (World Bank)

Pull Hong Kong unemployment rate (`SL.UEM.TOTL.ZS`) and CPI (`FP.CPI.TOTL` , 2010=100) and merge by year.

In [13]:
```python
def fetch_world_bank_indicator(indicator_id: str, value_name: str, start_year: int
    url = f"https://api.worldbank.org/v2/country/HKG/indicator/{indicator_id}?per_p
    resp = requests.get(url, timeout=30)
    resp.raise_for_status()
    data = resp.json()
    if len(data) < 2 or not isinstance(data[1], list):
        raise ValueError(f"Unexpected World Bank response for {indicator_id}")
    records: List[Dict[str, float]] = []
    for entry in data[1]:
        year_txt = entry.get('date')
        value = entry.get('value')
        if value is None or year_txt is None:
            continue
        try:
            year = int(year_txt)
        except ValueError:
            continue
        if start_year <= year <= end_year:
            records.append({'year': year, value_name: float(value)})
    out = pd.DataFrame(records).sort_values('year').reset_index(drop=True)
    return out
```

```
def build_macro_dataset(start_year: int = 2014, end_year: int = 2020) -> pd.DataFra
    unemployment = fetch_world_bank_indicator('SL.UEM.TOTL.ZS', 'unemployment_rate'
    cpi = fetch_world_bank_indicator('FP.CPI.TOTL', 'cpi_index', start_year, end_ye
    return pd.merge(unemployment, cpi, on='year', how='outer')


macro_df = build_macro_dataset(2014, 2020)
display(macro_df)
macro_df.to_csv(OUTPUT_DIR / 'macro_data.csv', index=False)
```

	year	unemployment_rate	cpi_index
0	2014	3.296	119.384997
1	2015	3.314	122.955621
2	2016	3.392	125.918000
3	2017	3.124	127.799054
4	2018	2.805	130.874071
5	2019	2.917	134.647443
6	2020	5.808	134.985357

5) Merge transactions + macro

Merge on year to enrich each transaction with unemployment/CPI.

In [14]:
```
merged_df = pd.merge(cleaned_df, macro_df, on='year', how='left')
display(merged_df[['date', 'district', 'price_hkd', 'saleable_area', 'price_per_sal
merged_df.to_csv(OUTPUT_DIR / 'transactions_with_macro.csv', index=False)
```

	date	district	price_hkd	saleable_area	price_per_saleable_sf	unemployment_rate	cpi_
0	2020-11-27	Diamond Hill	10000000	657.0	15220.70	5.808	134.9
1	2020-11-27	Mong Kok	4280000	214.0	20000.00	5.808	134.9
2	2020-11-27	Yau Yat Tsuen	11000000	991.0	11099.90	5.808	134.9
3	2020-11-27	Tai Kok Tsui	7150000	412.0	17354.37	5.808	134.9
4	2020-11-27	Mei Foo	2460000	457.0	5382.93	5.808	134.9

