

IAQF_2026

February 27, 2026

1 IAQF 2026 - Jupyter Notebook

1.1 Initialization

```
[1]: # Imports
import os
import warnings
from pathlib import Path
from itertools import combinations
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import grangercausalitytests
from scipy.stats import kurtosis
import numpy as np
import statsmodels.api as sm
import seaborn as sns

sns.set_theme(style="darkgrid")
pd.set_option("display.precision", 4)
REGIME_ORDER = ["calm", "stress", "post"]
```

```
[2]: # Data Paths
path_bnus_spot_btc_usd = 'Data/
    ↳ohlcv_1s_bnus_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_bnus_spot_btc_usdc = 'Data/
    ↳ohlcv_1s_bnus_spot_btc-usdc_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_bnus_spot_btc_usdt = 'Data/
    ↳ohlcv_1s_bnus_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_cbse_spot_btc_usd = 'Data/
    ↳ohlcv_1s_cbse_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_cbse_spot_btc_usdt = 'Data/
    ↳ohlcv_1s_cbse_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_krkn_spot_btc_usd = 'Data/
    ↳ohlcv_1s_krkn_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
```

```

path_krkn_spot_btc_usdc = 'Data/
↳ohlcv_1s_krkn_spot_btc-usdc_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_krkn_spot_btc_usdt = 'Data/
↳ohlcv_1s_krkn_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'

path_trades_bnus_btc_usd = 'Data/
↳trades_bnus_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_bnus_btc_usdc = 'Data/
↳trades_bnus_spot_btc-usdc_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_bnus_btc_usdt = 'Data/
↳trades_bnus_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_cbse_btc_usd = 'Data/
↳trades_cbse_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_cbse_btc_usdt = 'Data/
↳trades_cbse_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_krkn_btc_usd = 'Data/
↳trades_krkn_spot_btc-usd_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_krkn_btc_usdc = 'Data/
↳trades_krkn_spot_btc-usdc_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'
path_trades_krkn_btc_usdt = 'Data/
↳trades_krkn_spot_btc-usdt_2023-03-01T000000000Z_2023-03-21T235959999Z.csv'

trade_files = [
    {'exchange':'binance', 'pair':'BTC/USD', 'ohlcv_path':↳
↳path_bnus_spot_btc_usd, 'trade_path': path_trades_bnus_btc_usd},
    {'exchange':'binance', 'pair':'BTC/USDC', 'ohlcv_path':↳
↳path_bnus_spot_btc_usdc, 'trade_path': path_trades_bnus_btc_usdc},
    {'exchange':'binance', 'pair':'BTC/USDT', 'ohlcv_path':↳
↳path_bnus_spot_btc_usdt, 'trade_path': path_trades_bnus_btc_usdt},

    {'exchange':'coinbase', 'pair':'BTC/USD', 'ohlcv_path':↳
↳path_cbse_spot_btc_usd, 'trade_path': path_trades_cbse_btc_usd},
    {'exchange':'coinbase', 'pair':'BTC/USDT', 'ohlcv_path':↳
↳path_cbse_spot_btc_usdt, 'trade_path': path_trades_cbse_btc_usdt},

    {'exchange':'kraken', 'pair':'BTC/USD', 'ohlcv_path':↳
↳path_krkn_spot_btc_usd, 'trade_path': path_trades_krkn_btc_usd},
    {'exchange':'kraken', 'pair':'BTC/USDC', 'ohlcv_path':↳
↳path_krkn_spot_btc_usdc, 'trade_path': path_trades_krkn_btc_usdc},
    {'exchange':'kraken', 'pair':'BTC/USDT', 'ohlcv_path':↳
↳path_krkn_spot_btc_usdt, 'trade_path': path_trades_krkn_btc_usdt},
]

```

2 Data Preprocessing

2.0.1 Cleaning & Resampling

```
[3]: # adds regime labels
def add_regime_labels(df, ts_col=None):
    out = df.copy()

    if ts_col is not None:
        t = pd.to_datetime(out[ts_col], utc=True, errors="coerce")
        d = t.dt.normalize()
    else:
        t = pd.to_datetime(out.index, utc=True, errors="coerce")
        d = t.normalize()

    out["regime"] = np.select(
        [
            (d >= pd.Timestamp("2023-03-01", tz="UTC")) & (d <= pd.
↪Timestamp("2023-03-09", tz="UTC")),
            (d >= pd.Timestamp("2023-03-10", tz="UTC")) & (d <= pd.
↪Timestamp("2023-03-14", tz="UTC")),
            (d >= pd.Timestamp("2023-03-15", tz="UTC")) & (d <= pd.
↪Timestamp("2023-03-21", tz="UTC")),
        ],
        ["calm", "stress", "post_crash"],
        default="out_of_scope",
    )
    return out

# helper for displaying explanations
def explain_block(title, data_used, how_to_gauge):
    print("\n" + "=" * 90)
    print(title)
    print(f>Data used: {data_used}<
    print(f>How to gauge: {how_to_gauge}<
    print("=" * 90 + "\n")

# ensure proper ts index for ohlc df
def load_ohlc(path):
    ohlc = pd.read_csv(path)
    ohlc['ts'] = pd.to_datetime(ohlc['timestamp'], unit='ms', utc=True)
    ohlc = ohlc.sort_values('ts').set_index('ts')

    for c in ['open', 'high', 'low', 'close', 'volume']:
        ohlc[c] = pd.to_numeric(ohlc[c], errors='coerce')

    ohlc = ohlc.dropna(subset=['close'])
```

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ohlcl = ohlcl[ohlcl['volume'] > 0]
ohlcl = add_regime_labels(ohlcl)

return ohlcl

# ensure proper ts index for trades df
def load_trades_ohlcl(trades_path, ohlcl_path):
    ohlcl = load_ohlcl(ohlcl_path)

    # mid price proxy
    ohlcl['mid'] = (ohlcl['high'] + ohlcl['low']) / 2.0

    trades = pd.read_csv(trades_path)
    trades['ts'] = pd.to_datetime(trades['timestamp'], unit='ms', utc=True)
    trades = trades.sort_values('ts').set_index('ts')

    trades = add_regime_labels(trades)

    trades = pd.merge_asof(
        trades,
        ohlcl[['mid']],
        left_index=True,
        right_index=True,
        direction='backward'
    )

    # Merge 1-minute future mid price for Realized Spread
    trades['future_ts'] = trades.index + pd.Timedelta(minutes=1)
    trades = trades.reset_index()
    trades = pd.merge_asof(
        trades,
        ohlcl[['mid']].rename(columns={'mid': 'future_mid'}),
        left_on='future_ts',
        right_index=True,
        direction='forward'
    )
    trades = trades.set_index('ts')

    return trades, ohlcl

# resample ohlcl bars
def resample_ohlcl(ohlcl_df, bar='1min'):
    g = ohlcl_df.resample(bar)

    out = pd.DataFrame({
        'open': g['open'].first(),

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        'high': g['high'].max(),
        'low': g['low'].min(),
        'close': g['close'].last(),
        'volume': g['volume'].sum(),
    }).dropna(subset=['close', 'high', 'low'])

    out = out[out['volume'] > 0]
    out = add_regime_labels(out)

    return out

# format trades to 1m
def resample_trades(trades_df, freq='1min'):
    df = trades_df.copy()

    df['dollar'] = df['price'] * df['amount']
    df['sign'] = np.where(df['taker_side_sell'].astype(bool), -1.0, +1.0)
    df['signed_dollar'] = df['sign'] * df['dollar']

    # vwap
    vwap_1m = df['dollar'].resample('1min').sum() / df['amount'].
↳ resample('1min').sum()

    out = pd.DataFrame({
        'vwap': vwap_1m,
        'last': df['price'].resample('1min').last(),
        'vol_dollar': df['dollar'].resample('1min').sum(),
        'n_trades': df['price'].resample('1min').count(),
        'signed_dollar': df['signed_dollar'].resample('1min').sum(),
    })

    out['ret'] = np.log(out['vwap']).diff()
    out['rv_1m'] = out['ret']**2
    out['amihud_1m'] = out['ret'].abs() / out['vol_dollar'].replace(0, np.nan)

    out = add_regime_labels(out)
    out = out.dropna(subset=['vwap', 'ret', 'vol_dollar'])

    return out

def ohlc_from_trades(trades, bar="1min"):
    g = trades.resample(bar)
    out = pd.DataFrame({
        "open": g["price"].first(),
        "high": g["price"].max(),

```

```

        "low": g["price"].min(),
        "close": g["price"].last(),
        "volume": g["amount"].sum(),
        "n_trades": g["price"].count(),
    })
    out = out.dropna(subset=["open", "high", "low", "close"])
    out = out[out["n_trades"] > 0]
    return add_regime_labels(out)

def ensure_numeric(df):
    for col in ['open', 'high', 'low', 'close', 'volume']:
        if col in df.columns:
            df[col] = pd.to_numeric(df[col], errors='coerce')
    return df

def load_ohlc_one(path, exchange, pair):
    df = pd.read_csv(path)
    df["ts"] = pd.to_datetime(df["timestamp"], unit="ms", utc=True,
    ↪errors="coerce")
    for c in ["open", "high", "low", "close"]:
        df[c] = pd.to_numeric(df[c], errors="coerce")
    vol_col = "volume" if "volume" in df.columns else ("volume_traded" if
    ↪"volume_traded" in df.columns else None)
    df["volume"] = pd.to_numeric(df[vol_col], errors="coerce") if vol_col else
    ↪np.nan

    df = df.dropna(subset=["ts", "close"]).sort_values("ts").set_index("ts")
    df["exchange"] = exchange
    df["pair"] = pair
    return add_regime_labels(df)

def load_trades_one(path, exchange, pair):
    df = pd.read_csv(path)
    df["ts"] = pd.to_datetime(df["timestamp"], unit="ms", utc=True,
    ↪errors="coerce")
    df["price"] = pd.to_numeric(df["price"], errors="coerce")
    amount_col = "amount" if "amount" in df.columns else ("size" if "size" in
    ↪df.columns else None)
    if amount_col is None:
        raise ValueError(f"No amount/size column in {path}")
    df["amount"] = pd.to_numeric(df[amount_col], errors="coerce")

    if "taker_side_sell" in df.columns:
        raw = df["taker_side_sell"]

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        is_sell = raw if raw.dtype == bool else raw.astype(str).str.lower().
↪map({"true": True, "false": False, "1": True, "0": False}).fillna(False)
        df["sign"] = np.where(is_sell, -1.0, 1.0)
    else:
        df["sign"] = np.nan

    df = df.dropna(subset=["ts", "price", "amount"]).sort_values("ts").
↪set_index("ts")
    df["exchange"] = exchange
    df["pair"] = pair
    return add_regime_labels(df)

def load_all(all_files):
    ohlc_list, tr_list = [], [],

    for spec in all_files:
        ohlc_list.append(load_ohlc_one(spec['ohlc_path'], spec['exchange'],
↪spec['pair']))
        tr_list.append(load_trades_one(spec['trade_path'], spec['exchange'],
↪spec['pair']))

    ohlc = pd.concat(ohlc_list).sort_index() if ohlc_list else pd.DataFrame()
    trades = pd.concat(tr_list).sort_index() if tr_list else pd.DataFrame()

    return ohlc, trades

def clean_df(df):
    df = df.copy()
    if 'timestamp' in df.columns:
        if pd.api.types.is_numeric_dtype(df['timestamp']):
            df['timestamp'] = pd.to_datetime(df['timestamp'], unit='ms',
↪utc=True)
        else:
            df['timestamp'] = pd.to_datetime(df['timestamp'], utc=True)
    df.set_index('timestamp', inplace=True)
    elif not pd.api.types.is_datetime64_any_dtype(df.index):
        if pd.api.types.is_numeric_dtype(df.index):
            df.index = pd.to_datetime(df.index, unit='ms', utc=True)
        else:
            df.index = pd.to_datetime(df.index, utc=True)
    df.sort_index(inplace=True)
    df = df.reindex(master_index).ffill()
    df.dropna(inplace=True)
    return df

```

```
[4]: bnus_spot_btc_usd = ensure_numeric(pd.read_csv(path_bnus_spot_btc_usd))
bnus_spot_btc_usdc = ensure_numeric(pd.read_csv(path_bnus_spot_btc_usdc))
bnus_spot_btc_usdt = ensure_numeric(pd.read_csv(path_bnus_spot_btc_usdt))
cbse_spot_btc_usd = ensure_numeric(pd.read_csv(path_cbse_spot_btc_usd))
cbse_spot_btc_usdt = ensure_numeric(pd.read_csv(path_cbse_spot_btc_usdt))

trades_bnus_btc_usd = ensure_numeric(pd.read_csv(path_trades_bnus_btc_usd))
trades_bnus_btc_usdc = ensure_numeric(pd.read_csv(path_trades_bnus_btc_usdc))
trades_bnus_btc_usdt = ensure_numeric(pd.read_csv(path_trades_bnus_btc_usdt))
trades_cbse_btc_usd = ensure_numeric(pd.read_csv(path_trades_cbse_btc_usd))
trades_cbse_btc_usdt = ensure_numeric(pd.read_csv(path_trades_cbse_btc_usdt))

master_index = pd.date_range("2023-03-01 00:00:00", "2023-03-21 23:59:59",
    ↪freq='1s', tz='UTC')

ohlcv_all, trades_all = load_all(trade_files)

print("Cleaning data...")
bnus_usd_clean = clean_df(bnus_spot_btc_usd)
bnus_usdc_clean = clean_df(bnus_spot_btc_usdc)
bnus_usdt_clean = clean_df(bnus_spot_btc_usdt)
cbse_usd_clean = clean_df(cbse_spot_btc_usd)
cbse_usdt_clean = clean_df(cbse_spot_btc_usdt)
print(f" Rows per series: {len(bnus_usd_clean):,} (target ~1,814,400)")

print("Resampling to 1-minute OHLCV...")
bnus_usd_1m = bnus_usd_clean['close'].resample('1min').last()
bnus_usdc_1m = bnus_usdc_clean['close'].resample('1min').last()
bnus_usdt_1m = bnus_usdt_clean['close'].resample('1min').last()
cbse_usd_1m = cbse_usd_clean['close'].resample('1min').last()
cbse_usdt_1m = cbse_usdt_clean['close'].resample('1min').last()
```

Cleaning data...

Rows per series: 1,814,400 (target ~1,814,400)

Resampling to 1-minute OHLCV...

2.0.2 Data Summary

```
[5]: print("Computing implied stablecoin rates...")

