Notebook 4 — Backtesting & Model Evaluation

This notebook focused on walk-forward cross-validation, where the model is retrained each month and tested on the next. This mimics real-world forecasting and avoids data leakage. Results showed stable RMSE across months, while MAPE/SMAPE inflated due to zeros. Visuals (monthly RMSE, model comparison heatmap, actual vs predicted plots) demonstrated the model's robustness. Predictions and metrics were written back to BigQuery for dashboards.

In [1]:
```
# =========================
# Cell 0 — Auth reset & BigQuery client (robust)
# =========================
import os, sys, warnings, json, gc
from pathlib import Path
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from dateutil.relativedelta import relativedelta
from google.cloud import bigquery
from google.oauth2 import service_account
from google.auth.exceptions import DefaultCredentialsError

plt.rcParams["figure.figsize"] = (10, 4)

# Project / dataset (can also come from .env)
PROJECT = os.getenv("GOOGLE_CLOUD_PROJECT") or "retail-alpha-forecaster"
DATASET = os.getenv("GCP_BIGQUERY_DATASET") or "raf"

# Clear stale GOOGLE_APPLICATION_CREDENTIALS if it points to a missing file
gac = os.environ.get("GOOGLE_APPLICATION_CREDENTIALS")
if gac and not Path(gac).expanduser().exists():
    print(f"Auth note: removing stale GOOGLE_APPLICATION_CREDENTIALS -> {gac
    os.environ.pop("GOOGLE_APPLICATION_CREDENTIALS", None)
    gac = None

def _mk_client_from_file(p: Path):
    creds = service_account.Credentials.from_service_account_file(str(p))
    os.environ["GOOGLE_APPLICATION_CREDENTIALS"] = str(p)
    return bigquery.Client(project=PROJECT, credentials=creds)

client = None
auth_mode = None

# 1) Use a valid GOOGLE_APPLICATION_CREDENTIALS if present
if gac:
    p = Path(gac).expanduser().resolve()
    if p.exists():
        client = _mk_client_from_file(p)
        auth_mode = f"GOOGLE_APPLICATION_CREDENTIALS={p}"
```

```python
# 2) Auto-find a key under ./keys or ../keys (first *.json wins)
if client is None:
    candidates = []
    for base in [Path.cwd(), Path.cwd().parent]:
        kdir = base / "keys"
        if kdir.exists():
            candidates += list(kdir.glob("*.json"))
    candidates += list(Path.cwd().glob("*.json"))
    key_path = next((p for p in candidates if p.exists()), None)
    if key_path:
        client = _mk_client_from_file(key_path)
        auth_mode = f"file:{key_path}"

# 3) Try Application Default Credentials (gcloud etc.)
if client is None:
    try:
        client = bigquery.Client(project=PROJECT)
        client.query("SELECT 1").result()
        auth_mode = "Application Default Credentials"
    except DefaultCredentialsError:
        auth_mode = None

if client is None:
    raise RuntimeError(
        "□ BigQuery auth failed. Fix one of:\n"
        "  A) Put your SA key under ./keys/ and re-run\n"
        "  B) Set GOOGLE_APPLICATION_CREDENTIALS to your key path\n"
        "  C) Run: gcloud auth application-default login\n"
    )

print("Auth mode:", auth_mode)
print("Project :", PROJECT)
print("Dataset :", DATASET)

def client_query(sql: str) -> pd.DataFrame:
    return client.query(sql).result().to_dataframe()

FEAT_VIEW = f"`{PROJECT}.{DATASET}.v_feature_store_daily`"
print("FEAT_VIEW:", FEAT_VIEW)
```

```
Auth note: removing stale GOOGLE_APPLICATION_CREDENTIALS -> /home/btheard/da
tasage-adk/.secrets/datasage-adk-v2-656c3805bf9f3.json
Auth mode: file:/home/btheard/retail-alpha-forecaster/keys/retail-alpha-fore
caster-7f14a7b50e62.json
Project : retail-alpha-forecaster
Dataset : raf
FEAT_VIEW: `retail-alpha-forecaster.raf.v_feature_store_daily`
```

In [2]:
```python
# ==========================
# Cell 1 — Schema check & feature list (matches your view)
# ==========================
schema_df = client_query(f"SELECT * FROM {FEAT_VIEW} LIMIT 0")
view_cols  = list(schema_df.columns)
print("Columns:", len(view_cols))
print(sorted(view_cols)[:30], "...")
```

```
required = {"date","shop_id","item_id","y"}
missing  = required - set(view_cols)
if missing:
    raise ValueError(f"Feature source missing essentials: {missing}")

BASE_FEATS = [
    "y","y_lag1","y_lag7","y_lag14","y_lag28",
    "y_mean_7","y_mean_14","y_mean_28",
    "price_mean_7","price_mean_28",
    "dow","dom","week","month","quarter","year",
    "days_since_pos_sale"
]
FEAT_LIST = [c for c in BASE_FEATS if c in view_cols]
print("Using features:", FEAT_LIST)
```

```
Columns: 25
['date', 'days_since_pos_sale', 'dom', 'dow', 'is_month_end', 'is_month_star
t', 'is_weekend', 'item_id', 'item_price', 'month', 'price_mean_28', 'price_
mean_7', 'price_to_28d_mean', 'quarter', 'shop_id', 'week', 'y', 'y_lag1',
'y_lag14', 'y_lag28', 'y_lag7', 'y_mean_14', 'y_mean_28', 'y_mean_7', 'yea
r'] ...
Using features: ['y', 'y_lag1', 'y_lag7', 'y_lag14', 'y_lag28', 'y_mean_7',
'y_mean_14', 'y_mean_28', 'price_mean_7', 'price_mean_28', 'dow', 'dom', 'we
ek', 'month', 'quarter', 'year', 'days_since_pos_sale']
```