6) Exploratory Data Analysis

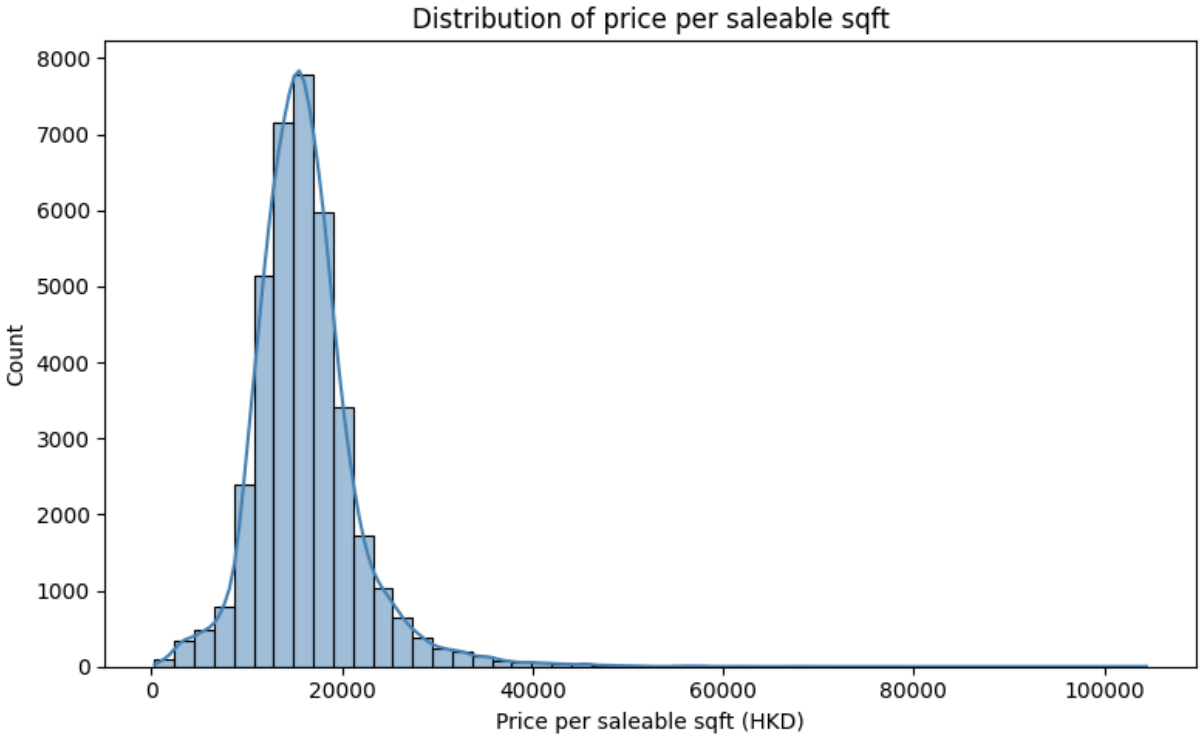
- Summary stats & missing values
- Top districts by count
- Distribution and scatter plots
- Monthly median price trend and yearly macro overlay