# implied_X/USD = BTC_USD / BTC_X (should equal 1.0 at peg)
implied_usdc_bnus = bnus_usd_1m / bnus_usdc_1m # Binance USDC/USD
implied_usdt_bnus = bnus_usd_1m / bnus_usdt_1m # Binance USDT/USD
implied_usdt_cbse = cbse_usd_1m / cbse_usdt_1m # Coinbase USDT/USD

# Implied USDT/USDC cross rate (Binance only - no Coinbase USDC pair)
# If BTC/USDC = 22000 and BTC/USDT = 21000, then 1 USDT = 22000/21000 USDC
```



```

implied_usdt_usdc_bnus = bnus_usdc_1m / bnus_usdt_1m # USDT in terms of USDC

# Premium / discount vs peg in basis points
# premium_bps > 0 means the stablecoin is trading ABOVE $1 (BTC is "cheaper" in
↳ that coin)
# premium_bps < 0 means the stablecoin is trading BELOW $1 (de-peg)
prem_usdc_bnus = (implied_usdc_bnus - 1.0) * 10_000 # bps
prem_usdt_bnus = (implied_usdt_bnus - 1.0) * 10_000 # bps
prem_usdt_cbse = (implied_usdt_cbse - 1.0) * 10_000 # bps

# USDT/USDC premium: deviation from 1.0 in bps
prem_usdt_usdc = (implied_usdt_usdc_bnus - 1.0) * 10_000 # bps

# REGIME DEFINITIONS
REGIMES = {
    'Pre-Crisis (Mar 1-9)' : ('2023-03-01', '2023-03-09'),
    'Crisis (Mar 10-14)' : ('2023-03-10', '2023-03-14'),
    'Recovery (Mar 15-21)' : ('2023-03-15', '2023-03-21'),
}

def regime_slice(series, start, end):
    return series.loc[start:end].dropna()

# PER EXCHANGE × COIN × REGIME SUMMARY TABLE
print("\n STABLECOIN PREMIUM SUMMARY TABLE ")
print(f"{'Exchange':<12} {'Coin':<10} {'Regime':<25} {'Avg Premium (bps)':>18}␣
↳ {'Std Premium (bps)':>18} {'Min (bps)':>10} {'Max (bps)':>10}")
print(" " * 100)

series_map = [
    ('Binance', 'USDC/USD', prem_usdc_bnus),
    ('Binance', 'USDT/USD', prem_usdt_bnus),
    ('Coinbase', 'USDT/USD', prem_usdt_cbse),
    ('Binance', 'USDT/USDC', prem_usdt_usdc),
]

summary_rows = []
for exchange, coin, series in series_map:
    for regime_name, (start, end) in REGIMES.items():
        sl = regime_slice(series, start, end)
        row = {
            'Exchange' : exchange,
            'Coin' : coin,
            'Regime' : regime_name,
            'Avg Premium (bps)': round(sl.mean(), 4),
            'Std Premium (bps)': round(sl.std(), 4),

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        'Min (bps)'      : round(sl.min(), 4),
        'Max (bps)'      : round(sl.max(), 4),
        'N (minutes)'    : len(sl),
    }
    summary_rows.append(row)
    print(f"{exchange:<12} {coin:<10} {regime_name:<25} {sl.mean():>18.4f}␣
↪{sl.std():>18.4f} {sl.min():>10.2f} {sl.max():>10.2f}")
    print()

summary_df = pd.DataFrame(summary_rows)
summary_df.to_csv('stablecoin_premium_summary.csv', index=False)
print("Summary table saved to stablecoin_premium_summary.csv")

```

Computing implied stablecoin rates...

STABLECOIN PREMIUM SUMMARY TABLE				
Exchange	Coin	Regime	Avg Premium (bps)	Std
Premium (bps)	Min (bps)	Max (bps)		
Binance	USDC/USD	Pre-Crisis (Mar 1-9)	-0.2046	
3.6814	-32.32	34.05		
Binance	USDC/USD	Crisis (Mar 10-14)	-197.0362	
268.6913	-1251.24	65.29		
Binance	USDC/USD	Recovery (Mar 15-21)	-3.9413	
9.3408	-61.63	50.22		
Binance	USDT/USD	Pre-Crisis (Mar 1-9)	0.1132	
2.0872	-30.62	25.05		
Binance	USDT/USD	Crisis (Mar 10-14)	46.1724	
35.5024	-9.54	165.88		
Binance	USDT/USD	Recovery (Mar 15-21)	27.5237	
9.5715	-18.50	75.65		
Coinbase	USDT/USD	Pre-Crisis (Mar 1-9)	0.2023	
2.6613	-56.16	30.00		
Coinbase	USDT/USD	Crisis (Mar 10-14)	43.9477	
83.6333	-742.11	187.69		
Coinbase	USDT/USD	Recovery (Mar 15-21)	21.2692	
57.3953	-361.22	214.83		
Binance	USDT/USDC	Pre-Crisis (Mar 1-9)	0.3191	
3.8155	-35.98	30.91		
Binance	USDT/USDC	Crisis (Mar 10-14)	256.6995	
314.9625	-38.83	1504.47		
Binance	USDT/USDC	Recovery (Mar 15-21)	31.4846	
12.2117	-20.40	88.20		

Summary table saved to stablecoin_premium_summary.csv

2.1 Cross-Exchange Dispersion (USDT/USD)

```
[8]: print("\n CROSS-EXCHANGE DISPERSION: USDT/USD (Binance vs Coinbase) ")

# Align both series to the same index (inner join)
disp_df = pd.DataFrame({
    'bnus': implied_usdt_bnus,
    'cbse': implied_usdt_cbse,
}).dropna()

# At each minute: cross-sectional std across the two venues
# std of 2 values = |x - y| / sqrt(2)
disp_df['cross_dispersion'] = disp_df[['bnus', 'cbse']].std(axis=1)
disp_df['cross_dispersion_bps'] = disp_df['cross_dispersion'] * 10_000

print(f"\n{'Regime':<25} {'Mean Dispersion (bps)':>22} {'Median Dispersion (bps)':>24} {'Max Dispersion (bps)':>21}")
print(" " * 95)

disp_rows = []
for regime_name, (start, end) in REGIMES.items():
    sl = disp_df['cross_dispersion_bps'].loc[start:end].dropna()
    disp_rows.append({
        'Regime' : regime_name,
        'Mean Dispersion (bps)' : round(sl.mean(), 4),
        'Median Dispersion (bps)' : round(sl.median(), 4),
        'Max Dispersion (bps)' : round(sl.max(), 4),
        'Pct time > 10 bps (%)' : round((sl > 10).mean() * 100, 2),
    })
    print(f"{'regime_name':<25} {sl.mean():>22.4f} {sl.median():>24.4f} {sl.max():>21.4f}")

disp_df_summary = pd.DataFrame(disp_rows)
disp_df_summary.to_csv('cross_exchange_dispersion.csv', index=False)
print("\nCross-exchange dispersion saved to cross_exchange_dispersion.csv")
```

CROSS-EXCHANGE DISPERSION: USDT/USD (Binance vs Coinbase)

Regime	Mean Dispersion (bps)	Median Dispersion (bps)	Max Dispersion (bps)
Pre-Crisis (Mar 1-9)	1.2817	0.9485	40.4137
Crisis (Mar 10-14)	14.2115	4.9328	

549.6853		
Recovery (Mar 15-21)	14.9514	3.5335
279.4883		

Cross-exchange dispersion saved to cross_exchange_dispersion.csv

2.2 Implied USDC/USD and USDT/USD Premiums on Binance

```
[7]: print("\nGenerating plots...")

CRISIS_START = pd.Timestamp('2023-03-10', tz='UTC')
CRISIS_END   = pd.Timestamp('2023-03-14', tz='UTC')

def shade_crisis(ax):
    ax.axvspan(CRISIS_START, CRISIS_END, color='red', alpha=0.08, label='Crisis_
    ↪Window')
    ax.axhline(0, color='black', linestyle='--', linewidth=0.8)

# Implied USDC/USD and USDT/USD (Binance)
fig, axes = plt.subplots(3, 1, figsize=(15, 12), sharex=True)
fig.suptitle('Stablecoin Dynamics: Implied Rates & Premia (March 2023)',
    ↪fontsize=14, fontweight='bold')

ax = axes[0]
ax.plot(prem_usdc_bnus.index, prem_usdc_bnus, color='red', lw=0.6,
    ↪label='USDC/USD Premium (Binance)')
ax.plot(prem_usdt_bnus.index, prem_usdt_bnus, color='green', lw=0.6,
    ↪label='USDT/USD Premium (Binance)', alpha=0.7)
shade_crisis(ax)
ax.set_ylabel('Premium vs Peg (bps)')
ax.set_title('USDC/USD and USDT/USD Implied Premia - Binance')
ax.legend(loc='lower left', fontsize=8)
ax.grid(True, alpha=0.3)
ax.set_ylim(-1500, 1500)

# USDT/USD cross-exchange comparison
ax = axes[1]
ax.plot(prem_usdt_bnus.index, prem_usdt_bnus, color='steelblue', lw=0.6,
    ↪label='USDT/USD Binance')
ax.plot(prem_usdt_cbse.index, prem_usdt_cbse, color='orange', lw=0.6,
    ↪label='USDT/USD Coinbase', alpha=0.8)
shade_crisis(ax)
ax.set_ylabel('Premium vs Peg (bps)')
ax.set_title('USDT/USD Implied Premium - Binance vs Coinbase')
ax.legend(loc='lower left', fontsize=8)
ax.grid(True, alpha=0.3)
ax.set_ylim(-500, 500)
```

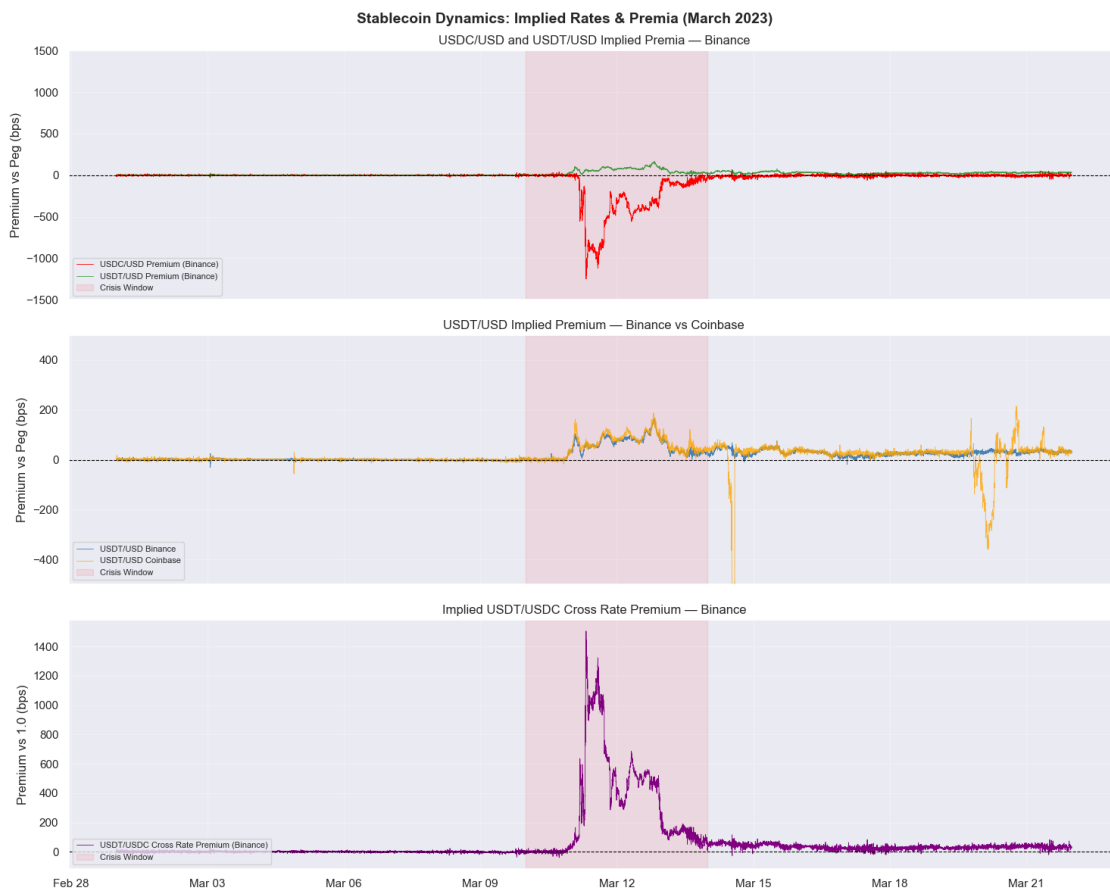
```

# USDT/USDC implied cross rate premium
ax = axes[2]
ax.plot(prem_usdt_usdc.index, prem_usdt_usdc, color='purple', lw=0.6,
        label='USDT/USDC Cross Rate Premium (Binance)')
shade_crisis(ax)
ax.set_ylabel('Premium vs 1.0 (bps)')
ax.set_title('Implied USDT/USDC Cross Rate Premium - Binance')
ax.legend(loc='lower left', fontsize=8)
ax.grid(True, alpha=0.3)
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b %d'))
ax.xaxis.set_major_locator(mdates.DayLocator(interval=3))

plt.tight_layout()
plt.savefig('stablecoin_premia_overview.png', dpi=150, bbox_inches='tight')
plt.show()
print(" Saved: stablecoin_premia_overview.png")

```

Generating plots...

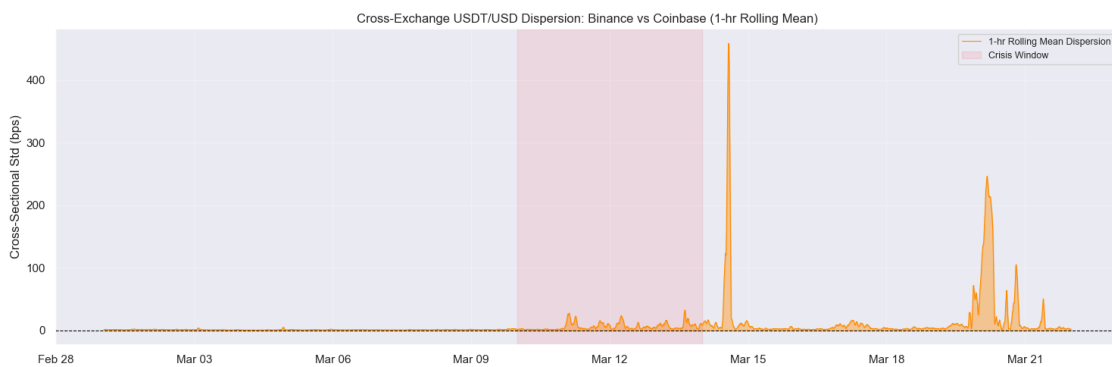


Saved: stablecoin_premia_overview.png

2.3 Cross-Exchange Dispersion over Time

```
[9]: # Cross-exchange dispersion over time
fig, ax = plt.subplots(figsize=(15, 5))