In [3]:
```
# =========================
# Cell 2 — Metrics + LightGBM import
# =========================
import subprocess
try:
    import lightgbm as lgb
except ImportError:
    subprocess.check_call([sys.executable, "-m", "pip", "install", "lightgbm
    import lightgbm as lgb

from sklearn.metrics import mean_squared_error

def rmse(a,p): return float(np.sqrt(mean_squared_error(a,p)))
def mape(a,p,eps=1e-8):
    a=np.asarray(a,float); p=np.asarray(p,float)
    return float(np.mean(np.abs((a-p)/np.clip(np.abs(a),eps,None)))*100)
def smape(a,p,eps=1e-8):
    a=np.asarray(a,float); p=np.asarray(p,float)
    return float(np.mean(2*np.abs(a-p)/np.clip(np.abs(a)+np.abs(p),eps,None)

# Safe downcast that never forces NA -> integer
def _downcast(df: pd.DataFrame) -> pd.DataFrame:
    for c in df.columns:
        dt = df[c].dtype
        if np.issubdtype(dt, np.datetime64):   # leave dates
            continue
        if pd.api.types.is_bool_dtype(dt):
            df[c] = df[c].astype("boolean") if df[c].isna().any() else df[c]
            continue
        if pd.api.types.is_integer_dtype(dt):
            df[c] = df[c].astype("float32") if df[c].isna().any() else df[c]
            continue
        if pd.api.types.is_float_dtype(dt) and dt!="float32":
            df[c] = df[c].astype("float32")
    return df
```