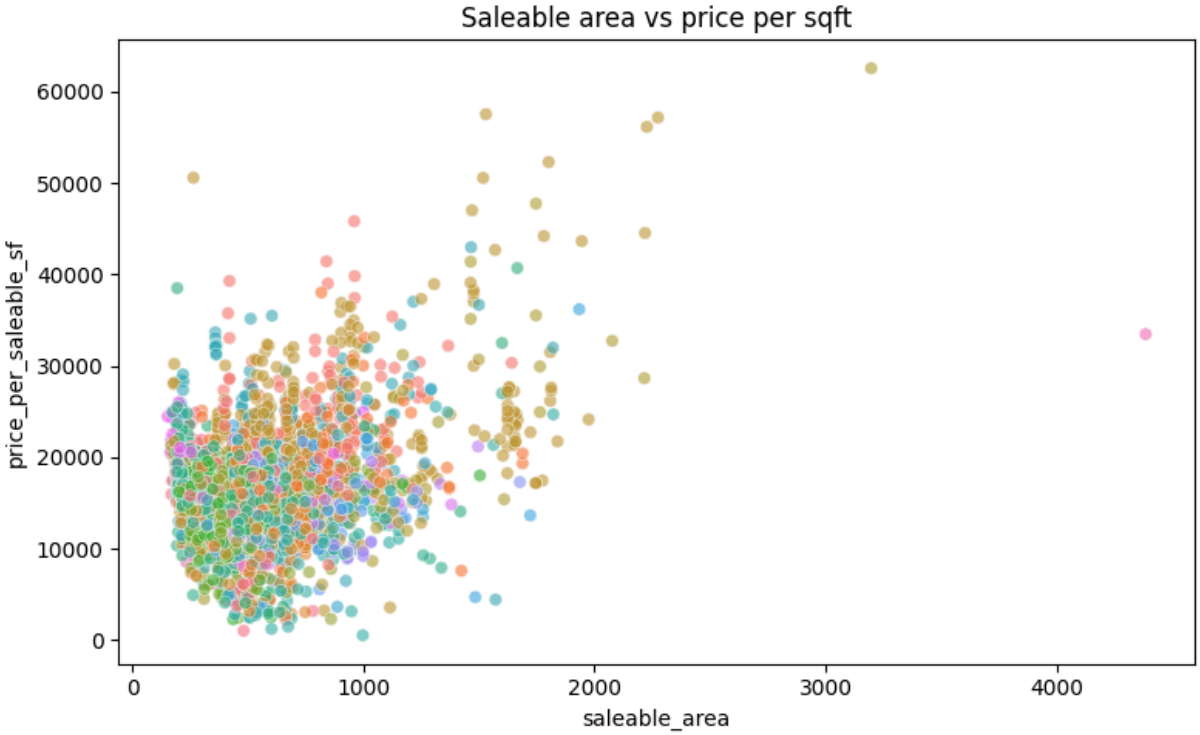
In [15]:
```
numeric_cols = ['price_hkd', 'saleable_area', 'gross_area', 'price_per_saleable_sf'
summary_stats = merged_df[numeric_cols].describe()
missing = merged_df[numeric_cols].isna().sum().sort_values(ascending=False)
top_districts = merged_df['district'].value_counts().head(10)

display(summary_stats)
display(missing)
display(top_districts)

plt.figure(figsize=(8, 5))
sns.histplot(x=merged_df['price_per_saleable_sf'], bins=50, kde=True, color='steelb
plt.xlabel('Price per saleable sqft (HKD)')
plt.title('Distribution of price per saleable sqft')
plt.tight_layout()
plt.show()

plt.figure(figsize=(8, 5))
sns.scatterplot(
    data=merged_df.sample(min(len(merged_df), 5000), random_state=42),
    x='saleable_area', y='price_per_saleable_sf', hue='district', alpha=0.6, legend
)
plt.title('Saleable area vs price per sqft')
plt.tight_layout()
plt.show()

monthly = merged_df.set_index('date')['price_per_saleable_sf'].resample('ME').media
monthly.plot(figsize=(9, 4), title='Monthly median price per saleable sqft')
plt.ylabel('HKD per sqft')
plt.tight_layout()
plt.show()

yearly = (
    merged_df.groupby('year')
    .agg(median_price_per_saleable_sf=('price_per_saleable_sf', 'median'), unemploy
    .dropna()
)
if not yearly.empty:
    fig, ax1 = plt.subplots(figsize=(9, 4))
    ax1.plot(yearly.index, yearly['median_price_per_saleable_sf'], marker='o', colo
    ax1.set_ylabel('Median price per saleable sqft (HKD)', color='tab:blue')
    ax1.tick_params(axis='y', labelcolor='tab:blue')

    ax2 = ax1.twinx()
    ax2.plot(yearly.index, yearly['unemployment_rate'], marker='s', color='tab:red'
    ax2.set_ylabel('Unemployment rate (%)', color='tab:red')
    ax2.tick_params(axis='y', labelcolor='tab:red')

    plt.title('Yearly price per sqft vs unemployment')
```

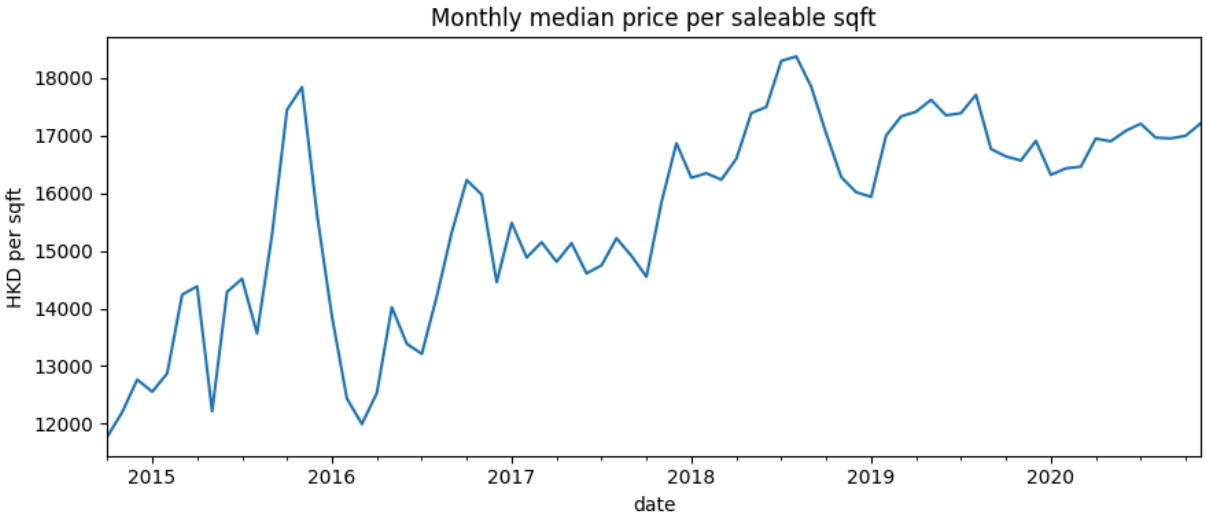
```
    fig.tight_layout()
    plt.show()
```