# Use 1-hour rolling mean to smooth
rolling_disp = disp_df['cross_dispersion_bps'].rolling(window=60).mean()
ax.fill_between(rolling_disp.index, rolling_disp, alpha=0.4, color='darkorange')
ax.plot(rolling_disp.index, rolling_disp, color='darkorange', lw=0.8,
        label='1-hr Rolling Mean Dispersion')
ax.axvspan(CRISIS_START, CRISIS_END, color='red', alpha=0.08, label='Crisis Window')
ax.axhline(0, color='black', linestyle='--', linewidth=0.8)
ax.set_title('Cross-Exchange USDT/USD Dispersion: Binance vs Coinbase (1-hr Rolling Mean)',
             fontsize=12)
ax.set_ylabel('Cross-Sectional Std (bps)')
ax.legend(fontsize=9)
ax.grid(True, alpha=0.3)
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b %d'))
ax.xaxis.set_major_locator(mdates.DayLocator(interval=3))
plt.tight_layout()
plt.savefig('cross_exchange_dispersion.png', dpi=150, bbox_inches='tight')
plt.show()
print(" Saved: cross_exchange_dispersion.png")
```



Saved: cross_exchange_dispersion.png

2.4 Regime Summary Statistics

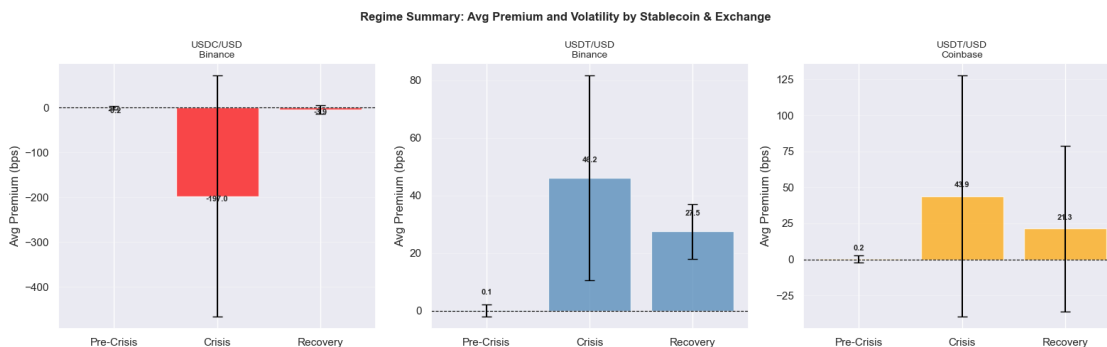
```
[10]: # Bar chart of regime summary statistics
fig, axes = plt.subplots(1, 3, figsize=(16, 5))
fig.suptitle('Regime Summary: Avg Premium and Volatility by Stablecoin & Exchange',
             fontsize=12, fontweight='bold')

pairs = [
    ('USDC/USD', 'Binance', prem_usdc_bnus, 'red'),
    ('USDT/USD', 'Binance', prem_usdt_bnus, 'steelblue'),
    ('USDT/USD', 'Coinbase', prem_usdt_cbse, 'orange'),
]

regime_labels = list(REGIMES.keys())
short_labels = ['Pre-Crisis', 'Crisis', 'Recovery']

for ax_idx, (coin, exch, series, color) in enumerate(pairs):
    ax = axes[ax_idx]
    avgs = [regime_slice(series, s, e).mean() for _, (s, e) in REGIMES.items()]
    stds = [regime_slice(series, s, e).std() for _, (s, e) in REGIMES.items()]
    bars = ax.bar(short_labels, avgs, color=color, alpha=0.7, yerr=stds,
                  capsize=5, ecolor='black')
    ax.axhline(0, color='black', linestyle='--', linewidth=0.8)
    ax.set_title(f'{coin}\n{exch}', fontsize=10)
    ax.set_ylabel('Avg Premium (bps)')
    ax.grid(True, alpha=0.3, axis='y')
    # Annotate bars
    for bar, avg, std in zip(bars, avgs, stds):
        ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + (5 if avg >= 0 else -15),
                f'{avg:.1f}', ha='center', va='bottom', fontsize=8,
                fontweight='bold')

plt.tight_layout()
plt.savefig('regime_bar_chart.png', dpi=150, bbox_inches='tight')
plt.show()
print(" Saved: regime_bar_chart.png")
```



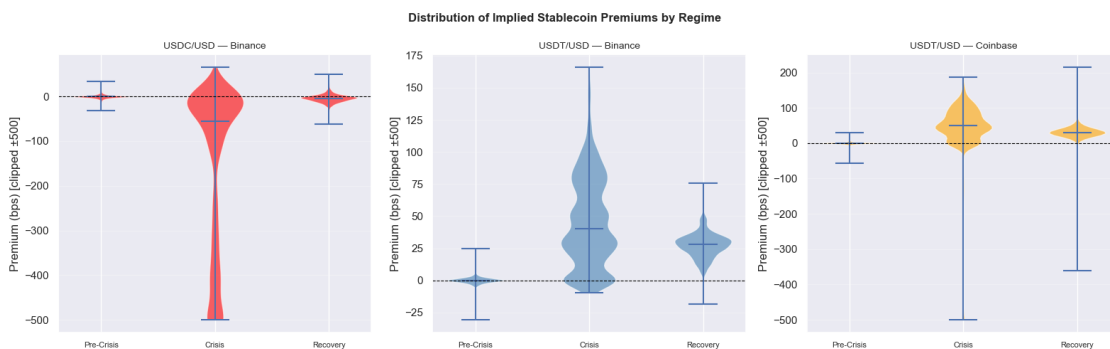
Saved: regime_bar_chart.png

2.5 Distribution of Premiums by Regime

```
[11]: # Distribution of premiums by regime (violin/box plot)
fig, axes = plt.subplots(1, 3, figsize=(16, 5))
fig.suptitle('Distribution of Implied Stablecoin Premiums by Regime',
             ↪fontsize=12, fontweight='bold')

for ax_idx, (coin, exch, series, color) in enumerate(pairs):
    ax = axes[ax_idx]
    data_by_regime = [regime_slice(series, s, e).clip(-500, 500).values
                      ↪for _, (s, e) in REGIMES.items()]
    vp = ax.violinplot(data_by_regime, positions=[1, 2, 3], showmedians=True,
    ↪showextrema=True)
    for body in vp['bodies']:
        body.set_facecolor(color)
        body.set_alpha(0.6)
    ax.set_xticks([1, 2, 3])
    ax.set_xticklabels(short_labels, fontsize=8)
    ax.set_title(f'{coin} - {exch}', fontsize=10)
    ax.set_ylabel('Premium (bps) [clipped ±500]')
    ax.axhline(0, color='black', linestyle='--', linewidth=0.8)
    ax.grid(True, alpha=0.3, axis='y')

plt.tight_layout()
plt.savefig('regime_distributions.png', dpi=150, bbox_inches='tight')
plt.show()
print(" Saved: regime_distributions.png")
```



Saved: regime_distributions.png

2.6 Dynamics Summary

```
[12]: print("\n" + " "*60)
print("COMPLETE SUMMARY")
print(" "*60)
print("\nPremium Summary Table:")
print(summary_df.to_string(index=False))
print("\nCross-Exchange Dispersion Summary:")
print(dispen_df_summary.to_string(index=False))
```

COMPLETE SUMMARY

Premium Summary Table:

Exchange	Coin	Regime	Avg Premium (bps)	Std Premium (bps)
Min (bps)	Max (bps)	N (minutes)		
Binance	USDC/USD	Pre-Crisis (Mar 1-9)	-0.2046	3.6814
-32.3174	34.0537	12960		
Binance	USDC/USD	Crisis (Mar 10-14)	-197.0362	268.6913
-1251.2423	65.2875	7200		
Binance	USDC/USD	Recovery (Mar 15-21)	-3.9413	9.3408
-61.6322	50.2217	10080		
Binance	USDT/USD	Pre-Crisis (Mar 1-9)	0.1132	2.0872
-30.6158	25.0534	12960		
Binance	USDT/USD	Crisis (Mar 10-14)	46.1724	35.5024
-9.5392	165.8770	7200		
Binance	USDT/USD	Recovery (Mar 15-21)	27.5237	9.5715
-18.5003	75.6462	10080		
Coinbase	USDT/USD	Pre-Crisis (Mar 1-9)	0.2023	2.6613
-56.1625	29.9994	12960		
Coinbase	USDT/USD	Crisis (Mar 10-14)	43.9477	83.6333
-742.1103	187.6887	7200		
Coinbase	USDT/USD	Recovery (Mar 15-21)	21.2692	57.3953
-361.2241	214.8261	10080		
Binance	USDT/USDC	Pre-Crisis (Mar 1-9)	0.3191	3.8155
-35.9768	30.9098	12960		
Binance	USDT/USDC	Crisis (Mar 10-14)	256.6995	314.9625
-38.8311	1504.4689	7200		
Binance	USDT/USDC	Recovery (Mar 15-21)	31.4846	12.2117
-20.3997	88.1951	10080		

Cross-Exchange Dispersion Summary:

Regime	Mean Dispersion (bps)	Median Dispersion (bps)	Max Dispersion (bps)	Pct time > 10 bps (%)
Pre-Crisis (Mar 1-9)	1.2817	0.9485		
	40.4137	0.12		

Crisis (Mar 10-14)		14.2115	4.9328
549.6853	28.69		
Recovery (Mar 15-21)		14.9514	3.5335
279.4883	20.01		

2.7 Kyle Lambda

```
[13]: # calc kyle lambda
def kyle_lambda_by_regime(trades_1m):
    df = trades_1m.copy()

    def fit_lambda(df):
        df = df[['ret', 'signed_dollar']].dropna()
        y = df['ret'].to_numpy()
        x = df['signed_dollar'].to_numpy()

        X = np.column_stack([np.ones_like(x), x])
        a, _, _, _ = np.linalg.lstsq(X, y, rcond=None)

        return float(a[1]) * 1000000.0

    kyle = df.groupby('regime', sort=False).apply(fit_lambda)
    kyle.name = 'lambda'

    return kyle
```

2.8 Roll Spread

```
[14]: def roll_from_trades(trades_df):
    g = trades_df.copy()
    g = g[pd.to_numeric(g['price'], errors="coerce") > 0]
    P = g['price'].astype(float)

    side = np.where(g['taker_side_sell'], -1, 1)
    r = np.log(P).diff().dropna()
    roll_cov = np.cov(r[1:], r[:-1])[0,1]

    if pd.isna(roll_cov) or roll_cov >= 0: return np.nan

    roll_spread = 2 * np.sqrt(-roll_cov)
    roll_spread_bps = roll_spread * 10_000

    return roll_spread_bps

def roll_by_regime_from_trades(trades_df):
    rs = trades_df.groupby("regime", sort=False).apply(lambda g:
↪roll_from_trades(g))
```

```
rs.name = "roll_spread"

return rs.reindex(REGIME_ORDER)
```

2.9 Effective Spread

```
[15]: def es_from_trades(trades_df, agg='median'):
    g = trades_df.copy()
    g = g[pd.to_numeric(g['price'], errors="coerce") > 0]
    P = g['price'].astype(float)

    side = np.where(g['taker_side_sell'], -1, 1)
    mid = g['mid'].astype(float)

    exp_spread = 2 * side * (P - mid)
    exp_spread_bps = (exp_spread / P) * 10000

    exp_spread_bps = exp_spread_bps.replace([np.inf, -np.inf], np.nan).dropna()
    exp_spread_bps = exp_spread_bps[(exp_spread_bps > -500) & (exp_spread_bps <=
↪500)]

    if agg == 'mean':
        return exp_spread_bps.mean()
    else:
        return exp_spread_bps.median()

def es_by_regime_from_trades(trades_df, agg='mean'):
    es = trades_df.groupby("regime", sort=False).apply(lambda g:
↪es_from_trades(g, agg=agg))
    es.name = "expected_spread"

    return es.reindex(REGIME_ORDER)
```

2.10 Realized Spread

```
[16]: def rs_from_trades(trades_df, agg='median'):
    g = trades_df.copy()
    g = g[pd.to_numeric(g['price'], errors="coerce") > 0]
    P = g['price'].astype(float)

    side = np.where(g['taker_side_sell'], -1, 1)

    future_mid = g['future_mid'].astype(float)

    realized_spread = 2 * side * (P - future_mid)
    realized_spread_bps = (realized_spread / P) * 10000
```

```

    realized_spread_bps = realized_spread_bps.replace([np.inf, -np.inf], np.
↪nan).dropna()
    realized_spread_bps = realized_spread_bps[(realized_spread_bps > -500) &
↪(realized_spread_bps < 500)]

    if agg == 'mean':
        return realized_spread_bps.mean()
    else:
        return realized_spread_bps.median()

def rs_by_regime_from_trades(trades_df, agg='mean'):
    rs = trades_df.groupby("regime", sort=False).apply(lambda g:
↪rs_from_trades(g, agg=agg))
    rs.name = "realized_spread"

    return rs.reindex(REGIME_ORDER)

```

2.11 Liquidity Summary

```

[17]: # generate analysis summary value table
def summarize_liquidity(trades_df, roll_series, kyle_series, es_series,
↪rs_series):

    def summ(g):
        nobs = len(g)
        n_trades = g['n_trades'].sum()
        vol_dollar = g['vol_dollar'].sum()
        rv_sum = g['rv_1m'].sum()
        rv_mean = g['rv_1m'].mean()
        sigma_ann = np.sqrt(rv_mean) * np.sqrt(525600)

        amihud_mean = g['amihud_1m'].mean()
        amihud_median = g['amihud_1m'].median()

        return pd.Series({
            'nobs': nobs,
            'n_trades': n_trades,
            'vol_dollar': vol_dollar,
            'rv_sum': rv_sum,
            'rv_mean': rv_mean,
            'sigma_ann': sigma_ann,
            'amihud_mean': amihud_mean,
            'amihud_median': amihud_median,
            'depth_proxy_vol_over_rv': vol_dollar / rv_mean if rv_mean > 0 else
↪np.nan,
            'inv_amihud_median': 1.0 / amihud_median if amihud_median > 0 else
↪np.nan,

```

```

        'n_trades_per_min': n_trades / nobs if nobs > 0 else np.nan,
        'avg_trade_dollar': vol_dollar / n_trades if n_trades > 0 else np.
↪nan,
    })

    summ_df = trades_df.groupby('regime', observed=True).apply(summ).
↪reindex(REGIME_ORDER)

    if roll_series is not None:
        summ_df['roll_spread'] = roll_series.reindex(REGIME_ORDER).to_numpy()
    if kyle_series is not None:
        summ_df['kyle_lambda_scaled'] = np.abs(kyle_series.
↪reindex(REGIME_ORDER).to_numpy())
    if es_series is not None:
        summ_df['es_spread'] = es_series.reindex(REGIME_ORDER).to_numpy()
    if rs_series is not None:
        summ_df['rs_spread'] = rs_series.reindex(REGIME_ORDER).to_numpy()

    return summ_df

# runs across all exchanges and types
def run_liquidity_block(trade_files, agg):
    rows = []
    panels = []
    for spec in trade_files:
        trades, ohlc = load_trades_ohlc(spec['trade_path'], spec['ohlc_path'])
        panel = resample_trades(trades)
        panels.append({'exchange': spec['exchange'], 'pair': spec['pair'],
↪'panel': panel})

        roll = roll_by_regime_from_trades(trades)
        kyle = kyle_lambda_by_regime(panel)
        es = es_by_regime_from_trades(trades, agg=agg)
        rs = rs_by_regime_from_trades(trades, agg=agg)

        summ = summarize_liquidity(panel, roll, kyle, es, rs)
        summ = summ.reset_index().rename(columns={'index': 'regime'})
        summ['exchange'] = spec['exchange']
        summ['pair'] = spec['pair']
        rows.append(summ)

    out = pd.concat(rows, ignore_index=True)
    out['regime'] = pd.Categorical(out['regime'], categories=REGIME_ORDER,
↪ordered=True)
    out = out.sort_values(['exchange', 'pair', 'regime']).reset_index(drop=True)

    return out, panels

```

```

# plot table for given metric
def plot_metric(all_summary, metric, title, log=False):
    piv = all_summary.pivot_table(index=['exchange', 'pair'], columns='regime',
    ↪ values=metric, aggfunc='mean')
    piv = piv.reindex(columns=REGIME_ORDER)
    ax = piv.plot(kind='bar', figsize=(10, 4))
    ax.set_title(title)
    ax.set_ylabel(metric)
    if log: ax.set_yscale('log')
    ax.tick_params(axis='x', labelrotation=45)
    ax.legend(title='regime')

    plt.tight_layout()
    plt.show()

all_summary, all_panels = run_liquidity_block(trade_files, agg='mean')
all_summary

```