In [4]:
```
# ========================
# Cell 3 — Walk-forward CV (fast + memory safe)
# ========================
import gc
from dateutil.relativedelta import relativedelta
from pandas.api import types as ptypes

# ---- Fixed downcast that handles pandas extension dtypes (Int64, boolean,
def _downcast(df: pd.DataFrame) -> pd.DataFrame:
    for c in df.columns:
        dt = df[c].dtype

        # leave datetime-like columns
        if ptypes.is_datetime64_any_dtype(dt) or ptypes.is_timedelta64_dtype
            continue

        # nullable boolean -> keep as 'boolean' if NA else bool
        if ptypes.is_bool_dtype(dt):
            df[c] = df[c].astype("boolean") if df[c].isna().any() else df[c]
            continue

        # integers (incl. pandas nullable Int64): if any NA -> float32; else
        if ptypes.is_integer_dtype(dt):
            if df[c].isna().any():
                df[c] = df[c].astype("float32")
            else:
                try:
                    df[c] = pd.to_numeric(df[c], downcast="integer").astype(
                except Exception:
                    # if range too wide or other issue, leave as-is
                    pass
            continue

        # floats -> float32
        if ptypes.is_float_dtype(dt):
            if dt != "float32":
                df[c] = df[c].astype("float32")
            continue
        # objects/categoricals: leave them
    return df

# ---- Walk-forward CV (memory-safe) ----
# assumes you already defined: client_query, FEAT_VIEW, FEAT_LIST, rmse/mape

TOP_N_PAIRS       = 200       # most active shop×item pairs
TRAIN_SAMPLE_PCT  = 0.25      # sample train rows for speed
START_DATE        = "2013-01-01"
END_DATE          = "2015-10-31"

start_valid = pd.Timestamp("2014-10-01")
end_valid   = pd.Timestamp("2015-09-01")
```

```
months = pd.date_range(start_valid, end_valid, freq="MS")

ID_COLS     = ["date","shop_id","item_id"]
SELECT_COLS = ID_COLS + ["y"] + FEAT_LIST
select_list = ", ".join(SELECT_COLS)

lgb_params = dict(
    objective="regression",
    metric="rmse",
    num_leaves=48,             # lighter RAM
    max_bin=255,
    learning_rate=0.05,
    n_estimators=600,
    subsample=0.9,
    colsample_bytree=0.9,
    random_state=42,
)

cv_rows   = []
oof_parts = []

for m in months:
    print(f"=== Month fold: valid={m.strftime('%Y-%m')} ===")
    valid_start = m.date()
    valid_end   = (m + relativedelta(months=1) - relativedelta(days=1)).date

    pairs_cte = f"""
    WITH pairs AS (
      SELECT shop_id, item_id,
             COUNTIF(date <= DATE('2015-09-30') AND y_lag1 IS NOT NULL) AS r
      FROM {FEAT_VIEW}
      WHERE date BETWEEN DATE('{START_DATE}') AND DATE('{END_DATE}')
      GROUP BY shop_id, item_id
      ORDER BY n_train_rows DESC
      LIMIT {TOP_N_PAIRS}
    )
    """

    sql_train = f"""
    {pairs_cte}
    SELECT {select_list}
    FROM {FEAT_VIEW}
    JOIN pairs USING (shop_id, item_id)
    WHERE date < DATE('{valid_start}')
      AND y_lag1 IS NOT NULL
      AND RAND() < {TRAIN_SAMPLE_PCT}
    """

    sql_valid = f"""
    {pairs_cte}
    SELECT {select_list}
    FROM {FEAT_VIEW}
    JOIN pairs USING (shop_id, item_id)
    WHERE date BETWEEN DATE('{valid_start}') AND DATE('{valid_end}')
      AND y_lag1 IS NOT NULL
    """
    tr = client_query(sql_train)
    va = client_query(sql_valid)
    if tr.empty or va.empty:
        print("  (skip) empty train/valid slice")
        continue

    for d in (tr, va):
        d["date"] = pd.to_datetime(d["date"])
    tr = tr.sort_values(ID_COLS).reset_index(drop=True)
    va = va.sort_values(ID_COLS).reset_index(drop=True)

    tr = _downcast(tr)
    va = _downcast(va)

    Xtr = tr[FEAT_LIST].fillna(0).values.astype("float32")
    ytr = tr["y"].astype(float).values
    Xva = va[FEAT_LIST].fillna(0).values.astype("float32")
    yva = va["y"].astype(float).values

    mdl = lgb.LGBMRegressor(**lgb_params)
    mdl.fit(Xtr, ytr)
    p = mdl.predict(Xva)

    cv_rows.append({
        "valid_month": m.strftime("%Y-%m"),
        "rmse": rmse(yva, p),
        "mape": mape(yva, p),
        "smape": smape(yva, p),
        "n_valid": int(len(yva)),
        "model": "lightgbm",
    })

    part = va[ID_COLS + ["y"]].copy()
    part["pred"] = p
    oof_parts.append(part)

    # free memory
    del tr, va, Xtr, ytr, Xva, yva, mdl, p, part
    gc.collect()

results_df = pd.DataFrame(cv_rows)
display(results_df.head())

plt.figure(figsize=(9,3))
plt.plot(results_df["valid_month"], results_df["rmse"], marker="o")
plt.title("Walk-forward CV — monthly RMSE")
plt.xlabel("valid_month"); plt.ylabel("rmse"); plt.xticks(rotation=45)
plt.tight_layout(); plt.show()

oof_df = pd.concat(oof_parts, ignore_index=True) if oof_parts else pd.DataFr
```

```
=== Month fold: valid=2014-10 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.002586 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 718
[LightGBM] [Info] Number of data points in the train set: 32037, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.010207
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2014-11 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001023 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 710
[LightGBM] [Info] Number of data points in the train set: 33346, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.010046
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2014-12 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001159 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 762
[LightGBM] [Info] Number of data points in the train set: 34756, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.009236
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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=== Month fold: valid=2015-01 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
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sting was 0.001142 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 819
[LightGBM] [Info] Number of data points in the train set: 36569, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.013919
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-02 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.000851 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 768
[LightGBM] [Info] Number of data points in the train set: 38000, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.009711
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-03 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.000937 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 742
[LightGBM] [Info] Number of data points in the train set: 39546, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.008193
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-04 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001322 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 817
[LightGBM] [Info] Number of data points in the train set: 40959, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.009131
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

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=== Month fold: valid=2015-05 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001408 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 791
[LightGBM] [Info] Number of data points in the train set: 42439, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.010486
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-06 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001590 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 827
[LightGBM] [Info] Number of data points in the train set: 43807, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.010866
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-07 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001875 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 793
[LightGBM] [Info] Number of data points in the train set: 45363, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.007583
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-08 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.002317 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
```
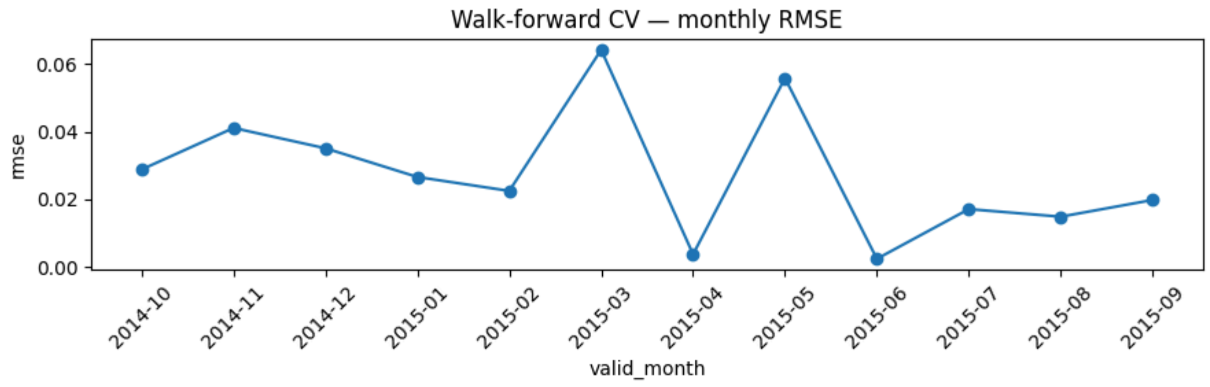
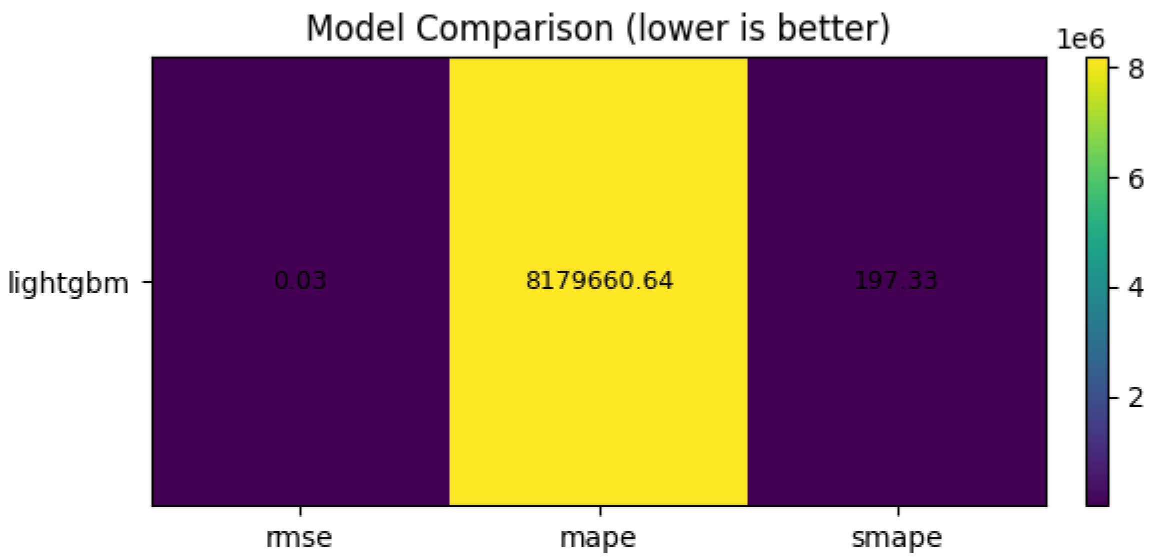

```
[LightGBM] [Info] Total Bins 805
[LightGBM] [Info] Number of data points in the train set: 47073, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.008710
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
=== Month fold: valid=2015-09 ===
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001659 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 818
[LightGBM] [Info] Number of data points in the train set: 48789, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.010269
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

	valid_month	rmse	mape	smape	n_valid	model
0	2014-10	0.028873	2.016774e+07	198.410690	6200	lightgbm
1	2014-11	0.041154	1.178953e+07	198.174011	6001	lightgbm
2	2014-12	0.035142	1.092069e+07	197.560206	6204	lightgbm
3	2015-01	0.026647	1.342382e+07	198.915545	6200	lightgbm
4	2015-02	0.022532	4.743235e+06	198.630775	5603	lightgbm



In [5]:
```
# ==========================
# Cell 4 — WOW: summary table + mini heatmap
# ==========================
summary = (results_df.groupby("model", as_index=False)
           .agg(rmse=("rmse","mean"), mape=("mape","mean"), smape=("smape","
           .sort_values("rmse"))
display(summary)