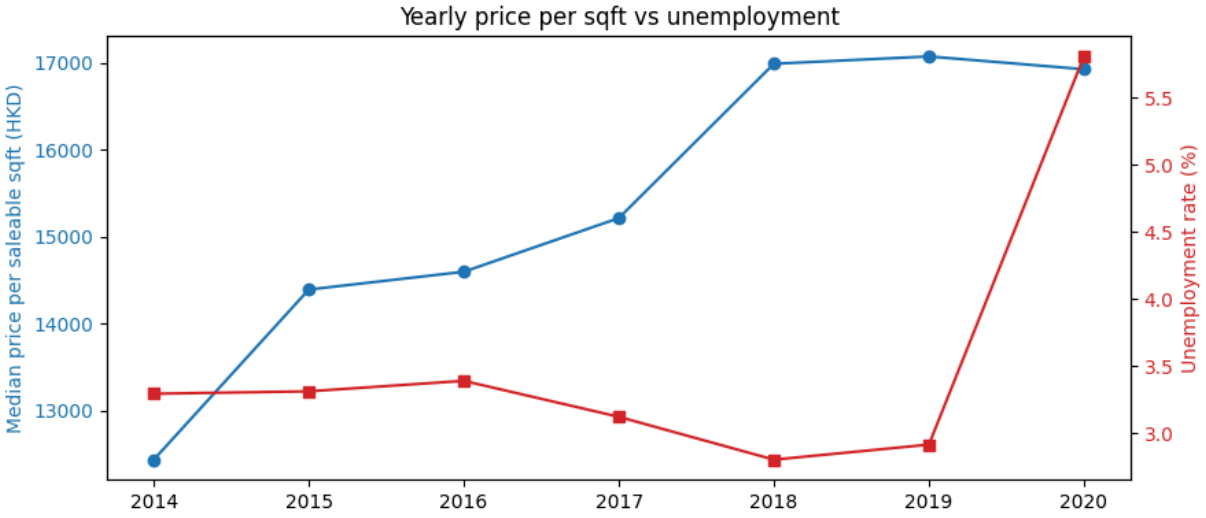
	price_hkd	saleable_area	gross_area	price_per_saleable_sf	price_per_gross_sf
count	3.825700e+04	38257.000000	25191.000000	38257.000000	38257.000000
mean	9.146396e+06	537.478658	729.950736	16146.472138	7467.315900
std	9.317771e+06	275.987299	301.597647	5506.599411	6094.495547
min	1.375000e+05	152.000000	238.000000	352.560000	0.000000
25%	5.128000e+06	372.000000	550.000000	12949.640000	0.000000
50%	7.000000e+06	496.000000	663.000000	15618.450000	9288.890000
75%	9.776400e+06	612.000000	823.000000	18459.570000	11996.780000
max	4.238000e+08	4414.000000	6168.000000	104418.100000	79324.590000

```
gross_area               13066
price_hkd                    0
saleable_area                0
price_per_saleable_sf        0
price_per_gross_sf           0
dtype: int64
district
Hung Hom          4453
Ho Man Tin        3573
To Kwa Wan        2794
Olympic           2680
Kowloon Bay       2666
Cheung Sha Wan    2424
Lam Tin           2398
Mei Foo           2299
Lai Chi Kok       2179
Tai Kok Tsui      1765
Name: count, dtype: int64
```


Distribution of price per saleable sqft
Count
Price per saleable sqft (HKD)
0
1000
2000
3000
4000
5000
6000
7000
8000
0
20000
40000
60000
80000
100000


Saleable area vs price per sqft
price_per_saleable_sf
saleable_area
0
10000
20000
30000
40000
50000
60000
0
1000
2000
3000
4000





7) Modeling price per saleable sqft

Two models: linear regression (baseline) and random forest. Features include size, floor, holding period, win/loss, macro indicators, and district (one-hot).