```

[17]:

```

	regime	nobs	n_trades	vol_dollar	rv_sum	rv_mean	sigma_ann	\
0	calm	12818.0	1010373.0	1.1282e+09	0.0033	2.5387e-07	0.3653	
1	stress	7198.0	1601108.0	1.3028e+09	0.0072	1.0030e-06	0.7261	
2	post	NaN	NaN	NaN	NaN	NaN	NaN	
3	calm	4614.0	39506.0	2.9594e+07	0.0029	6.2668e-07	0.5739	
4	stress	3660.0	61338.0	2.4318e+07	0.0281	7.6747e-06	2.0084	
5	post	NaN	NaN	NaN	NaN	NaN	NaN	
6	calm	12069.0	418606.0	4.3146e+08	0.0033	2.7424e-07	0.3797	
7	stress	7053.0	413888.0	5.8810e+08	0.0072	1.0268e-06	0.7346	
8	post	NaN	NaN	NaN	NaN	NaN	NaN	
9	calm	12674.0	2636263.0	2.3746e+09	0.0033	2.6266e-07	0.3716	
10	stress	6945.0	2428945.0	3.0797e+09	0.0070	1.0107e-06	0.7288	
11	post	NaN	NaN	NaN	NaN	NaN	NaN	
12	calm	9815.0	108378.0	8.9399e+07	0.0036	3.6635e-07	0.4388	
13	stress	6408.0	121142.0	1.2580e+08	0.0088	1.3781e-06	0.8511	
14	post	NaN	NaN	NaN	NaN	NaN	NaN	
15	calm	12865.0	271136.0	5.6661e+08	0.0035	2.7066e-07	0.3772	
16	stress	7200.0	395459.0	1.1508e+09	0.0086	1.1971e-06	0.7932	
17	post	NaN	NaN	NaN	NaN	NaN	NaN	
18	calm	2243.0	8913.0	1.7961e+07	0.0023	1.0427e-06	0.7403	
19	stress	4254.0	67890.0	1.2885e+08	0.0324	7.6175e-06	2.0009	
20	post	NaN	NaN	NaN	NaN	NaN	NaN	
21	calm	4748.0	23277.0	3.8702e+07	0.0026	5.4879e-07	0.5371	
22	stress	4956.0	66998.0	1.1424e+08	0.0081	1.6329e-06	0.9264	
23	post	NaN	NaN	NaN	NaN	NaN	NaN	

	amihud_mean	amihud_median	depth_proxy_vol_over_rv	inv_amihud_median	\
0	3.5856e-08	4.7147e-09	4.4438e+15	2.1210e+08	

1	1.2216e-08	4.1701e-09	1.2989e+15	2.3980e+08
2	NaN	NaN	NaN	NaN
3	1.1024e-06	1.1812e-07	4.7223e+13	8.4656e+06
4	7.4358e-06	2.6044e-07	3.1686e+12	3.8396e+06
5	NaN	NaN	NaN	NaN
6	1.4314e-07	1.3253e-08	1.5733e+15	7.5456e+07
7	1.8860e-07	9.2672e-09	5.7274e+14	1.0791e+08
8	NaN	NaN	NaN	NaN
9	6.1543e-09	1.8785e-09	9.0405e+15	5.3235e+08
10	2.4353e-09	1.5268e-09	3.0471e+15	6.5498e+08
11	NaN	NaN	NaN	NaN
12	7.9505e-06	8.6780e-08	2.4402e+14	1.1523e+07
13	1.1966e-05	6.8747e-08	9.1285e+13	1.4546e+07
14	NaN	NaN	NaN	NaN
15	3.3012e-07	1.4923e-08	2.0934e+15	6.7012e+07
16	6.8361e-08	6.3541e-09	9.6131e+14	1.5738e+08
17	NaN	NaN	NaN	NaN
18	2.2155e-05	7.8588e-07	1.7226e+13	1.2725e+06
19	1.2472e-05	1.6363e-07	1.6915e+13	6.1114e+06
20	NaN	NaN	NaN	NaN
21	7.2366e-06	2.9423e-07	7.0522e+13	3.3987e+06
22	6.4502e-06	1.0990e-07	6.9958e+13	9.0992e+06
23	NaN	NaN	NaN	NaN

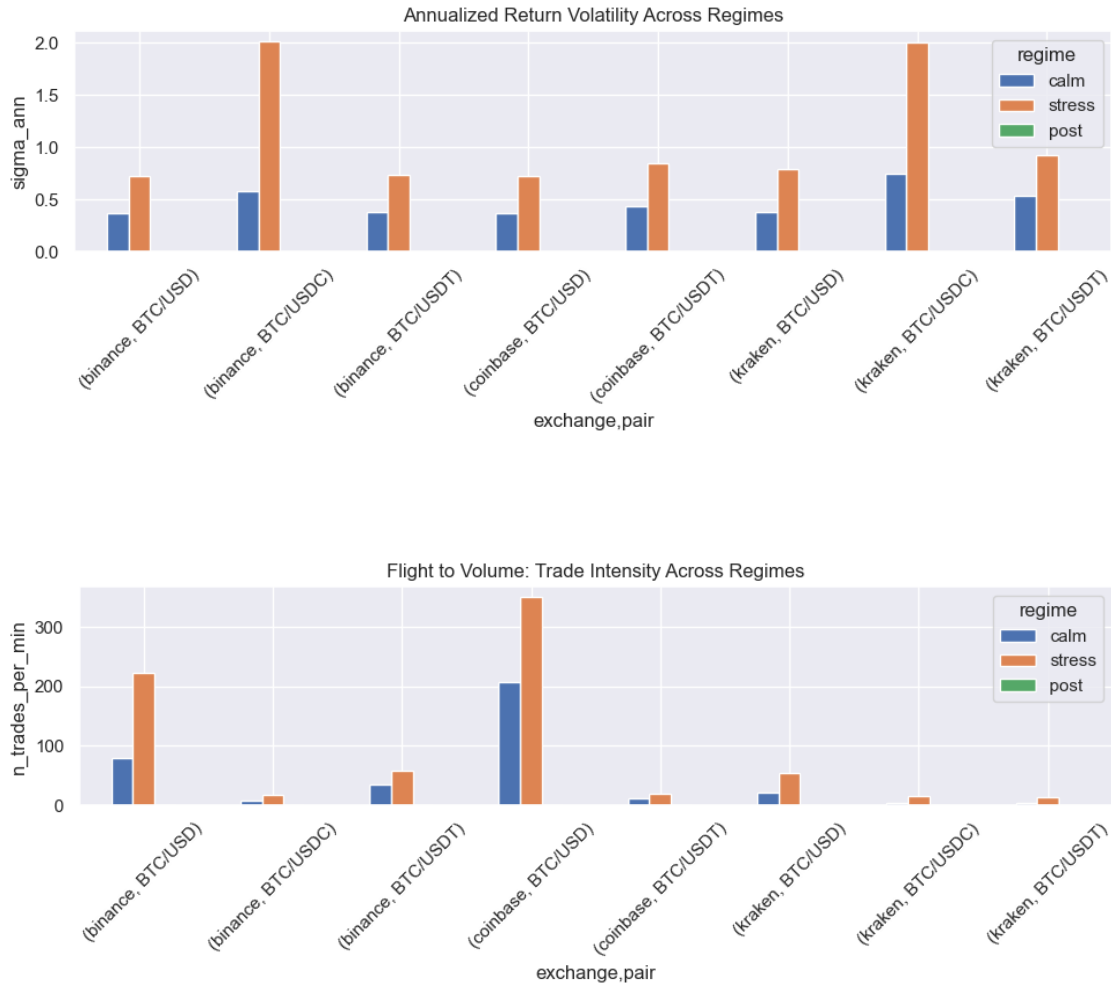
	n_trades_per_min	avg_trade_dollar	roll_spread	kyle_lambda_scaled \
0	78.8245	1116.5874	0.9781	0.0027
1	222.4379	813.7027	1.8801	0.0034
2	NaN	NaN	NaN	NaN
3	8.5622	749.1046	0.8691	0.0278
4	16.7590	396.4553	17.2087	0.0591
5	NaN	NaN	NaN	NaN
6	34.6844	1030.7044	1.1412	0.0066
7	58.6825	1420.9089	1.7904	0.0054
8	NaN	NaN	NaN	NaN
9	208.0056	900.7499	0.4200	0.0012
10	349.7401	1267.9009	1.1149	0.0014
11	NaN	NaN	NaN	NaN
12	11.0421	824.8793	0.8673	0.0072
13	18.9048	1038.4442	1.4402	0.0080
14	NaN	NaN	NaN	NaN
15	21.0755	2089.7556	0.8867	0.0018
16	54.9249	2910.1130	1.8958	0.0017
17	NaN	NaN	NaN	NaN
18	3.9737	2015.1590	0.9878	0.0079
19	15.9591	1897.9836	17.5528	0.0102
20	NaN	NaN	NaN	NaN
21	4.9025	1662.6776	0.6946	0.0043

22	13.5186	1705.0762	2.0262	0.0034
23	NaN	NaN	NaN	NaN
	es_spread	rs_spread	exchange	pair
0	-0.4636	-0.0008	binance	BTC/USD
1	-0.9191	0.0492	binance	BTC/USD
2	NaN	NaN	binance	BTC/USD
3	-0.2739	1.3643	binance	BTC/USDC
4	-1.8006	-6.1392	binance	BTC/USDC
5	NaN	NaN	binance	BTC/USDC
6	-0.2345	0.7373	binance	BTC/USDT
7	-0.6788	0.4012	binance	BTC/USDT
8	NaN	NaN	binance	BTC/USDT
9	0.1601	-0.4524	coinbase	BTC/USD
10	0.4816	-0.3747	coinbase	BTC/USD
11	NaN	NaN	coinbase	BTC/USD
12	0.2279	-1.2136	coinbase	BTC/USDT
13	0.3240	-1.3634	coinbase	BTC/USDT
14	NaN	NaN	coinbase	BTC/USDT
15	0.1752	-2.7115	kraken	BTC/USD
16	0.5676	-2.2971	kraken	BTC/USD
17	NaN	NaN	kraken	BTC/USD
18	-0.0146	-2.6587	kraken	BTC/USDC
19	4.6317	14.8456	kraken	BTC/USDC
20	NaN	NaN	kraken	BTC/USDC
21	0.0263	-3.8076	kraken	BTC/USDT
22	0.1164	-1.2217	kraken	BTC/USDT
23	NaN	NaN	kraken	BTC/USDT

2.12 Volatility Dynamics During Market Stress

- The empirical data reveals a crystal-clear signature of the March 2023 USDC depeg, most notably in the volatility profiles of stablecoin versus fiat quote currencies. Looking at the Annualized Return Volatility chart, Binance BTC/USDC experienced extreme instability where volatility jumped from 57% in the calm regime to a massive 200% during the stress regime, before settling back to 83% post-crisis.
- This volatility was accompanied by a severe panic-induced “flight to volume.” As seen in the Trade Intensity chart, despite the stress period lasting only four days, BTC/USDC recorded 61,338 trades—vastly outpacing the 39,506 trades seen in the entire prolonged calm period preceding it. Without the robust framework of the GENIUS Act, legacy stablecoins were highly susceptible to traditional banking panics, transmitting off-chain banking risk directly into severe microstructure volatility in cross-currency crypto pairs.

```
[18]: plot_metric(all_summary, 'sigma_ann', 'Annualized Return Volatility Across_
      ↪Regimes')
      plot_metric(all_summary, 'n_trades_per_min', 'Flight to Volume: Trade Intensity_
      ↪Across Regimes')
```

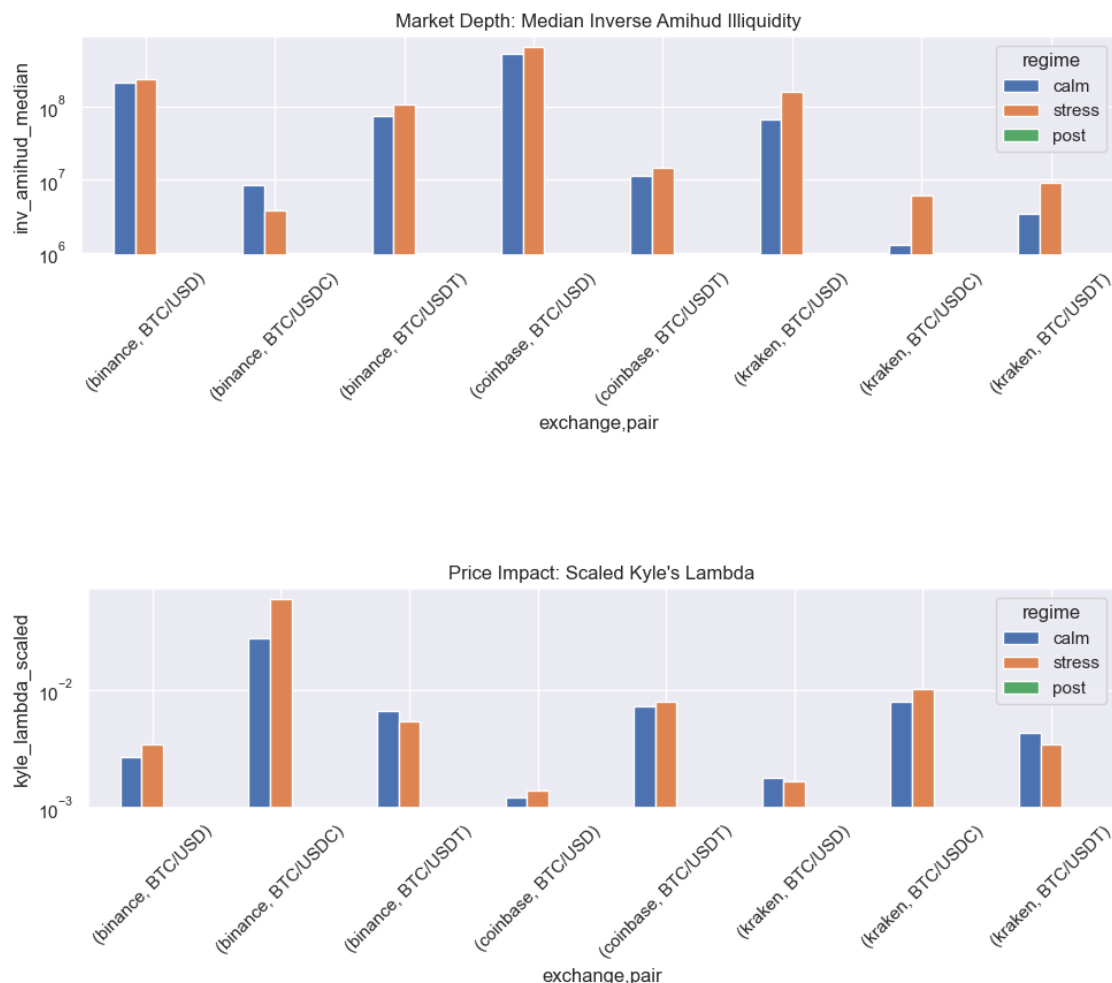



2.13 Market Depth and Resilience

- When analyzing order book absorption and price impact, pure fiat pairs were better in liquidity depth compared to their stablecoin counterparts. The Median Inverse Amihud Illiquidity chart illustrates that Fiat USD acts as an uncontested liquidity anchor. Coinbase BTC/USD's inverse Amihud depth completely dwarfs all other pairs by orders of magnitude (note the logarithmic scale).
- The fiat pairs demonstrated remarkable resilience. During the height of the banking stress, the Amihud median for Coinbase BTC/USD actually remained stable and even slightly improved (from 1.87×10^{-9} to 1.52×10^{-9}). The higher inverse values imply deeper market depth, meaning the fiat order book effortlessly absorbed the massive volume surge with minimal price impact for traders. In contrast, unregulated stablecoin pairs lacked this structural resilience when the peg came under pressure.