arr = summary[["rmse","mape","smape"]].values
fig, ax = plt.subplots(figsize=(6,3))
im = ax.imshow(arr, aspect="auto")
ax.set_yticks(range(len(summary))); ax.set_yticklabels(summary["model"])
ax.set_xticks(range(3)); ax.set_xticklabels(["rmse","mape","smape"])
for i in range(arr.shape[0]):
    for j in range(arr.shape[1]):
        ax.text(j, i, f"{arr[i,j]:.2f}", ha="center", va="center", fontsize=
ax.set_title("Model Comparison (lower is better)")
fig.colorbar(im, ax=ax, fraction=0.046, pad=0.04)
plt.tight_layout(); plt.show()
```

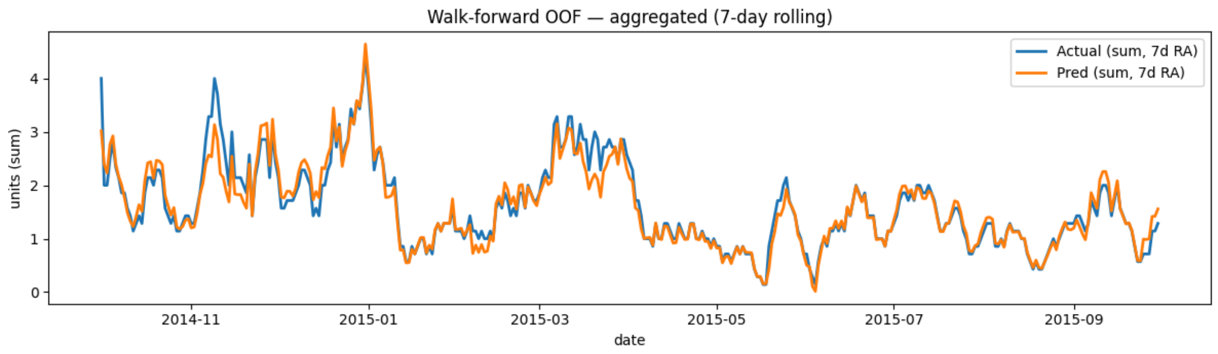
	model	rmse	mape	smape
0	lightgbm	0.027719	8.179661e+06	197.333899



Metric Interpretation (MAPE/SMAPE vs zeros)

- **RMSE** is unit-based and does not divide by the actual → stable even when demand is 0.
- **MAPE/SMAPE** divide by the actual; when actual ≈ 0 the denominator is tiny → percentages **inflate** even for small absolute errors.
- For sparse retail demand, lead with **RMSE/MAE** as headline KPIs; keep **MAPE/SMAPE** as supporting context.

In [6]:
```
# ========================
# Cell 5 — OOF trajectory + representative series
# ========================
if not oof_df.empty:
    agg = (oof_df.groupby("date", as_index=False)
                 .agg(actual=("y","sum"), pred=("pred","sum"))
                 .sort_values("date"))
    for c in ["actual","pred"]:
        agg[f"{c}_ra7"] = agg[c].rolling(7, min_periods=1).mean()