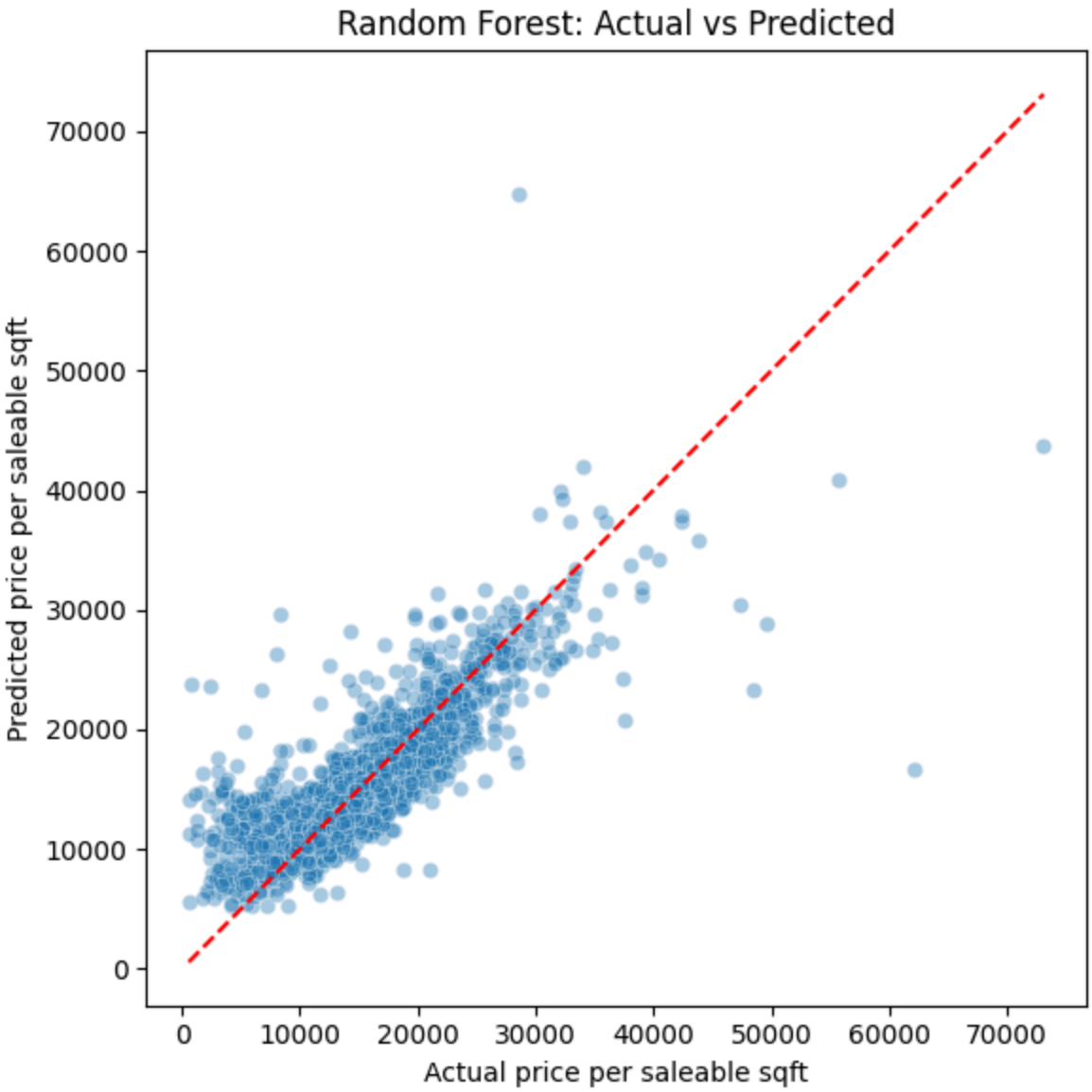
In [16]:
```
target = 'price_per_saleable_sf'
feature_columns = [
    'saleable_area', 'gross_area', 'floor_num', 'holding_period_years', 'winloss_pc
    'pre_sale_flag', 'unemployment_rate', 'cpi_index', 'year', 'district'
]

model_df = merged_df.dropna(subset=feature_columns + [target]).copy()
X = model_df[feature_columns]
y = model_df[target]

categorical_cols = ['district']
numeric_cols = [c for c in feature_columns if c not in categorical_cols]

preprocessor = ColumnTransformer(
    transformers=[
        ('categorical', OneHotEncoder(handle_unknown='ignore'), categorical_cols),
```