```
[19]: plot_metric(all_summary, 'inv_amihud_median', 'Market Depth: Median Inverse_
      ↪Amihud Illiquidity', True) # higher
```

```
plot_metric(all_summary, 'kyle_lambda_scaled', 'Price Impact: Scaled Kyle\'s_λ ↪Lambda', True) # lower
```

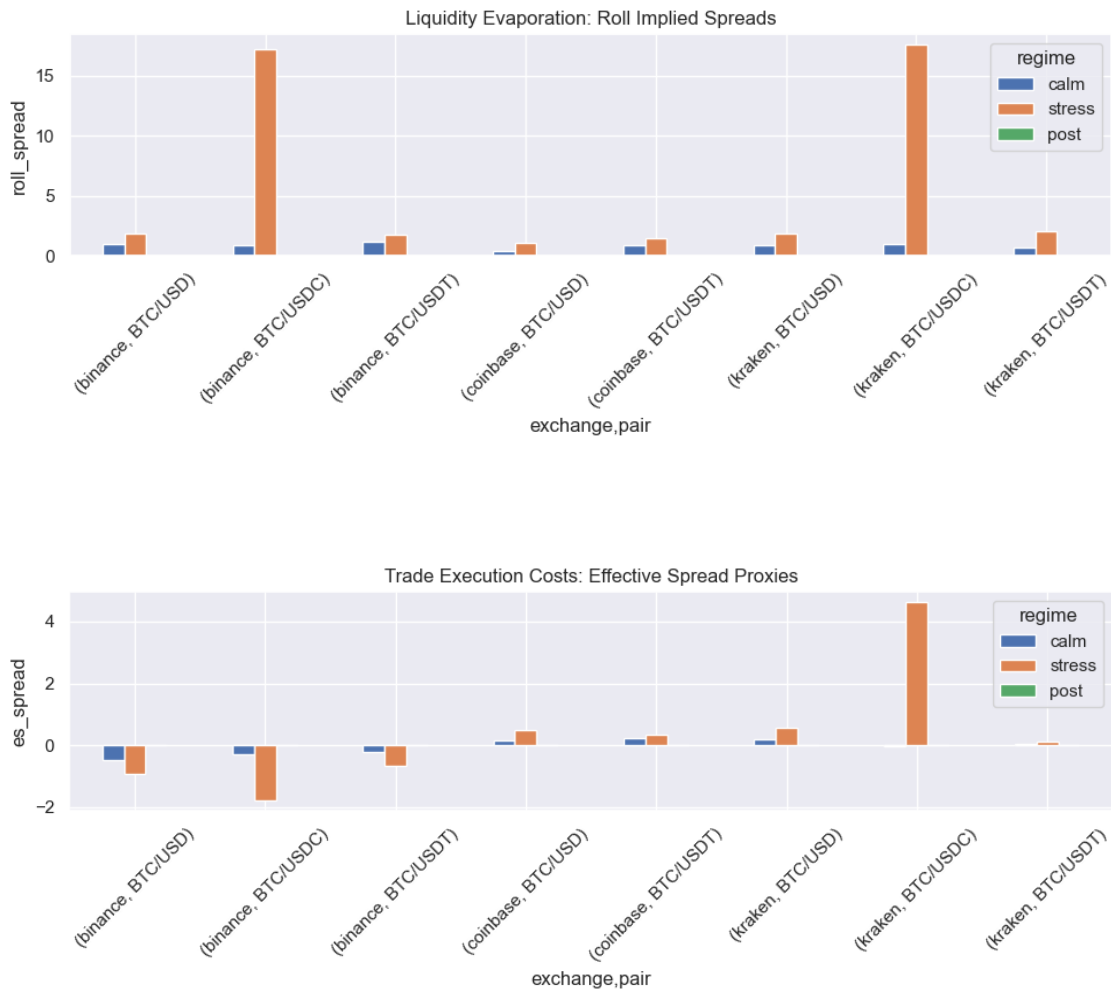


2.14 Spread Proxies

- Bid-ask spread proxies further illustrate the fragmentation of liquidity across quote currencies. The Roll Implied Spreads chart starkly captures the evaporation of liquidity in the stablecoin market during the crisis. For Binance BTC/USDC, the roll spread spiked from a baseline of 0.86 bps to an astonishing 17.2 bps during the stress regime.
- Conversely, Coinbase BTC/USD maintained the tightest spread by far. In the calm period, it averaged just 0.42 bps, compared to Binance BTC/USDT (1.14 bps) and Binance BTC/USDC (0.86 bps). Even during the peak of the stress period, Coinbase's BTC/USD spread widened to a mere 1.11 bps, effectively resisting the contagion that drove USDC spreads up by 20x.
- The Effective Spread show values hovering around -0.5 to +0.5 bps. These metrics were estimated using 1-second OHLC mid-prices due to the absence of Level 2 quote (order book) data, which introduces intra-second microstructure latency artifacts. Because we are using

1-second OHLC data to proxy the mid-price, high-frequency trades often appear to execute “inside” or “past” the stale 1-second mid-price, resulting in slightly negative effective spreads. Interestingly, Coinbase leans slightly positive while Binance leans slightly negative, likely due to micro-differences in how their respective matching engines report trade timestamps. Because of these L2 data limitations, this study relies on the Roll Spread, Kyle’s Lambda, and Amihud Illiquidity, all of which are calculated from executed trades as the most robust measures of market friction.

```
[20]: plot_metric(all_summary, "roll_spread", "Liquidity Evaporation: Roll Implied_
↳Spreads")
plot_metric(all_summary, "es_spread", "Trade Execution Costs: Effective Spread_
↳Proxies")
```



2.15 Volume Fragmentation

```
[21]: explain_block(
    "Volume Fragmentation (HHI + venue shares + dominance shifts).",
    "Trades data, 1-minute bins, volume=amount. Pairs: BTC/USD & BTC/USDT_
    ↪ across bnus/cbse/krkn; BTC/USDC across bnus/krkn.",
    "Higher HHI = more concentration. Dominance shift is significant only if >5_
    ↪ percentage points."
)

PAIR_VENUE_MAP = {
    "BTC/USD": ["binance", "coinbase", "kraken"],
    "BTC/USDT": ["binance", "coinbase", "kraken"],
    "BTC/USDC": ["binance", "kraken"],
}

def volume_fragmentation_multi(trades_df, pair_venue_map, freq="1min", sig_pp=5.
    ↪ 0):
    hhi_all, share_all = [], []

    for pair, venues in pair_venue_map.items():
        d = trades_df[
            (trades_df["pair"] == pair) & (trades_df["exchange"].isin(venues))
        ].copy()

        d["time_bin"] = d.index.floor(freq)

        # per-minute venue volume
        vv = (
            d.groupby(["time_bin", "exchange"], as_index=False)["amount"]
              .sum()
              .rename(columns={"amount": "venue_vol"})
        )

        # full grid (avoid missing-minute bias)
        minutes = pd.date_range("2023-03-01", "2023-03-21 23:59:00", freq=freq,
            ↪ tz="UTC")
        grid = pd.MultiIndex.from_product(
            [minutes, venues], names=["time_bin", "exchange"]
        ).to_frame(index=False)

        vv = grid.merge(vv, on=["time_bin", "exchange"], how="left").
            ↪ fillna({"venue_vol": 0.0})

        tot = (
            vv.groupby("time_bin", as_index=False)["venue_vol"]
              .sum()
```

```

        .rename(columns={"venue_vol": "total_vol"})
    )

    s = vv.merge(tot, on="time_bin", how="left")
    s["share"] = np.where(s["total_vol"] > 0, s["venue_vol"] /
↪s["total_vol"], np.nan)
    s["pair"] = pair
    s = add_regime_labels(s, ts_col="time_bin")
    s = s[s["regime"] != "out_of_scope"]
    share_all.append(s)

    h = (
        s.groupby(["pair", "time_bin"], as_index=False)
        .agg(hhi=("share", lambda x: np.nansum(np.square(x))))
    )
    h = add_regime_labels(h, ts_col="time_bin")
    h = h[h["regime"] != "out_of_scope"]
    hhi_all.append(h)

shares_df = pd.concat(share_all, ignore_index=True)
hhi_ts_df = pd.concat(hhi_all, ignore_index=True)

hhi_summary = (
    hhi_ts_df.groupby(["pair", "regime"], as_index=False)
    .agg(
        mean_hhi=("hhi", "mean"),
        median_hhi=("hhi", "median"),
        p90_hhi=("hhi", lambda x: np.nanpercentile(x, 90)),
        n_bins=("hhi", "count"),
    )
    .sort_values(["pair", "regime"])
)

share_summary = (
    shares_df.groupby(["pair", "regime", "exchange"], as_index=False)
    .agg(mean_share=("share", "mean"))
    .sort_values(["pair", "regime", "exchange"])
)

# dominant venue + significance vs calm
valid_share_summary = share_summary.dropna(subset=["mean_share"]).copy()

if valid_share_summary.empty:
    dom = pd.DataFrame(columns=[
        "pair", "regime", "dominant_exchange", "dominant_share",
        "calm_dominant_exchange", "calm_dominant_share",
        "delta_vs_calm_pp", "significance"
    ])

```

```

    ])
    else:
        dom_idx = valid_share_summary.groupby(["pair", "regime"])["mean_share"].
        ↪idxmax()
        dom = valid_share_summary.loc[dom_idx].copy()

        dom = dom.rename(
            columns={"exchange": "dominant_exchange", "mean_share": ↪
            ↪"dominant_share"}
        )

        calm_ref = dom[dom["regime"] == "calm"][
            ["pair", "dominant_exchange", "dominant_share"]
        ].rename(
            columns={
                "dominant_exchange": "calm_dominant_exchange",
                "dominant_share": "calm_dominant_share",
            }
        )

        dom = dom.merge(calm_ref, on="pair", how="left")
        dom["delta_vs_calm_pp"] = (dom["dominant_share"] - ↪
        ↪dom["calm_dominant_share"]) * 100
        dom["significance"] = np.where(
            dom["delta_vs_calm_pp"].abs() > sig_pp,
            "significant",
            "insignificant"
        )

    return shares_df, hhi_ts_df, hhi_summary, share_summary, dom

shares_df, hhi_ts_df, hhi_summary_df, share_summary_df, dom_summary_df = ↪
    ↪volume_fragmentation_multi(
        trades_all, PAIR_VENUE_MAP, freq="1min", sig_pp=5.0
    )

display(hhi_summary_df)
display(share_summary_df)
display(dom_summary_df.sort_values(["pair", "regime"]))

```

```

=====
=====

```

Volume Fragmentation (HHI + venue shares + dominance shifts).
 Data used: Trades data, 1-minute bins, volume=amount. Pairs: BTC/USD & BTC/USDT
 across bnus/cbse/krkn; BTC/USDC across bnus/krkn.
 How to gauge: Higher HHI = more concentration. Dominance shift is significant

only if >5 percentage points.

=====

	pair	regime	mean_hhi	median_hhi	p90_hhi	n_bins
0	BTC/USD	calm	0.5714	0.5321	0.7999	12960
1	BTC/USD	post_crash	0.5000	0.4801	0.6707	10080
2	BTC/USD	stress	0.5324	0.5040	0.7319	7200
3	BTC/USDC	calm	0.6323	0.9887	1.0000	12960
4	BTC/USDC	post_crash	0.7121	0.9795	1.0000	10080
5	BTC/USDC	stress	0.7876	0.9715	1.0000	7200
6	BTC/USDT	calm	0.7606	0.7805	0.9990	12960
7	BTC/USDT	post_crash	0.6842	0.6325	0.9972	10080
8	BTC/USDT	stress	0.7044	0.7025	0.9668	7200

	pair	regime	exchange	mean_share
0	BTC/USD	calm	binance	0.2930
1	BTC/USD	calm	coinbase	0.5999
2	BTC/USD	calm	kraken	0.1072
3	BTC/USD	post_crash	binance	0.2991
4	BTC/USD	post_crash	coinbase	0.5541
5	BTC/USD	post_crash	kraken	0.1468
6	BTC/USD	stress	binance	0.2472
7	BTC/USD	stress	coinbase	0.5756
8	BTC/USD	stress	kraken	0.1772
9	BTC/USDC	calm	binance	0.6776
10	BTC/USDC	calm	kraken	0.3224
11	BTC/USDC	post_crash	binance	0.5921
12	BTC/USDC	post_crash	kraken	0.4079
13	BTC/USDC	stress	binance	0.4177
14	BTC/USDC	stress	kraken	0.5823
15	BTC/USDT	calm	binance	0.7520
16	BTC/USDT	calm	coinbase	0.1645
17	BTC/USDT	calm	kraken	0.0835
18	BTC/USDT	post_crash	binance	0.6585
19	BTC/USDT	post_crash	coinbase	0.2368
20	BTC/USDT	post_crash	kraken	0.1047
21	BTC/USDT	stress	binance	0.7040
22	BTC/USDT	stress	coinbase	0.1645
23	BTC/USDT	stress	kraken	0.1315

	pair	regime	dominant_exchange	dominant_share \
0	BTC/USD	calm	coinbase	0.5999
1	BTC/USD	post_crash	coinbase	0.5541
2	BTC/USD	stress	coinbase	0.5756
3	BTC/USDC	calm	binance	0.6776
4	BTC/USDC	post_crash	binance	0.5921
5	BTC/USDC	stress	kraken	0.5823

6	BTC/USDT	calm	binance	0.7520
7	BTC/USDT	post_crash	binance	0.6585
8	BTC/USDT	stress	binance	0.7040

	calm_dominant_exchange	calm_dominant_share	delta_vs_calm_pp	significance
0	coinbase	0.5999	0.0000	insignificant
1	coinbase	0.5999	-4.5777	insignificant
2	coinbase	0.5999	-2.4225	insignificant
3	binance	0.6776	0.0000	insignificant
4	binance	0.6776	-8.5492	significant
5	binance	0.6776	-9.5359	significant
6	binance	0.7520	0.0000	insignificant
7	binance	0.7520	-9.3512	significant
8	binance	0.7520	-4.8017	insignificant

2.16 Rolling Venue Volume Share

Assumption: A dominance shift is considered significant only if the dominant venue share changes by more than 5 percentage points.

In the three-exchange setting (bnus, cbse, krkn), volume fragmentation still shows mostly stable leadership during stress for BTC/USD and BTC/USDT, but with a stronger shift in BTC/USDC. For BTC/USD, Coinbase remains dominant across all regimes (59.99% calm, 57.56% stress, 55.41% post-crash), and the calm-to-stress change is -2.43 percentage points, which is insignificant under the 5-point threshold. For BTC/USDT, Binance remains dominant (75.20% calm, 70.40% stress, 65.85% post-crash); the calm-to-stress shift is -4.80 points (insignificant), while the post-crash decline versus calm is -9.35 points (significant), indicating meaningful rebalancing away from Binance but not a leadership reversal. The strongest structural shift appears in BTC/USDC (bnus vs krkn), where dominance flips from Binance in calm (67.76%) to Kraken in stress (58.23%), a significant crash-time migration, before partially reverting post-crash (Binance 59.21%). Overall, the evidence indicates that stress primarily widened pricing frictions, while large venue-share migration was concentrated in the USDC-quoted market rather than broad-based across all pairs.