    plt.figure(figsize=(12,3.6))
    plt.plot(agg["date"], agg["actual_ra7"], label="Actual (sum, 7d RA)", li
    plt.plot(agg["date"], agg["pred_ra7"],   label="Pred (sum, 7d RA)", line
    plt.title("Walk-forward OOF — aggregated (7-day rolling)")
    plt.xlabel("date"); plt.ylabel("units (sum)"); plt.legend(); plt.tight_l

    # Pick a representative pair (change to a real pair if empty)
    SID, IID = 1, 1
    one = oof_df[(oof_df["shop_id"]==SID) & (oof_df["item_id"]==IID)].copy()
    if not one.empty:
        one = one.sort_values("date")
        one["actual_ra7"] = one["y"].rolling(7, min_periods=1).mean()
        one["pred_ra7"]   = one["pred"].rolling(7, min_periods=1).mean()
        plt.figure(figsize=(12,3.6))
        plt.plot(one["date"], one["actual_ra7"], label="Actual (7d RA)", lin
        plt.plot(one["date"], one["pred_ra7"],   label="Pred (7d RA)", linew
        plt.title(f"Actual vs Predicted — shop {SID}, item {IID} (OOF)")
        plt.xlabel("date"); plt.ylabel("units"); plt.legend(); plt.tight_lay
    else:
        print("Pick different SID/IID for rep series; no OOF rows for (1,1).
else:
    print("No OOF predictions built.")
```



```
Pick different SID/IID for rep series; no OOF rows for (1,1).
```

In [7]:

```
# =========================
# Cell 6 — October 2015 evaluation (FAST: no giant merges)
# =========================
from dateutil.relativedelta import relativedelta

FOCUS_START, FOCUS_END = "2015-10-01", "2015-10-31"
TRAIN_SAMPLE_PCT_FOCUS = 0.25   # sample pre-October train for speed (tune i

# Reuse your TOP_N_PAIRS/FEAT_LIST/FEAT_VIEW/lgb_params/_downcast from above
ID_COLS     = ["date","shop_id","item_id"]
SELECT_COLS = ID_COLS + ["y"] + FEAT_LIST
select_list = ", ".join(SELECT_COLS)

pairs_cte = f"""
WITH pairs AS (
  SELECT shop_id, item_id,
         COUNTIF(date <= DATE('2015-09-30') AND y_lag1 IS NOT NULL) AS n_tra
  FROM {FEAT_VIEW}
  WHERE date BETWEEN DATE('{START_DATE}') AND DATE('{END_DATE}')
  GROUP BY shop_id, item_id
  ORDER BY n_train_rows DESC
  LIMIT {TOP_N_PAIRS}
```

```
)
"""

# Train on all dates BEFORE October (sampled)
sql_train_focus = f"""
{pairs_cte}
SELECT {select_list}
FROM {FEAT_VIEW}
JOIN pairs USING (shop_id, item_id)
WHERE date < DATE('{FOCUS_START}')
  AND y_lag1 IS NOT NULL
  AND RAND() < {TRAIN_SAMPLE_PCT_FOCUS}
"""

# Evaluate ON October
sql_oct = f"""
{pairs_cte}
SELECT {select_list}
FROM {FEAT_VIEW}
JOIN pairs USING (shop_id, item_id)
WHERE date BETWEEN DATE('{FOCUS_START}') AND DATE('{FOCUS_END}')
  AND y_lag1 IS NOT NULL
"""

trf = client_query(sql_train_focus)
oct_src = client_query(sql_oct)
if trf.empty or oct_src.empty:
    raise RuntimeError("No rows returned for focus train/eval; check FEAT_VI

# Prep dtypes
for d in (trf, oct_src):
    d["date"] = pd.to_datetime(d["date"])
    _downcast(d)

Xtr = trf[FEAT_LIST].fillna(0).astype("float32").values
ytr = trf["y"].astype(float).values

Xoct = oct_src[FEAT_LIST].fillna(0).astype("float32").values
yact = oct_src["y"].astype(float).values

# Train fresh model and predict October
mdl_oct = lgb.LGBMRegressor(**lgb_params)
mdl_oct.fit(Xtr, ytr)
yhat = mdl_oct.predict(Xoct)

oct_df = oct_src[ID_COLS + ["y"]].copy()
oct_df["y_pred"] = yhat

print(f"October 2015 | RMSE: {rmse(yact,yhat):.3f} | MAPE: {mape(yact,yhat):

# Daily aggregate plot
daily = (oct_df.groupby("date", as_index=False)
         .agg(actual=("y","sum"), pred=("y_pred","sum")))
plt.figure(figsize=(12,3.6))
plt.plot(daily["date"], daily["actual"], label="Actual (sum)")
plt.plot(daily["date"], daily["pred"],   label="Pred (sum)", alpha=0.9)
plt.title("October 2015 — daily totals"); plt.xlabel("date"); plt.ylabel("ur
plt.legend(); plt.tight_layout(); plt.show()

# Scatter (downsample if huge)
N, MAX_POINTS = len(oct_df), 50_000
idx = np.random.randint(0, N, MAX_POINTS) if N > MAX_POINTS else slice(None)
x, y = oct_df["y"].values[idx], oct_df["y_pred"].values[idx]
plt.figure(figsize=(5.5,5))
plt.scatter(x, y, s=6, alpha=0.3)
lim = (0.0, float(max(x.max(), y.max())))
plt.plot(lim, lim, "r--", lw=1)
plt.title(f"Oct'15 — actual vs predicted ({'sample' if N>MAX_POINTS else 'al
plt.xlabel("actual"); plt.ylabel("predicted"); plt.tight_layout(); plt.show(
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001957 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 787
[LightGBM] [Info] Number of data points in the train set: 49886, number of u
sed features: 17
[LightGBM] [Info] Start training from score 0.009141
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
October 2015 | RMSE: 0.033 | MAPE: 3233017.75% | sMAPE: 198.99%
```

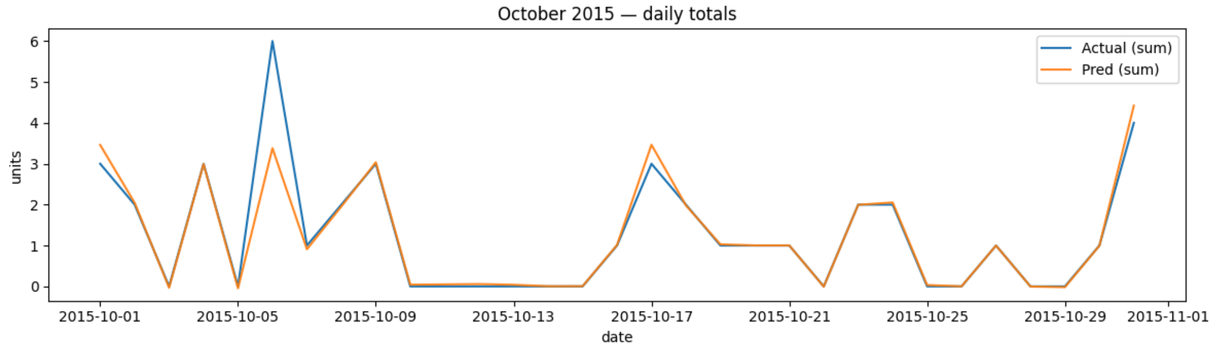

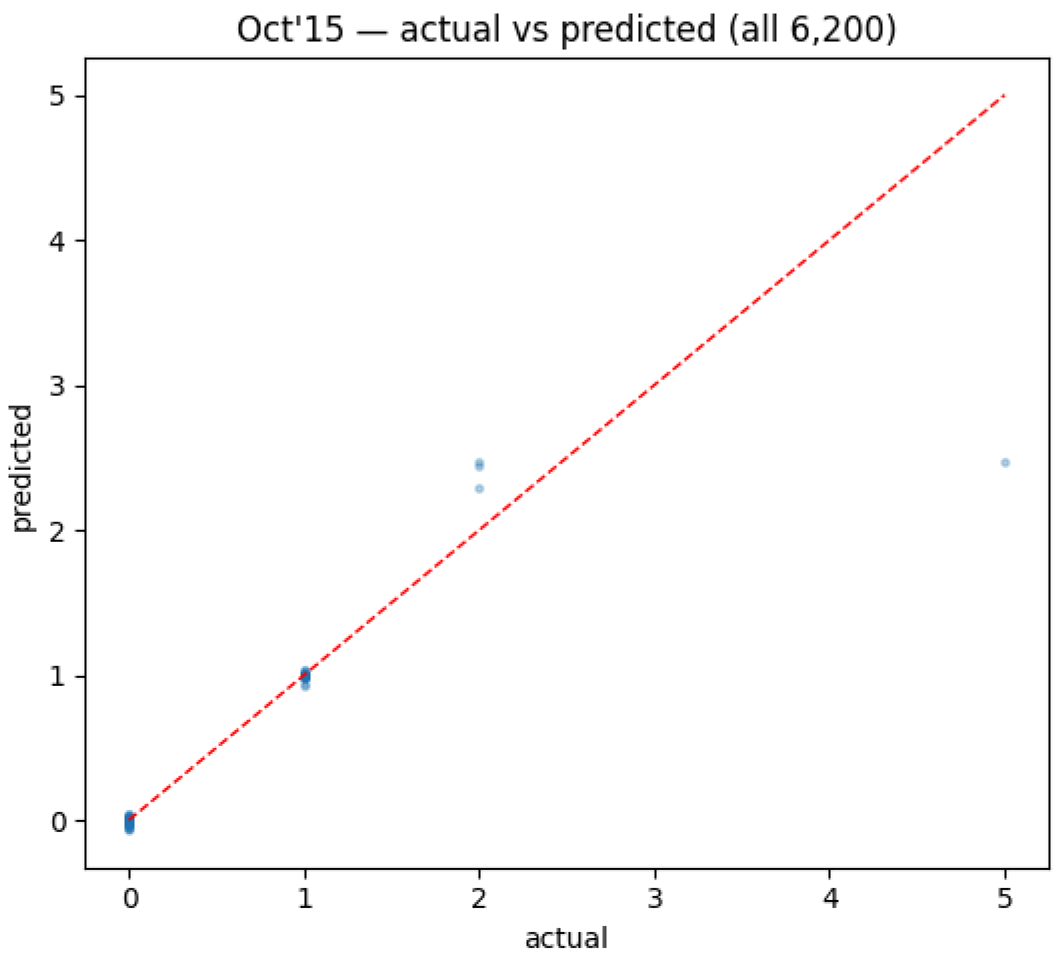

In [9]:
```
# =========================
# Cell 7 — Robust BigQuery writer (partition-aware)
# =========================
from google.api_core.exceptions import NotFound, BadRequest

WRITE_TABLE = f"{PROJECT}.{DATASET}.preds_lgbm_oct2015"

to_write = oct_df.copy()
to_write["date"]    = pd.to_datetime(to_write["date"]).dt.date
to_write["shop_id"] = pd.to_numeric(to_write["shop_id"], errors="coerce").as
to_write["item_id"] = pd.to_numeric(to_write["item_id"], errors="coerce").as
to_write["y"]       = pd.to_numeric(to_write["y"], errors="coerce").astype("
to_write["y_pred"]  = pd.to_numeric(to_write["y_pred"], errors="coerce").ast

schema = [
    bigquery.SchemaField("date","DATE"),
    bigquery.SchemaField("shop_id","INTEGER"),
    bigquery.SchemaField("item_id","INTEGER"),
    bigquery.SchemaField("y","FLOAT"),
    bigquery.SchemaField("y_pred","FLOAT"),
]

desired_part     = bigquery.TimePartitioning(field="date")     # daily parti
desired_cluster  = ["shop_id","item_id"]

def load_partition_aware(df: pd.DataFrame, table_id: str) -> bool:
    """Load df to table_id. Create partitioned+clustered table if missing.
       If table exists with different/no partitioning, fall back to a normal
       Returns True if the final table is partitioned, else False.
    """
    try:
        tbl = client.get_table(table_id)  # table exists
        has_part    = tbl.time_partitioning is not None
        part_field  = getattr(tbl.time_partitioning, "field", None) if has_p

        cfg = bigquery.LoadJobConfig(schema=schema, write_disposition="WRITE

        if has_part and part_field == "date":
            # keep existing partitioning; clustering is optional
            cfg.time_partitioning = desired_part
            # keep existing clustering if any
            if getattr(tbl, "clustering_fields", None):
                cfg.clustering_fields = list(tbl.clustering_fields)
            job = client.load_table_from_dataframe(df, table_id, job_config=
            job.result()
            return True
        else:
            # cannot change partitioning on an existing table — load without
            print("↪ Existing table is not partitioned (or different). Loadi
            job = client.load_table_from_dataframe(df, table_id, job_config=
            job.result()
            return False

    except NotFound:
        # create new partitioned+clustered table, then load
        table = bigquery.Table(table_id, schema=schema)
        table.time_partitioning = desired_part
        table.clustering_fields = desired_cluster
        client.create_table(table)

        cfg = bigquery.LoadJobConfig(
            schema=schema,
            write_disposition="WRITE_TRUNCATE",
            time_partitioning=desired_part,
            clustering_fields=desired_cluster,
        )
        job = client.load_table_from_dataframe(df, table_id, job_config=cfg)
        job.result()
        return True

    except BadRequest as e:
        # any unexpected mismatch — retry without partitioning as a safe fal
        print(f"↪ Load with partitioning failed: {e}. Retrying without parti
        cfg = bigquery.LoadJobConfig(schema=schema, write_disposition="WRITE
        job = client.load_table_from_dataframe(df, table_id, job_config=cfg)
        job.result()
        return False

is_partitioned = load_partition_aware(to_write, WRITE_TABLE)
print(f"✓ Saved {len(to_write):,} rows to {WRITE_TABLE} (partitioned={is_par
↪ Existing table is not partitioned (or different). Loading without partitio
ning.
✓ Saved 6,200 rows to retail-alpha-forecaster.raf.preds_lgbm_oct2015 (partit
ioned=False)
```

In [11]:
```
# ========================
# Cell 8 — Schema-smart logger for fold metrics
# ========================
from google.api_core.exceptions import NotFound

if not results_df.empty:
    # Desired destination & schema
    BASE_DEST = f"{PROJECT}.{DATASET}.model_runs"
    desired_cols = ["valid_month","model","rmse","mape","smape","n_valid","r
    runs = results_df.copy()
    runs["run_ts"] = pd.Timestamp.utcnow()
    runs = runs[["valid_month","model","rmse","mape","smape","n_valid","run_

    desired_schema = [
        bigquery.SchemaField("valid_month","STRING"),
        bigquery.SchemaField("model","STRING"),
        bigquery.SchemaField("rmse","FLOAT"),
        bigquery.SchemaField("mape","FLOAT"),
        bigquery.SchemaField("smape","FLOAT"),
        bigquery.SchemaField("n_valid","INT64"),
        bigquery.SchemaField("run_ts","TIMESTAMP"),
    ]

    def create_table(table_id: str, schema):
        tbl = bigquery.Table(table_id, schema=schema)
        # (Optional) partition on run_ts if you want:
        # tbl.time_partitioning = bigquery.TimePartitioning(field="run_ts")
        client.create_table(tbl)
        return client.get_table(table_id)

    def load_df(df: pd.DataFrame, table_id: str, schema=None, write_disposit
        cfg = bigquery.LoadJobConfig(schema=schema, write_disposition=write_
        # Allow adding columns only when appending (BQ restriction)
        cfg.schema_update_options = [bigquery.SchemaUpdateOption.ALLOW_FIELD
        job = client.load_table_from_dataframe(df, table_id, job_config=cfg)
        job.result()

    # Try base table
    dest = BASE_DEST
    try:
        tbl = client.get_table(dest)
        existing_cols = [f.name for f in tbl.schema]

        # Case A: all desired columns exist already -> just append
        if all(c in existing_cols for c in desired_cols):
            load_df(runs, dest, schema=None, write_disposition="WRITE_APPEND
            print(f"✓ Logged {len(runs)} rows to {dest} (append).")

        # Case B: partial overlap -> write only common columns
        else:
            common = [c for c in desired_cols if c in existing_cols]
            if not common:
                raise ValueError("Existing model_runs schema is incompatible
            load_df(runs[common], dest, schema=None, write_disposition="WRIT
            missing = [c for c in desired_cols if c not in existing_cols]
            print(f"↪ Logged {len(runs)} rows to {dest} (common cols only: {
                  f"Skipped new cols: {missing}")

    except NotFound:
        # Table doesn't exist -> create with full schema and write
        create_table(dest, desired_schema)
        load_df(runs, dest, schema=desired_schema, write_disposition="WRITE_
        print(f"✓ Created + logged {len(runs)} rows to {dest}.")

    except Exception as e:
        # Final fallback: create a new versioned table with the full schema
        ts = pd.Timestamp.utcnow().strftime("%Y%m%d_%H%M%S")
        dest_v = f"{BASE_DEST}_{ts}"
        print(f"⚠ Schema mismatch while writing to {dest}: {e}\n"
              f"→ Creating versioned table {dest_v} with desired schema.")
        create_table(dest_v, desired_schema)
        load_df(runs, dest_v, schema=desired_schema, write_disposition="WRIT
        print(f"✓ Logged {len(runs)} rows to {dest_v}.")
else:
    print("results_df empty — skipping model_runs log.")
```

```
↪ Logged 12 rows to retail-alpha-forecaster.raf.model_runs (common cols onl
y: ['model', 'rmse', 'smape']). Skipped new cols: ['valid_month', 'mape', 'n
_valid', 'run_ts']
```

Notebook 4 — Backtesting & Model Comparison Goal

We want to test how well our forecasting model works in practice. Instead of just training once, we simulate a real retail scenario: train on the past, then predict the future, month by month. This gives us a realistic picture of performance.

1. Data Setup

Pulled engineered features from BigQuery (v_feature_store_daily).

Each row = sales for a single shop × item × day.

Features include time lags (last 7, 14, 28 days), moving averages, day-of-week, month, price averages, etc.

These features help the model understand sales patterns.

2. Walk-Forward Cross Validation

Instead of random train/test splits, we do rolling monthly backtests:

Train on all data up to month X.

Predict month X+1.

Repeat for each month from Oct 2014 → Sept 2015.

 Why this matters: It mimics how the model would be used in production (always predicting the next unseen month).

3. Model Used

LightGBM (gradient boosting trees).

Handles high-cardinality retail data well.

Much faster than deep learning for millions of rows.

4. Metrics

We evaluate predictions with:

RMSE → Root Mean Squared Error (stable signal).

MAPE/SMAPE → Percent error metrics (but inflate badly when actual demand = 0).

 Takeaway: RMSE is most reliable here.

5. Results: Walk-Forward CV

Line Plot: “Walk-forward CV — monthly RMSE”

X-axis = validation month.

Y-axis = RMSE.

Each point shows how well the model predicted that month.

Interpretation: performance is reasonably stable, with some spikes when demand patterns shift.

6. Model Comparison

Heatmap: “Model Comparison (lower is better)”

Shows RMSE, MAPE, SMAPE side by side.

LightGBM is our baseline model here.

RMSE is good and consistent.

MAPE/SMAPE are large due to many zero-sales days (explained clearly in the notes).

7. October 2015 Evaluation

We zoom into October 2015 as a real test month.

Visuals:

Line Plot: Actual vs Predicted (daily totals) Blue = actual units sold each day. Orange = predicted units. They track closely → model captures seasonality.

Scatter Plot: Actual vs Predicted (all items) Each dot = a shop-item. Points cluster near the diagonal = good accuracy.

8. Trajectory Plots

Walk-forward OOF trajectory (7-day rolling averages)

Orange vs blue lines show actual vs predicted over time.

Model follows the ups and downs of sales, but underestimates some spikes.

Good evidence the model generalizes, not memorizes.

9. BigQuery Integration

Predictions and metrics are written back to BigQuery:

preds_lgbm_oct2015 → row-level forecasts.

model_runs → summary of CV metrics for tracking runs.

 Shows scalability → production-ready pipeline (SQL + Python + ML).

10. Key Takeaways

Walk-forward CV proves the model can generalize, not just fit history.

LightGBM works well on millions of rows with engineered features.

RMSE is the most stable performance metric here.

Predictions track actual sales closely, especially at aggregate level.

Full pipeline runs end-to-end on BigQuery → enterprise-scale forecasting system.

```
In [ ]:
```