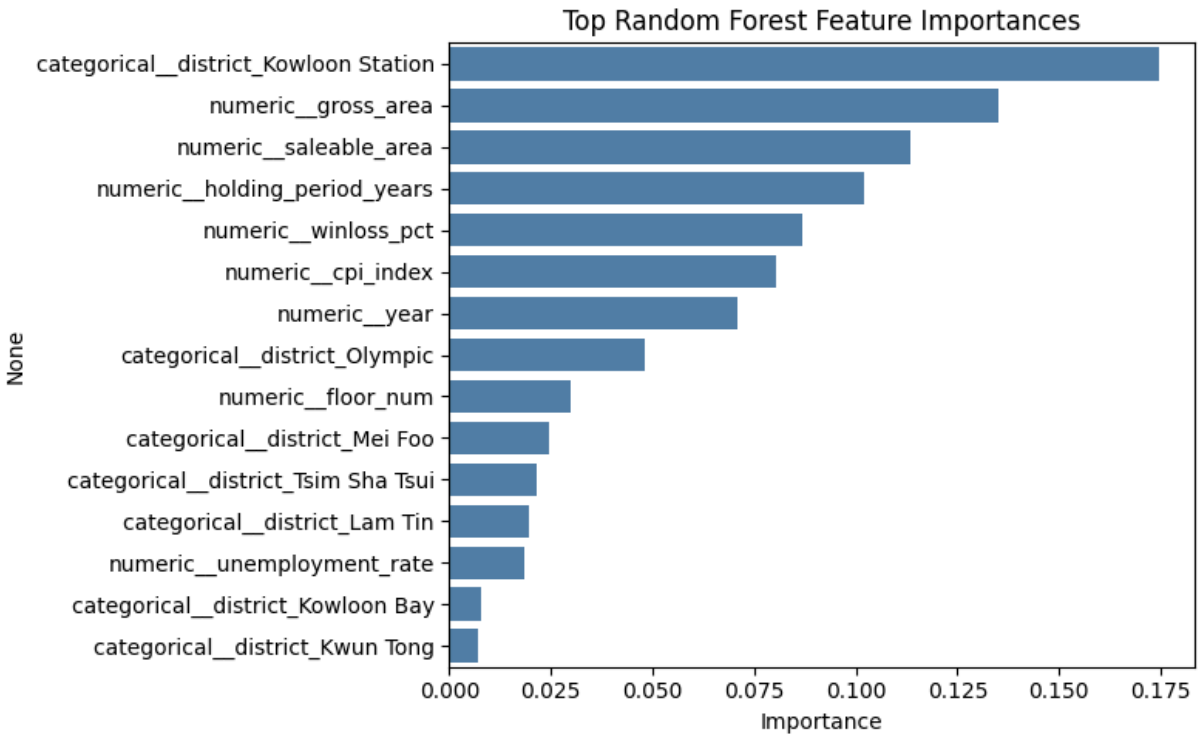
```
        ('numeric', 'passthrough', numeric_cols),
    ]
)

models = {
    'LinearRegression': LinearRegression(),
    'RandomForest': RandomForestRegressor(n_estimators=120, random_state=42, n_jobs
}

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

results = []
feature_importances = None

for name, model in models.items():
    clf = Pipeline(steps=[('preprocess', preprocessor), ('model', model)])
    clf.fit(X_train, y_train)
    preds = clf.predict(X_test)
    mae = mean_absolute_error(y_test, preds)
    r2 = r2_score(y_test, preds)
    results.append({'model': name, 'mae': mae, 'r2': r2})

    if name == 'RandomForest':
        model_step = clf.named_steps['model']
        feat_names = clf.named_steps['preprocess'].get_feature_names_out()
        importances = pd.Series(model_step.feature_importances_, index=feat_names)
        feature_importances = importances.sort_values(ascending=False).head(15)

results_df = pd.DataFrame(results)
display(results_df)

if feature_importances is not None:
    display(feature_importances)
```