```
[22]: for pair, venues in PAIR_VENUE_MAP.items():
    d = shares_df[shares_df["pair"] == pair].copy()
    w = d.pivot_table(index="time_bin", columns="exchange", values="share",
    ↪aggfunc="mean").sort_index()
    w = w[venues].rolling("6H").mean() # smooth

    fig, ax = plt.subplots(figsize=(13, 4))
    for ex in venues:
        ax.plot(w.index, w[ex], label=ex, linewidth=1.2)
    shade_crisis(ax)
    ax.set_title(f"{pair} | 6H Rolling Venue Volume Share")
    ax.set_ylabel("Share")
    ax.set_ylim(0, 1)
    ax.grid(alpha=0.3)
    ax.legend(loc="upper right")
```



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



2.17 Cross-Venue Dislocation

Cross-venue dislocation clearly worsens during stress in the three-exchange setup, and the strongest damage remains in BTC/USD (with the most extreme break in BTC/USDC). For BTC/USD, aggregate mean pairwise dislocation rises from 1.57 bps in calm to 7.79 bps in stress (about 5.0x), confirming a material divergence in cross-venue prices when markets were under pressure. Post-crash conditions improve relative to stress but remain above calm (mean 5.82 bps), which indicates

incomplete reintegration.

For BTC/USDT, stress dislocation also increases but at a lower magnitude: mean rises from 1.69 to 3.75 bps (about 2.2x), with post-crash still elevated at 3.29 bps. For BTC/USDC (bnus-krkn), the stress effect is much larger: mean dislocation jumps from 3.45 to 52.04 bps (about 15x), then declines to 5.98 bps post-crash. The key takeaway is that stress primarily damaged cross-venue price integration, with the sharpest breakdown in USDC-quoted markets and a strong but smaller breakdown in USD-quoted markets.

```
[23]: explain_block(
    "Cross-venue dislocation (pairwise and aggregate).",
    "Trades data, 1-minute VWAP per venue. For 3 venues: all pairwise_
↪dislocations + mean/max pairwise per minute.",
    "Higher bps = weaker cross-venue integration; stress amplification_
↪indicates market friction."
)

def dislocation_multi(trades_df, pair_venue_map, freq="1min"):
    pairwise_rows, agg_rows = [], []

    for pair, venues in pair_venue_map.items():
        d = trades_df[(trades_df["pair"] == pair) & (trades_df["exchange"]
↪isin(venues))].copy()
        d["time_bin"] = d.index.floor(freq)
        d["notional"] = d["price"] * d["amount"]

        v = d.groupby(["time_bin", "exchange"], as_index=False).
↪agg(notional=("notional", "sum"), vol=("amount", "sum"))
        v["vwap"] = np.where(v["vol"] > 0, v["notional"] / v["vol"], np.nan)
        w = v.pivot(index="time_bin", columns="exchange", values="vwap").
↪sort_index()

        bps_cols = []
        for a, b in combinations(venues, 2):
            z = w[[a, b]].dropna().copy()
            z["abs_bps"] = ((z[a] - z[b]).abs() / ((z[a] + z[b]) / 2.0)) *_
↪10000.0
            z["pair"] = pair
            z["venue_pair"] = f"{a}-{b}"
            z = add_regime_labels(z)
            z = z[z["regime"] != "out_of_scope"]
            pairwise_rows.append(z[["pair", "venue_pair", "regime", "abs_bps"]])

            w[f"bps_{a}_{b}"] = ((w[a] - w[b]).abs() / ((w[a] + w[b]) / 2.0)) *_
↪10000.0
            bps_cols.append(f"bps_{a}_{b}")
```

```

# aggregate across all available venue pairs each minute
if bps_cols:
    m = w[bps_cols].copy()
    m["pair"] = pair
    m["mean_pairwise_bps"] = m[bps_cols].mean(axis=1, skipna=True)
    m["max_pairwise_bps"] = m[bps_cols].max(axis=1, skipna=True)
    m = m.dropna(subset=["mean_pairwise_bps"])
    m["time_bin"] = m.index
    m = add_regime_labels(m, ts_col="time_bin")
    m = m[m["regime"] != "out_of_scope"]
    agg_rows.append(m[["pair", "regime", "mean_pairwise_bps",
↪ "max_pairwise_bps"]])

pairwise_df = pd.concat(pairwise_rows, ignore_index=True)
pairwise_summary = (
    pairwise_df.groupby(["pair", "venue_pair", "regime"], as_index=False)
    .agg(
        mean_bps=("abs_bps", "mean"),
        median_bps=("abs_bps", "median"),
        p90_bps=("abs_bps", lambda x: np.nanpercentile(x, 90)),
        max_bps=("abs_bps", "max"),
        n_minutes=("abs_bps", "count"),
    )
    .sort_values(["pair", "venue_pair", "regime"])
)

agg_df = pd.concat(agg_rows, ignore_index=True)
agg_summary = (
    agg_df.groupby(["pair", "regime"], as_index=False)
    .agg(
        mean_pairwise_bps=("mean_pairwise_bps", "mean"),
        p90_pairwise_bps=("mean_pairwise_bps", lambda x: np.
↪ nanpercentile(x, 90)),
        max_pairwise_bps=("max_pairwise_bps", "max"),
        n_minutes=("mean_pairwise_bps", "count"),
    )
    .sort_values(["pair", "regime"])
)
return pairwise_df, pairwise_summary, agg_summary

disloc_pairwise_df, disloc_pairwise_summary_df, disloc_agg_summary_df =
↪ dislocation_multi(
    trades_all, PAIR_VENUE_MAP, freq="1min"
)

display(disloc_agg_summary_df)
display(disloc_pairwise_summary_df)

```

```

=====
=====
Cross-venue dislocation (pairwise and aggregate).
Data used: Trades data, 1-minute VWAP per venue. For 3 venues: all pairwise
dislocations + mean/max pairwise per minute.
How to gauge: Higher bps = weaker cross-venue integration; stress amplification
indicates market friction.
=====
=====

```

	pair	regime	mean_pairwise_bps	p90_pairwise_bps \
0	BTC/USD	calm	1.5670	3.1116
1	BTC/USD	post_crash	5.8203	12.7225
2	BTC/USD	stress	7.7921	16.2198
3	BTC/USDC	calm	3.4541	7.5131
4	BTC/USDC	post_crash	5.9846	13.0750
5	BTC/USDC	stress	52.0415	111.1709
6	BTC/USDT	calm	1.6867	3.5870
7	BTC/USDT	post_crash	3.2920	6.4108
8	BTC/USDT	stress	3.7518	7.5501

	max_pairwise_bps	n_minutes
0	28.3305	12958
1	55.0855	10080
2	89.7188	7200
3	33.0486	2880
4	37.4441	3487
5	1149.8126	3587
6	37.0319	11790
7	127.8113	9406
8	72.7963	7035

	pair	venue_pair	regime	mean_bps	median_bps	p90_bps \
0	BTC/USD	binance-coinbase	calm	1.0085	0.7432	2.0847
1	BTC/USD	binance-coinbase	post_crash	4.4758	2.8022	11.2370
2	BTC/USD	binance-coinbase	stress	9.4359	6.0300	22.5307
3	BTC/USD	binance-kraken	calm	1.9706	1.4677	4.2573
4	BTC/USD	binance-kraken	post_crash	6.8042	4.5856	16.4595
5	BTC/USD	binance-kraken	stress	8.3579	5.6839	19.6270
6	BTC/USD	coinbase-kraken	calm	1.7271	1.2258	3.8943
7	BTC/USD	coinbase-kraken	post_crash	6.1696	3.5646	17.4931
8	BTC/USD	coinbase-kraken	stress	5.4295	3.6547	12.3138
9	BTC/USDC	binance-kraken	calm	3.4541	2.5432	7.5131
10	BTC/USDC	binance-kraken	post_crash	5.9846	4.5544	13.0750
11	BTC/USDC	binance-kraken	stress	52.0415	12.0810	111.1709
12	BTC/USDT	binance-coinbase	calm	1.2697	0.9080	2.6907
13	BTC/USDT	binance-coinbase	post_crash	2.4865	1.9379	5.2661

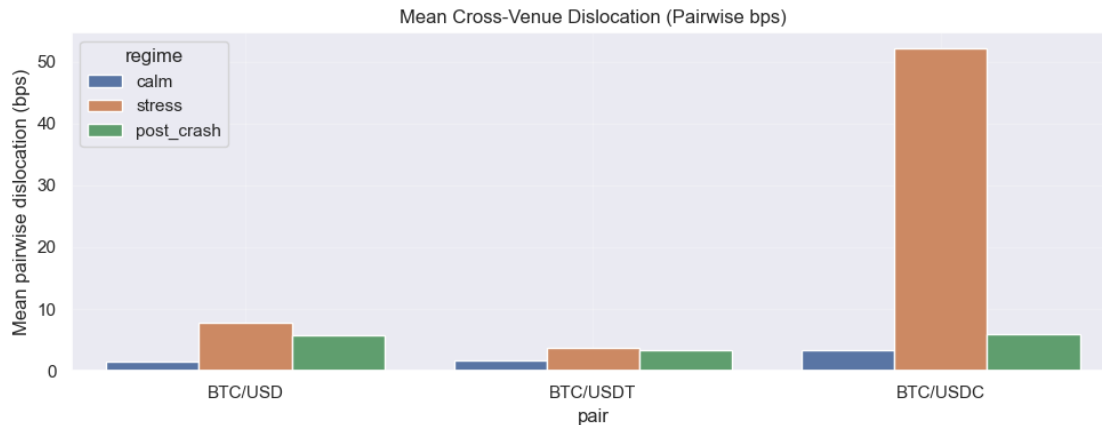
14	BTC/USDT	binance-coinbase	stress	2.9929	2.0819	6.5282
15	BTC/USDT	binance-kraken	calm	2.3119	1.5830	5.2155
16	BTC/USDT	binance-kraken	post_crash	3.9989	3.1247	8.2965
17	BTC/USDT	binance-kraken	stress	4.2981	3.0366	9.2821
18	BTC/USDT	coinbase-kraken	calm	2.4609	1.6527	5.6297
19	BTC/USDT	coinbase-kraken	post_crash	4.1286	3.1419	8.5895
20	BTC/USDT	coinbase-kraken	stress	4.7870	3.4813	10.5732

	max_bps	n_minutes
0	28.3305	12609
1	47.1406	10080
2	89.7188	6946
3	22.9346	12841
4	44.3444	10068
5	61.4623	7199
6	22.5726	12632
7	55.0855	10068
8	59.4554	6947
9	33.0486	2880
10	37.4441	3487
11	1149.8126	3587
12	27.0275	10731
13	50.9502	8035
14	41.3725	6687
15	34.0855	7174
16	126.1775	7117
17	71.5760	5797
18	37.0319	6391
19	127.8113	5816
20	72.7963	5543

2.17.1 Dislocation Regime Comparison

```
[24]: fig, ax = plt.subplots(figsize=(10, 4))
sns.barplot(
    data=disloc_agg_summary_df,
    x="pair",
    y="mean_pairwise_bps",
    hue="regime",
    order=["BTC/USD", "BTC/USDT", "BTC/USDC"],
    hue_order=["calm", "stress", "post_crash"],
    ax=ax
)
ax.set_title("Mean Cross-Venue Dislocation (Pairwise bps)")
ax.set_ylabel("Mean pairwise dislocation (bps)")
ax.grid(alpha=0.25)
plt.tight_layout()
```

```
plt.show()
```



2.18 Price Discovery

Price discovery in the three-exchange setting still indicates fast transmission at the 1-minute horizon, with stress showing up more in directional asymmetry than in timing delays. Lag-correlation results keep a best lag of 0 across pairs and venue combinations, implying no clear minute-level delay in price adjustment. Contemporaneous co-movement remains high for BTC/USD (bnus-cbse around 0.97; bnus-krkn and cbse-krkn rising into roughly 0.91–0.93 in stress/post-crash), while BTC/USDT is slightly lower but still strong (about 0.77–0.91 depending on venue pair and regime).

Granger results provide the directional detail: BTC/USD is largely bidirectional across regimes, but flow into Kraken is often statistically stronger than the reverse direction. For BTC/USDT, the key stress asymmetry persists in bnus-cbse: Binance → Coinbase remains strongly significant, while Coinbase → Binance becomes insignificant in stress ($p = 0.175$), indicating Binance-led information flow under pressure. For BTC/USDC (bnus-krkn), contemporaneous correlation drops sharply in stress (to about 0.34) even though Granger remains significant both ways, showing that stress can weaken synchronous alignment without eliminating predictive linkage. Overall, prices move together in real time, but stress redistributes influence and weakens integration quality in a pair-dependent way.