	model	mae	r2
0	LinearRegression	2167.713444	0.518777
1	RandomForest	1526.606547	0.702724

```
categorical__district_Kowloon Station    0.175065
numeric__gross_area                      0.134998
numeric__saleable_area                   0.113979
numeric__holding_period_years            0.101680
numeric__winloss_pct                     0.087914
numeric__cpi_index                       0.075811
numeric__year                            0.075326
categorical__district_Olympic            0.047672
numeric__floor_num                       0.029133
categorical__district_Mei Foo            0.024992
categorical__district_Tsim Sha Tsui      0.020887
categorical__district_Lam Tin            0.019602
numeric__unemployment_rate               0.018308
categorical__district_Kowloon Bay        0.007940
categorical__district_Kwun Tong          0.007104
dtype: float64
```

In [17]:
```
# Random forest diagnostics: fit and visualize feature influence
rf_clf = Pipeline([
    ('preprocess', preprocessor),
    ('model', RandomForestRegressor(n_estimators=200, random_state=42, n_jobs=-1, m
])
rf_clf.fit(X_train, y_train)
rf_preds = rf_clf.predict(X_test)

# Actual vs predicted scatter
rf_diag = pd.DataFrame({'actual': y_test, 'pred': rf_preds})
plt.figure(figsize=(6, 6))
sns.scatterplot(data=rf_diag, x='actual', y='pred', alpha=0.4)
lims = [min(rf_diag.min()), max(rf_diag.max())]
plt.plot(lims, lims, '--', color='red')
plt.xlabel('Actual price per saleable sqft')
plt.ylabel('Predicted price per saleable sqft')
plt.title('Random Forest: Actual vs Predicted')
plt.tight_layout()
plt.show()

# Feature importances
feat_names = rf_clf.named_steps['preprocess'].get_feature_names_out()
rf_importances = pd.Series(rf_clf.named_steps['model'].feature_importances_, index=
rf_top = rf_importances.sort_values(ascending=False).head(15)
plt.figure(figsize=(8, 5))
sns.barplot(x=rf_top.values, y=rf_top.index, color='steelblue')
plt.title('Top Random Forest Feature Importances')
plt.xlabel('Importance')
plt.tight_layout()
plt.show()

# Save artifacts
rf_diag.to_csv(OUTPUT_DIR / 'rf_predictions_notebook.csv', index=False)
rf_top.to_frame('importance').to_csv(OUTPUT_DIR / 'rf_feature_importances_notebook.
rf_importances.to_frame('importance').to_csv(OUTPUT_DIR / 'rf_feature_importances_f
```


Random Forest: Actual vs Predicted
Predicted price per saleable sqft
Actual price per saleable sqft
0
10000
20000
30000
40000
50000
60000
70000



8) Findings & Next Steps

- Location is the single biggest driver: Kowloon Station, Olympic, Mei Foo, Tsim Sha Tsui, Lam Tin, etc., carry strong premiums/discounts (see feature importance bar chart).
- Unit size matters: larger gross/saleable areas explain a lot of price-per-sqft variation; price-per-sqft tapers for very large flats.
- Time-in-market and deal performance show up: holding period and win/loss % have non-trivial weight, hinting that recent resale performance correlates with pricing.
- Macro cycle effects are present: CPI and (to a lesser extent) unemployment contribute, capturing market-level shifts across years.
- Model fit: Random Forest R2 ~0.70 and MAE ~1.5k HKD/sqft; linear regression lags (R2 ~0.52).
- Next steps: try more granular building/room types, transaction type, and hyperparameter tuning; add cross-validation and SHAP for deeper interpretability.