```
[25]: explain_block(
    "Price discovery across exchange pairs (lag-correlation + Granger).",
    "OHLC close prices, resampled to 1-minute returns; tested pairwise across_
    ↪venue combinations.",
    "best_lag=0 => synchronous minute updates; Granger p<0.05 => predictive_
    ↪information flow in that direction."
)

warnings.filterwarnings(
    "ignore",
```

```

        message="verbose is deprecated since functions should not print results",
        category=FutureWarning
    )

def price_discovery_multi(ohlc_df, pair_venue_map, freq="1min", max_lag=5):
    rows = []

    for pair, venues in pair_venue_map.items():
        d = ohlc_df[(ohlc_df["pair"] == pair) & (ohlc_df["exchange"]
↪isin(venues))].copy()
        d["time_bin"] = d.index.floor(freq)
        close_1m = d.groupby(["time_bin", "exchange"], as_index=False)["close"].
↪last()
        w = close_1m.pivot(index="time_bin", columns="exchange",
↪values="close").sort_index()

        for a, b in combinations(venues, 2):
            x = w[[a, b]].dropna().copy()
            x["ret_a"] = np.log(x[a]).diff()
            x["ret_b"] = np.log(x[b]).diff()
            x = x.dropna(subset=["ret_a", "ret_b"])
            x = add_regime_labels(x)
            x = x[x["regime"] != "out_of_scope"]

            for rg in ["calm", "stress", "post_crash"]:
                y = x[x["regime"] == rg]
                if y.empty:
                    continue

                # best lag corr
                best_lag, best_corr = None, None
                for lag in range(-max_lag, max_lag + 1):
                    c = y["ret_a"].corr(y["ret_b"].shift(lag))
                    if pd.isna(c):
                        continue
                    if best_corr is None or abs(c) > abs(best_corr):
                        best_corr, best_lag = c, lag

                # Granger both directions
                if len(y) >= 200:
                    r_b_to_a = grangercausalitytests(y[["ret_a", "ret_b"]],
↪maxlag=max_lag, verbose=False)
                    p_b_to_a = min(r_b_to_a[L][0]["ssr_ftest"][1] for L in
↪range(1, max_lag + 1))

                    r_a_to_b = grangercausalitytests(y[["ret_b", "ret_a"]],
↪maxlag=max_lag, verbose=False)

```

```

        p_a_to_b = min(r_a_to_b[L][0]["ssr_ftest"][1] for L in
↪range(1, max_lag + 1))
    else:
        p_b_to_a, p_a_to_b = np.nan, np.nan

    rows.append({
        "pair": pair,
        "venue_pair": f"{a}-{b}",
        "regime": rg,
        "best_lag_min": best_lag,
        "best_corr": best_corr,
        "p_b_to_a_min": p_b_to_a,
        "p_a_to_b_min": p_a_to_b,
        "n_obs": len(y),
    })

    out = pd.DataFrame(rows).sort_values(["pair", "venue_pair", "regime"])
    ↪return out

pd_summary_df = price_discovery_multi(ohlc_all, PAIR_VENUE_MAP, freq="1min",
↪max_lag=5)
display(pd_summary_df)

```

```

=====
=====
Price discovery across exchange pairs (lag-correlation + Granger).
Data used: OHLC close prices, resampled to 1-minute returns; tested pairwise
across venue combinations.
How to gauge: best_lag=0 => synchronous minute updates; Granger p<0.05 =>
predictive information flow in that direction.
=====
=====

```

	pair	venue_pair	regime	best_lag_min	best_corr \
0	BTC/USD	binance-coinbase	calm	0	0.9725
2	BTC/USD	binance-coinbase	post_crash	0	0.9759
1	BTC/USD	binance-coinbase	stress	0	0.9739
3	BTC/USD	binance-kraken	calm	0	0.8633
5	BTC/USD	binance-kraken	post_crash	0	0.9257
4	BTC/USD	binance-kraken	stress	0	0.9090
6	BTC/USD	coinbase-kraken	calm	0	0.8702
8	BTC/USD	coinbase-kraken	post_crash	0	0.9294
7	BTC/USD	coinbase-kraken	stress	0	0.9332
18	BTC/USDC	binance-kraken	calm	0	0.8216
20	BTC/USDC	binance-kraken	post_crash	0	0.8342
19	BTC/USDC	binance-kraken	stress	0	0.3371

9	BTC/USDT	binance-coinbase	calm	0	0.8773
11	BTC/USDT	binance-coinbase	post_crash	0	0.8973
10	BTC/USDT	binance-coinbase	stress	0	0.9114
12	BTC/USDT	binance-kraken	calm	0	0.7720
14	BTC/USDT	binance-kraken	post_crash	0	0.7806
13	BTC/USDT	binance-kraken	stress	0	0.8254
15	BTC/USDT	coinbase-kraken	calm	0	0.8071
17	BTC/USDT	coinbase-kraken	post_crash	0	0.8328
16	BTC/USDT	coinbase-kraken	stress	0	0.8485

	p_b_to_a_min	p_a_to_b_min	n_obs
0	8.8901e-32	7.1208e-06	12608
2	2.5434e-14	8.2169e-06	10080
1	7.3623e-04	3.0920e-02	6946
3	1.4265e-07	1.3242e-180	12840
5	3.4367e-04	7.0472e-92	10068
4	1.7468e-02	3.9622e-65	7199
6	7.5129e-04	1.2475e-195	12631
8	6.1828e-02	2.7830e-101	10068
7	1.0683e-02	3.5703e-47	6947
18	1.2620e-03	7.2510e-64	2879
20	5.1652e-09	5.4284e-48	3487
19	1.4620e-13	7.1385e-18	3587
9	1.7185e-21	6.2722e-149	10730
11	5.1627e-16	9.7073e-60	8035
10	1.7520e-01	3.3618e-89	6687
12	1.3497e-04	3.5823e-237	7173
14	3.5637e-09	1.6906e-219	7117
13	3.9396e-03	4.1433e-193	5797
15	2.4706e-06	3.0265e-151	6390
17	6.1859e-07	1.6845e-128	5816
16	3.8705e-07	1.7239e-96	5543

2.19 Cross-Currency Basis Analysis

For transaction costs, we model a round-trip two-leg basis trade (BTC/USD leg + BTC/USDT leg; open + close = 4 fills) with exchange-specific taker fees (Binance 1 bps/fill, Coinbase 25 bps/fill, Kraken 22 bps/fill) and regime-dependent execution friction: 12 bps in calm/post-crash and 25 bps in stress. This yields exchange- and regime-specific thresholds rather than one flat cutoff, which is more consistent with observed stress-time microstructure conditions.

Before costs, basis is near parity in calm and widens sharply in stress across all venues (calm means close to zero: bnus -0.11 bps, cbse -0.19 bps, krkn -0.43 bps; stress means around -45 to -54 bps), with post-crash still materially negative. After costs, persistence remains highly venue-dependent: Binance still clears threshold frequently because fee burden is low, while Coinbase and Kraken require much larger wedges and therefore clear costs mainly in the largest stress windows. This confirms that basis stress is broad at the gross level, but economically tradable persistence depends strongly on venue fee architecture and execution frictions.

The driver regression is consistent with this interpretation: stress and post-crash dummies are strongly positive across venues, and cross-venue dislocation is also positively significant. In other words, basis widening is not random noise; it is systematically linked to stress regime and market-integration breakdown, with net realizability filtered by exchange-specific cost structure.

```
[26]: # Cross-Currency Basis Analysis (exchange-specific costs)

explain_block(
    "Cross-currency basis (BTC/USDT vs BTC/USD)",
    "OHLC close prices, 1-minute frequency, exchanges: bnus/cbse/krkn",
    "Near-zero basis = parity; large/persistent |basis| and above-cost episodes,
    ⇨= meaningful cross-currency friction."
)

# CONFIG
REF_PAIR = "BTC/USD"
Q_PAIR = "BTC/USDT"
EXCHANGES = ["binance", "coinbase", "kraken"]

# Assumed fee tiers (bps per fill)
FEE_BPS = {
    "binance": {"maker": 0.0, "taker": 1.0},
    "coinbase": {"maker": 15.0, "taker": 25.0},
    "kraken": {"maker": 12.0, "taker": 22.0},
}

FEE_MODE = "taker"          # "taker" or "maker"
EXTRA_FRICTION_BPS = 10.0   # slippage/latency buffer
MAX_LAG_HAC = 5             # HAC lag for regression standard errors

# BASIS PANEL
d = ohlc_all[
    (ohlc_all["pair"].isin([REF_PAIR, Q_PAIR])) &
    (ohlc_all["exchange"].isin(EXCHANGES))
].copy()

d["time_bin"] = d.index.floor("1min")
close_1m = d.groupby(["time_bin", "exchange", "pair"], as_index=False)["close"].
    ⇨last()

basis_ts_df = close_1m.pivot(index=["time_bin", "exchange"], columns="pair",
    ⇨values="close").reset_index()
basis_ts_df = basis_ts_df.dropna(subset=[REF_PAIR, Q_PAIR]).copy()

basis_ts_df["basis_bps"] = ((basis_ts_df[Q_PAIR] - basis_ts_df[REF_PAIR]) /
    ⇨basis_ts_df[REF_PAIR]) * 10000.0
```

```

basis_ts_df["abs_basis_bps"] = basis_ts_df["basis_bps"].abs()
basis_ts_df = add_regime_labels(basis_ts_df, ts_col="time_bin")
basis_ts_df = basis_ts_df[basis_ts_df["regime"] != "out_of_scope"].copy()

# REGIME SUMMARY
basis_summary_df = (
    basis_ts_df.groupby(["exchange", "regime"], as_index=False)
    .agg(
        mean_basis_bps=("basis_bps", "mean"),
        median_basis_bps=("basis_bps", "median"),
        p90_abs_basis_bps=("abs_basis_bps", lambda x: np.nanpercentile(x, 90)),
        max_abs_basis_bps=("abs_basis_bps", "max"),
        n_minutes=("basis_bps", "count"),
    )
    .sort_values(["exchange", "regime"])
)

# EXCHANGE + REGIME SPECIFIC COSTS
# round-trip two-leg (4 fills) + regime-dependent friction

FEE_TAKER_BPS = {
    "binance": 1.0, # Binance 0.01% (BTC/USD and BTC/USDT are both tier-0
    ↪pairs)
    "coinbase": 25.0, # Coinbase assumed tier (50-100K monthly volume)
    "kraken": 22.0, # Kraken assumed tier (100K monthly volume)
}

def extra_friction_bps(regime):
    # your chosen regime-specific friction
    if regime == "stress":
        return 25.0 # stress = higher slippage/latency
    return 12.0 # calm + post_crash

basis_cost_df = basis_ts_df.copy()
basis_cost_df["fee_component_bps"] = 4.0 * basis_cost_df["exchange"].
    ↪map(FEE_TAKER_BPS)
basis_cost_df["extra_friction_bps"] = basis_cost_df["regime"].
    ↪map(extra_friction_bps)
basis_cost_df["cost_bps"] = basis_cost_df["fee_component_bps"] +
    ↪basis_cost_df["extra_friction_bps"]

basis_cost_df["net_edge_bps"] = basis_cost_df["abs_basis_bps"] -
    ↪basis_cost_df["cost_bps"]
basis_cost_df["above_cost"] = basis_cost_df["net_edge_bps"] > 0

# updated summary
basis_cost_summary_df = (

```

```

basis_cost_df.groupby(["exchange", "regime"], as_index=False)
    .agg(
        mean_abs_basis_bps=("abs_basis_bps", "mean"),
        mean_fee_component_bps=("fee_component_bps", "mean"),
        mean_extra_friction_bps=("extra_friction_bps", "mean"),
        mean_cost_bps=("cost_bps", "mean"),
        pct_minutes_above_cost=("above_cost", "mean"),
        mean_net_edge_bps=("net_edge_bps", "mean"),
        n_minutes=("basis_bps", "count"),
    )
    .sort_values(["exchange", "regime"])
)
basis_cost_summary_df["pct_minutes_above_cost"] *= 100.0

display(basis_cost_summary_df)

# PERSISTENCE EPISODES
eps_rows = []
for (ex, rg), g in basis_cost_df.sort_values(["exchange", "time_bin"]).
    ↪groupby(["exchange", "regime"]):
    h = g.copy()
    h["grp"] = (h["above_cost"] != h["above_cost"].shift(1)).cumsum()
    e = h[h["above_cost"]].groupby("grp", as_index=False).
    ↪agg(duration_min=("above_cost", "size"))
    if len(e) == 0:
        eps_rows.append({
            "exchange": ex, "regime": rg,
            "n_episodes": 0, "mean_duration_min": 0.0,
            "p90_duration_min": 0.0, "max_duration_min": 0.0
        })
    else:
        eps_rows.append({
            "exchange": ex, "regime": rg,
            "n_episodes": int(len(e)),
            "mean_duration_min": float(e["duration_min"].mean()),
            "p90_duration_min": float(np.nanpercentile(e["duration_min"], 90)),
            "max_duration_min": float(e["duration_min"].max()),
        })

basis_episode_summary_df = pd.DataFrame(eps_rows).sort_values(["exchange",
    ↪"regime"])

# CROSS-VENUE BASIS DISPERSION
basis_wide = basis_ts_df.pivot(index="time_bin", columns="exchange",
    ↪values="basis_bps")
basis_disp_ts_df = pd.DataFrame({
    "time_bin": basis_wide.index,

```

```

        "basis_std_across_venues": basis_wide.std(axis=1, skipna=True)
    })
basis_disp_ts_df = add_regime_labels(basis_disp_ts_df, ts_col="time_bin")
basis_disp_ts_df = basis_disp_ts_df[basis_disp_ts_df["regime"] != "
↳out_of_scope"]

basis_disp_summary_df = (
    basis_disp_ts_df.groupby("regime", as_index=False)
    .agg(
        mean_std_bps=("basis_std_across_venues", "mean"),
        median_std_bps=("basis_std_across_venues", "median"),
        p90_std_bps=("basis_std_across_venues", lambda x: np.nanpercentile(x,
↳90)),
        max_std_bps=("basis_std_across_venues", "max"),
        n_minutes=("basis_std_across_venues", "count"),
    )
    .sort_values("regime")
)

# DRIVER REGRESSION FOR /BASIS/
# Driver 1: regime dummies
# Driver 2: cross-venue BTC/USD dislocation proxy (mean pairwise bps by minute)
# Driver 3: 1-min abs return on BTC/USD (volatility proxy)
def build_dislocation_proxy(ohlc_df, pair="BTC/USD", exchanges=None):
    x = ohlc_df[(ohlc_df["pair"] == pair)].copy()
    if exchanges is not None:
        x = x[x["exchange"].isin(exchanges)].copy()
    x["time_bin"] = x.index.floor("1min")
    p = x.groupby(["time_bin", "exchange"], as_index=False)["close"].last().
↳pivot(index="time_bin", columns="exchange", values="close")

    rows = []
    cols = list(p.columns)
    from itertools import combinations
    for t, r in p.iterrows():
        z = r.dropna()
        if len(z) < 2:
            rows.append((t, np.nan))
            continue
        bps = []
        for a, b in combinations(z.index, 2):
            bps.append(abs(z[a] - z[b]) / ((z[a] + z[b]) / 2.0) * 10000.0)
        rows.append((t, float(np.mean(bps))))
    return pd.DataFrame(rows, columns=["time_bin", "mean_pairwise_disloc_bps"])

disloc_proxy_df = build_dislocation_proxy(ohlc_all, pair=REF_PAIR,
↳exchanges=EXCHANGES)

```

```

reg_rows = []
for ex, g in basis_ts_df.groupby("exchange"):
    z = g.copy().sort_values("time_bin")
    z["ret_ref"] = np.log(z[REF_PAIR]).diff()
    z["abs_ret_ref_bps"] = z["ret_ref"].abs() * 10000.0
    z = z.merge(disloc_proxy_df, on="time_bin", how="left")

    z["is_stress"] = (z["regime"] == "stress").astype(int)
    z["is_post"] = (z["regime"] == "post_crash").astype(int)

    use_cols = ["is_stress", "is_post", "mean_pairwise_disloc_bps",
↪ "abs_ret_ref_bps"]
    zz = z.dropna(subset=["abs_basis_bps"] + use_cols).copy()

    if len(zz) < 300:
        reg_rows.append({"exchange": ex, "n_obs": len(zz), "note":
↪ "insufficient rows"})
        continue

    Y = zz["abs_basis_bps"]
    X = sm.add_constant(zz[use_cols])
    m = sm.OLS(Y, X).fit(cov_type="HAC", cov_kws={"maxlags": MAX_LAG_HAC})

    row = {"exchange": ex, "n_obs": int(m.nobs), "adj_r2": float(m.
↪ rsquared_adj)}
    for c in use_cols:
        row[f"coef_{c}"] = float(m.params[c])
        row[f"p_{c}"] = float(m.pvalues[c])
    reg_rows.append(row)

basis_driver_df = pd.DataFrame(reg_rows)

display(basis_summary_df)
display(basis_cost_summary_df)
display(basis_episode_summary_df)
display(basis_disp_summary_df)
display(basis_driver_df)

```

=====

Cross-currency basis (BTC/USDT vs BTC/USD)

Data used: OHLC close prices, 1-minute frequency, exchanges: bnus/cbse/krkn

How to gauge: Near-zero basis = parity; large/persistent |basis| and above-cost episodes = meaningful cross-currency friction.

=====

=====

	exchange	regime	mean_abs_basis_bps	mean_fee_component_bps	\
0	binance	calm	1.5608	4.0	
1	binance	post_crash	27.4505	4.0	
2	binance	stress	45.7261	4.0	
3	coinbase	calm	1.7685	100.0	
4	coinbase	post_crash	30.7967	100.0	
5	coinbase	stress	54.5034	100.0	
6	kraken	calm	2.7668	88.0	
7	kraken	post_crash	26.4511	88.0	
8	kraken	stress	51.1455	88.0	

	mean_extra_friction_bps	mean_cost_bps	pct_minutes_above_cost	\
0	12.0	16.0	0.0322	
1	12.0	16.0	87.3986	
2	25.0	29.0	62.7914	
3	12.0	112.0	0.0000	
4	12.0	112.0	0.0000	
5	25.0	125.0	3.2490	
6	12.0	100.0	0.0000	
7	12.0	100.0	0.0000	
8	25.0	113.0	5.2146	

	mean_net_edge_bps	n_minutes
0	-14.4392	12427
1	11.4505	9983
2	16.7261	7122
3	-110.2315	11005
4	-81.2033	8103
5	-70.4966	6525
6	-97.2332	7397
7	-73.5489	7165
8	-61.8545	5849

	exchange	regime	mean_basis_bps	median_basis_bps	p90_abs_basis_bps	\
0	binance	calm	-0.1135	-0.1341	3.3731	
1	binance	post_crash	-27.4452	-28.0714	38.2937	
2	binance	stress	-45.4952	-38.7190	92.9121	
3	coinbase	calm	-0.1925	-0.2478	3.8090	
4	coinbase	post_crash	-30.7967	-30.0696	41.4979	
5	coinbase	stress	-54.1291	-49.8764	108.9874	
6	kraken	calm	-0.4313	-0.3573	6.1430	
7	kraken	post_crash	-26.4406	-26.2867	38.7905	
8	kraken	stress	-50.4356	-45.1951	101.9983	

	max_abs_basis_bps	n_minutes
0	30.7098	12427

1	75.0783	9983
2	163.1704	7122
3	29.9096	11005
4	73.3683	8103
5	184.2309	6525
6	37.2924	7397
7	71.1905	7165
8	166.7971	5849

	exchange	regime	mean_abs_basis_bps	mean_fee_component_bps	\
0	binance	calm	1.5608	4.0	
1	binance	post_crash	27.4505	4.0	
2	binance	stress	45.7261	4.0	
3	coinbase	calm	1.7685	100.0	
4	coinbase	post_crash	30.7967	100.0	
5	coinbase	stress	54.5034	100.0	
6	kraken	calm	2.7668	88.0	
7	kraken	post_crash	26.4511	88.0	
8	kraken	stress	51.1455	88.0	

	mean_extra_friction_bps	mean_cost_bps	pct_minutes_above_cost	\
0	12.0	16.0	0.0322	
1	12.0	16.0	87.3986	
2	25.0	29.0	62.7914	
3	12.0	112.0	0.0000	
4	12.0	112.0	0.0000	
5	25.0	125.0	3.2490	
6	12.0	100.0	0.0000	
7	12.0	100.0	0.0000	
8	25.0	113.0	5.2146	

	mean_net_edge_bps	n_minutes
0	-14.4392	12427
1	11.4505	9983
2	16.7261	7122
3	-110.2315	11005
4	-81.2033	8103
5	-70.4966	6525
6	-97.2332	7397
7	-73.5489	7165
8	-61.8545	5849

	exchange	regime	n_episodes	mean_duration_min	p90_duration_min	\
0	binance	calm	3	1.3333	1.8	
1	binance	post_crash	266	32.8008	14.5	
2	binance	stress	147	30.4218	23.0	
3	coinbase	calm	0	0.0000	0.0	
4	coinbase	post_crash	0	0.0000	0.0	
5	coinbase	stress	23	9.2174	16.6	

6	kraken	calm	0	0.0000	0.0
7	kraken	post_crash	0	0.0000	0.0
8	kraken	stress	46	6.6304	7.5

	max_duration_min
0	2.0
1	1612.0
2	2638.0
3	0.0
4	0.0
5	137.0
6	0.0
7	0.0
8	158.0

	regime	mean_std_bps	median_std_bps	p90_std_bps	max_std_bps \
0	calm	1.6614	1.2933	3.4554	22.5114
1	post_crash	5.0956	4.0382	10.9316	28.8831
2	stress	6.5394	5.0275	13.7446	46.0152

	n_minutes
0	11761
1	9406
2	7024

	exchange	n_obs	adj_r2	coef_is_stress	p_is_stress	coef_is_post \
0	binance	29531	0.5037	42.0088	1.0950e-293	24.5255
1	coinbase	25632	0.5916	43.8384	2.0374e-275	22.8671
2	kraken	20409	0.5109	44.1197	1.1067e-268	20.9579

	p_is_post	coef_mean_pairwise_disloc_bps	p_mean_pairwise_disloc_bps \
0	0.0	0.4462	5.9170e-08
1	0.0	1.6041	3.4964e-66
2	0.0	0.7440	2.5863e-16

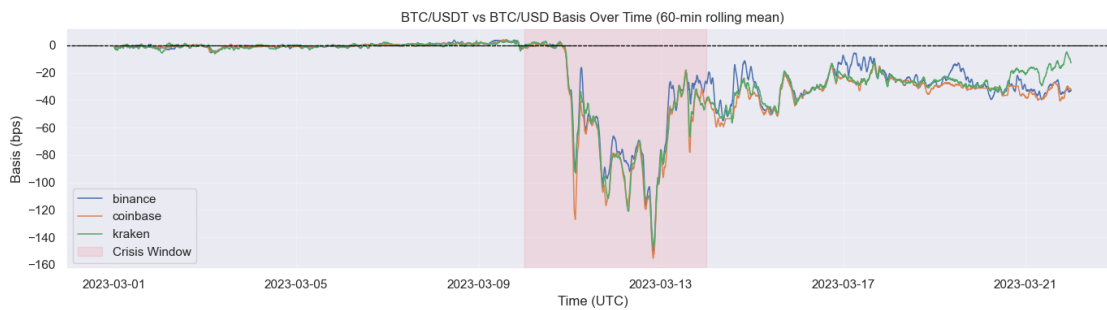
	coef_abs_ret_ref_bps	p_abs_ret_ref_bps
0	-0.1287	6.5905e-05
1	-0.1116	6.0268e-05
2	-0.0585	3.6079e-02

```
[27]: fig, ax = plt.subplots(figsize=(14, 4))
for ex in sorted(basis_ts_df["exchange"].unique()):
    x = basis_ts_df[basis_ts_df["exchange"] == ex].sort_values("time_bin").
    ↪copy()
    # smooth for readability
    x["basis_roll"] = x["basis_bps"].rolling(60, min_periods=10).mean() #_
    ↪60-min rolling mean
    ax.plot(x["time_bin"], x["basis_roll"], linewidth=1.1, label=ex)
```

```

shade_crisis(ax)
ax.axhline(0, color="black", linestyle="--", linewidth=0.9)
ax.set_title("BTC/USDT vs BTC/USD Basis Over Time (60-min rolling mean)")
ax.set_ylabel("Basis (bps)")
ax.set_xlabel("Time (UTC)")
ax.grid(alpha=0.25)
ax.legend()
plt.tight_layout()
plt.show()

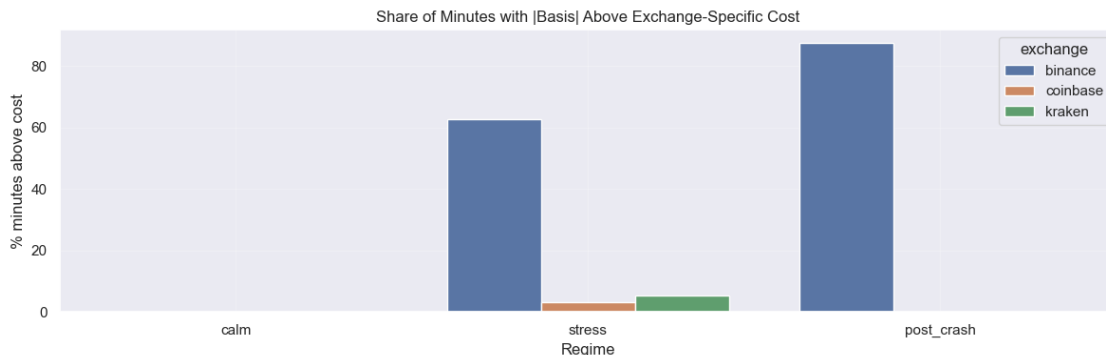
```



```

[28]: fig, ax = plt.subplots(figsize=(12, 4))
sns.barplot(
    data=basis_cost_summary_df,
    x="regime",
    y="pct_minutes_above_cost",
    hue="exchange",
    order=["calm", "stress", "post_crash"],
    ax=ax
)
ax.set_title("Share of Minutes with |Basis| Above Exchange-Specific Cost")
ax.set_ylabel("% minutes above cost")
ax.set_xlabel("Regime")
ax.grid(alpha=0.25)
plt.tight_layout()
plt.show()

```



2.20 GENIUS Act

2.20.1 Liquidity

The empirical findings of this study demonstrate that in the absence of federal regulation, stablecoins acted as vectors for traditional financial contagion. Without regulation, the depegging of USDC severely disrupted digital asset market microstructure. During the March 2023 banking stress, the collapse of SVB caused uncertainty surrounding stablecoin USDC reserve backing triggered a massive flight-to-volume, causing stablecoin volatility to surge to 200% and bid-ask spreads to widen by over 20x compared to calm market conditions (seen in Roll Spread). In stark contrast, native fiat USD order books maintained robust depth and stable execution costs, proving that the liquidity crisis was an artifact of stablecoin credit risk, not fundamental cryptocurrency valuation.

The GENIUS Act is a protection measure, and, more importantly, a critical prerequisite for market efficiency. By mandating strict reserve backing, transparent auditing, and direct oversight by banking regulators, the GENIUS Act effectively would have eliminated the informational asymmetry and default risk that forced market makers to drastically pull liquidity during the 2023 crisis. Under the new regulatory framework, stablecoins are transformed from speculative credit instruments into trusted, structurally sound settlement rails. Consequently, we question whether the GENIUS Act would have successfully eliminated the the systemic microstructure fragmentation observed in this study.

While the empirical data demonstrates that fiat USD pairs maintain superior liquidity during stress events, it is critical to acknowledge the limitations of the GENIUS Act. If this regulatory framework had been active during the March 2023 crisis, it would not have fully insulated stablecoins from the observed microstructure breakdown.

First, the 2023 USDC depeg was not a failure of crypto-native collateral, but a manifestation of traditional commercial bank counterparty risk. Unless regulatory frameworks grant stablecoin issuers direct access to Federal Reserve Master Accounts, 1:1 reserve requirements merely transfer risk from the blockchain to uninsured deposits at commercial banks, leaving stablecoins vulnerable to fractional-reserve bank runs.

Second, regulation cannot resolve the temporal friction between continuous 24/7 cryptocurrency markets and legacy banking infrastructure. The evaporation of liquidity—evidenced by the 20x spike in the BTC/USDC Roll Spread—was severely exacerbated by the weekend closure of fiat settlement rails (Fedwire), which prevented arbitrageurs from minting and redeeming tokens to

enforce the peg. Therefore, while the GENIUS Act improves transparency and baseline solvency, structural market fragmentation and volatility will persist during banking panics until continuous 24/7 fiat settlement infrastructure is fully realized.

2.20.2 Fragmentation and CC Basis

The three-exchange evidence (Binance, Coinbase, Kraken) reinforces the same core diagnosis with stronger cross-sectional support: the main stress failure was not participation collapse, but pricing and convertibility friction. Volume fragmentation shows that leadership was mostly stable in BTC/USD (Coinbase-led) and BTC/USDT (Binance-led), with limited calm-to-stress dominant-share shifts under the 5pp significance rule; the only clear crash-time reallocation appears in BTC/USDC, where dominance flips toward Kraken in stress. In contrast, price alignment metrics deteriorate sharply: cross-venue dislocation rises materially in stress for BTC/USD and BTC/USDT, and most severely for BTC/USDC. Price-discovery timing remains fast (best lag = 0), but directional asymmetry increases under stress, especially in BTC/USDT where Binance’s predictive influence dominates. Cross-currency basis then confirms the same mechanism: BTC/USDT vs BTC/USD moves from near parity in calm to large, persistent stress/post-crash wedges. Taken together, markets stayed active and connected at the minute horizon, yet parity enforcement weakened exactly where redemption confidence, settlement certainty, and quote-currency trust become binding.

From a policy perspective, this pattern is precisely why regulated stablecoins can alter trading behavior. When market participants have stronger confidence in reserve quality, redemption mechanics, and supervisory credibility, the stablecoin-specific risk premium embedded in cross-currency pricing should compress. In microstructure terms, that should reduce stress-time basis persistence, lower dislocation tails, and restore more symmetric information flow across venues. The GENIUS Act (enacted July 18, 2025) is directionally aligned with these empirical weaknesses: reserve and disclosure requirements, issuer oversight, and redemption clarity target the channels through which trust shocks became pricing wedges in March 2023. Payment-network settlement adoption (e.g., card-network stablecoin rails) strengthens this channel further by improving practical settlement continuity and accelerating convergence.

At the same time, our results imply a clear boundary on what regulation can do. GENIUS-type rules can reduce stablecoin credit-opacity risk, but they cannot eliminate exchange-level liquidity withdrawal, inventory constraints, latency, fee heterogeneity, or broader fiat-rail bottlenecks during stress. This is visible in exchange-specific cost-adjusted basis outcomes: gross wedges are broad, but net persistence differs sharply by venue because market structure and trading frictions differ. The right policy benchmark is therefore not “zero dislocation,” but a measurable shift toward fewer, smaller, and shorter stress-time wedges, plus faster post-shock reintegration across venues and quote currencies.

[]: