>>> LIQUIDITY POOL TVL DEMO



Automated Market Makers (AMMs) are an innovative new class of smart contracts introduced in decentralized exchange protocols like Uniswap, allowing users to permissionlessly provision liquidity for digital asset trading activity without needing a traditional central order book. However, an important aspect of providing users of these pools is understanding how the total USD value of the assets allocated to the contract can fluctuate over time, leading to impermanent loss for liquidity providers. In this notebook, we explore how Coin Metrics DEX market metadata can be combined with Reference Rates and ATLAS search engine capabilities to construct a timeseries representation pool TVL, allowing market participants to make more informed decisions about DEX market making and trading.

Resources

This notebook demonstrates basic functionality offered by the Coin Metrics Python API Client, ATLAS blockchain search engine, and DEX Market Data.

Coin Metrics offers a vast assortment of data for hundreds of cryptoassets. The Python API Client allows for easy access to this data using Python without needing to create your own wrappers using requests and other such libraries.

To understand the data that Coin Metrics offers, feel free to peruse the resources below.

- The Coin Metrics API v4 website contains the full set of endpoints and data offered by Coin Metrics.
- The Coin Metrics Knowledge Base gives detailed, conceptual explanations of the data that Coin Metrics offers.
- The API Spec contains a full list of functions.

Notebook Setup

```
In [1]: from os import environ
        import sys
        import pandas as pd
        import numpy as np
        import logging
        from datetime import date, datetime, timedelta
        from coinmetrics.api_client import CoinMetricsClient
        import plotly.graph_objs as go
        import logging
        from pytz import timezone as timezone_conv
        from datetime import timezone as timezone_info
        from dateutil.relativedelta import relativedelta
        import matplotlib.dates as mdates
        import matplotlib.pyplot as plt
        %matplotlib inline
In [2]: logging.basicConfig(
            format='%(asctime)s %(levelname)-8s %(message)s',
            level=logging.INFO,
            datefmt='%Y-%m-%d %H:%M:%S'
In [3]: # We recommend privately storing your API key in your local environment.
            api kev = environ["CM API KEY"]
            logging.info("Using API key found in environment")
        except KevError:
            logging.info("API key not found. Using community client")
        client = CoinMetricsClient(api kev)
      2024-04-13 10:32:37 INFO Using API key found in environment
```

DEX Market Reference Data

The reference-data/markets endpoint returns a list of available markets meeting specified criteria. Users can pass in a list of markets, exchanges, or market types (spot, futures, options). For DEX markets, the endpoint also returns key liquidity pool metadata, such as fee tier and pool contract address.

Out[5]:		market	exchange	type	base	quote	pair	pool_co	onfia id	contract_a	address	fee	bası
	0	uniswap_v3_eth- 1-1inch-dai-spot	uniswap_v3_eth		1inch	dai	1inch-dai		1	063332bbf9f8385e4106919b5c6ae2e6a4		0.01	1111111111117dc0aa78b770fa6a7380
	1	uniswap_v3_eth- 1-1inch-usdc- spot	uniswap_v3_eth	spot	1inch	usdc	1inch-usdc		1	2ee7e6e459fffbbc655f09f2e1b3131abf	98c397	0.01	1111111111117dc0aa78b770fa6a7380(
	2	uniswap_v3_eth- 1-1inch-weth- spot	uniswap_v3_eth	spot	1inch	weth	1inch-weth		1	1d1284e43da1de5ee8dd6acbb03f3624cf	bd872c	0.01	111111111117dc0aa78b770fa6a7380(
	3	uniswap_v3_eth- 1-ageur_eth- usdc-spot	uniswap_v3_eth	spot	ageur_eth	usdc	ageur_eth- usdc		1	735a26a57a0a0069dfabd41595a970faf5	5e1ee8b	0.01	1a7e4e63778b4f12a199c062f3efdd2
	4	uniswap_v3_eth- 1-ape-weth-spot	uniswap_v3_eth	spot	ape	weth	ape-weth		1	a82815da610e55e582dc3c433bb2a44923	d63542	0.01	4d224452801aced8b2f0aebe155379bb
	•••												
	1519	uniswap_v3_eth- agg-yfi-cvx-spot	uniswap_v3_eth	spot	yfi	CVX	yfi-cvx		-1		<na></na>	<na></na>	0bc529c00c6401aef6d220be8c6ea16
	1520	uniswap_v3_eth- agg-yfi-link-spot	uniswap_v3_eth	spot	yfi	link	yfi-link		-1		<na></na>	<na></na>	0bc529c00c6401aef6d220be8c6ea16
	1521	uniswap_v3_eth- agg-yfi-usdc- spot	uniswap_v3_eth	spot	yfi	usdc	yfi-usdc		-1		<na></na>	<na></na>	0bc529c00c6401aef6d220be8c6ea16
	1522	uniswap_v3_eth- agg-yfi-wbtc- spot	uniswap_v3_eth	spot	yfi	wbtc	yfi-wbtc		-1		<na></na>	<na></na>	0bc529c00c6401aef6d220be8c6ea16
	1523	uniswap_v3_eth- agg-yfi-weth- spot	uniswap_v3_eth	spot	yfi	weth	yfi-weth		-1		<na></na>	<na></na>	0bc529c00c6401aef6d220be8c6ea16
	1524 r	ows × 12 columns											
In [6]:	weth_	usdc_markets =	uni_v3_markets	.loc[(uni_v3_ma	rkets['	base']=='u	ısdc') &	(uni_v	<pre>3_markets['quote']=='weth')]</pre>			
In [7]:		usdc_pools = we usdc_pools	th_usdc_market	s.drop	ona(subset	=['cont	ract_addre	ess'])					
Out[7]:		market	exchange	type	base quot	e pai	r pool_con	fig_id		contract_address f	ee		base_address
	55	uniswap_v3_eth- 1-usdc-weth- spot	uniswap_v3_eth	spot	usdc wet	th usdc		1 e	0554a476	Sa092703abdb3ef35c80e0d76d32939f 0.	.01 a0b8	36991c6	3218b36c1d19d4a2e9eb0ce3606eb48
	241	uniswap_v3_eth- 2-usdc-weth- spot	uniswap_v3_eth	spot	usdc wet	th usdc wetl		2	88e6a0c2	2ddd26feeb64f039a2c41296fcb3f5640 0.	05 a0b8	36991c6	3218b36c1d19d4a2e9eb0ce3606eb48
	568	uniswap_v3_eth- 3-usdc-weth- spot	uniswap_v3_eth	spot	usdc wet	th usdc wetl		3	8ad599d	:3a0ff1de082011efddc58f1908eb6e6d8 (0.3 a0b8	36991c6	3218b36c1d19d4a2e9eb0ce3606eb48
	926	uniswap_v3_eth- 4-usdc-weth- spot	uniswap_v3_eth	spot	usdc wet	th usdc		4	7bea3986	37e4169dbe237d55c8242a8f2fcdcc387	1.0 a0b8	36991c6	3218b36c1d19d4a2e9eb0ce3606eb48

Fetch contract balances over time with ATLAS

Now that we have a list of target liquidity pool contracts, we can use ATLAS blockchain search engine to query for balance updates in the pool for each asset.

```
In [8]: assets = ['usdc','weth']
                          pools = weth_usdc_pools['contract_address'].to_list()
pools_tvl = pd.DataFrame()
                           start = datetime.now() - timedelta(days=30)
                          for asset in assets:
    tvl = client.get_list_of_balance_updates_v2(
                                           asset=asset,
                                                 accounts=pools,
                                                 start time = start
                                     ).parallel(max_workers=10,time_increment=relativedelta(days=1)).to_dataframe()
                                      # Add the asset name to a new 'asset' column
                                      tvl['asset'] = asset
                                      pools_tvl = pd.concat([pools_tvl, tvl], axis=0)
                       Exporting to dataframe type: 68% | | 21/31 [00:22<00:08, 1.16it/s]2024-04-13 10:33:28 INFO
                                                                                                                                                                                                                                                                                                                                                 no data to export
                      Exporting to dataframe type: 100% 31/31 [00:31<00:00, 1.035/it] [00:31<00:00, 1.035/it] [00:30<00:00, 1.035/it] [00:30<00:00, 1.035/it]
  In [9]: # Create a mapping from contract_address to market
                           contract_to_market = weth_usdc_pools.set_index('contract_address')['market']
                          contract_to_market
 Out[9]: contract address
                            e0554a476a092703abdb3ef35c80e0d76d32939f uniswap_v3_eth-1-usdc-weth-spot
                           88e6a0c2ddd26feeb64f039a2c41296fcb3f5640 uniswap_v3_eth-2-usdc-weth-spot uniswap_v3_eth-2-usdc-weth-spot uniswap_v3_eth-4-usdc-weth-spot uniswap_v3_eth-4-usdc
                           Name: market, dtype: string
In [10]: pools_tvl['market'] = pools_tvl['account'].map(contract_to_market)
In [11]: pools_tvl
```

Out[11]:		chain_sequence_number		account	account_creation_heigh	t change	previous_balance	new_balance	transaction_sequence_	
	0	83462733663567872	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 -53891.323631	90400786.260267	90346894.936636		
	1	83462737958535168	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 -1825.310434	90346894.936636	90345069.626202		
	2	83462737958535179	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 6710.02311	90345069.626202	90351779.649312		
	3	83462737958535189	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	3511.911269	90351779.649312	90355291.560581		
	4	83462742253502464	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 -397.849747	90355291.560581	90354893.710834		
	235162	84379262504665167	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 0.06	22993.783003	22993.843003		
	235163	84379262504665199	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	9 0.641	22993.843003	22994.484003		
	235164	84379266799632464	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	-0.461357	22994.484003	22994.022646		
	235165	84379266799632469	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	0.641	22994.022646	22994.663646		
	235166	84379271094599756	88e6a0c2ddd26feeb64f039a2c41296f	cb3f5640	1237672	-11.053992	22994.663646	22983.609655		
	470671 rows × 21 columns									
In [12]:	# Sort by 'consensus_time', 'market', and 'chain_sequence_number' pools_tvl_sorted = pools_tvl.sort_values(by=['consensus_time', 'market', 'chain_sequence_number'], ascending=[True, True, False]) # Drop duplicates, keeping only the first occurrence (in this case, the highest 'chain_sequence_number')									
In [13]:	<pre>pools_tvl_deduplicated = pools_tvl_sorted.drop_duplicates(subset=['consensus_time', 'market', 'asset'], keep='first') pools_tvl_clean = pools_tvl_deduplicated[['market', 'consensus_time', 'asset', 'new_balance']].copy() pools_tvl_clean('new_balance'] = pools_tvl_clean.apply(lambda row: -row['new_balance'] if row['asset'] == 'weth' else row['new_balance'], axis=1) pools_tvl_clean</pre>									
Out[13]:			market consensus_time	accet	new_balance					
ouc[15].			_		1.648163e+03					
			eth-spot 2024-03-14 10:33:23+00:00							
			eth-spot 2024-03-14 10:33:23+00:00		0.034689e+07					
			eth-spot 2024-03-14 10:33:35+00:00		.646056e+03					
			eth-spot 2024-03-14 10:33:35+00:00		0.035529e+07					
	5	uniswap_v3_eth-2-usdc-we	eth-spot 2024-03-14 10:33:47+00:00	weth -4	1.650156e+03					
			eth-spot 2024-04-13 10:32:47+00:00		7.469295e+07					
			eth-spot 2024-04-13 10:32:59+00:00		.299448e+04					
			eth-spot 2024-04-13 10:32:59+00:00		7.472405e+07					
			eth-spot 2024-04-13 10:33:11+00:00		.299466e+04					
		uniswap_v3_eth-2-usdc-we ows × 4 columns	eth-spot 2024-04-13 10:33:23+00:00	weth -2	2.298361e+04					
In [14]:	df['cons # Split	the DataFrame by marke lfs = {market: group.pi	<pre>lean) datetime(df['consensus_time']) st and store in a dictionary ivot(index='consensus_time', col up in df.groupby('market')}</pre>	umns='ass	set', values='new_bala	nce').ffill()				
In [15]:	display	market_dfs)								

```
{'uniswap_v3_eth-1-usdc-weth-spot': asset
                                                                      usdc
                                                                                weth
consensus time
2024-03-14 10:58:11+00:00 23461.368412 -3.525245
2024-03-14 11:05:23+00:00 23662.238412 -3.474646
2024-03-14 11:15:23+00:00 23652.198473 -3.477165
2024-03-14 11:39:59+00:00 23457.101070 -3.526335
2024-03-14 14:39:23+00:00 23181.148846 -3.596606
2024-04-12 21:51:11+00:00 19870.578310 -3.065966
2024-04-13 01:19:47+00:00 19870.255341 -3.066066
2024-04-13 01:19:59+00:00 19867.032773 -3.067066
2024-04-13 05:12:11+00:00 19878.305647 -3.063586
2024-04-13 07:57:59+00:00 19878.305321 -3.063586
[2771 rows x 2 columns],
 'uniswap_v3_eth-2-usdc-weth-spot': asset
                                                                      usdc
                                                                                   weth
consensus_time
2024-03-14 10:33:23+00:00 9.034689e+07 -4648.163465
2024-03-14 10:33:35+00:00 9.035529e+07 -4646.055509
2024-03-14 10:33:47+00:00 9.033898e+07 -4650.155509
2024-03-14 10:33:59+00:00 9.032670e+07 -4653.243577
2024-03-14 10:34:47+00:00 9.065965e+07 -4569.671932
2024-04-13 10:32:35+00:00 7.469298e+07 -23003.986469
2024-04-13 10:32:47+00:00 7.469295e+07 -23003.995469
2024-04-13 10:32:59+00:00 7.472405e+07 -22994.484003
2024-04-13 10:33:11+00:00 7.472405e+07 -22994.663646
2024-04-13 10:33:23+00:00 7.472405e+07 -22983.609655
[126067 rows x 2 columns],
 'uniswap_v3_eth-3-usdc-weth-spot': asset
                                                                      usdc
                                                                                   weth
consensus_time
2024-03-14 10:49:23+00:00 2.864290e+07 -5245.181793
2024-03-14 10:50:47+00:00 2.857072e+07 -5263.348992
2024-03-14 10:52:59+00:00 2.857051e+07 -5263.402223
2024-03-14 10:55:59+00:00 2.849030e+07 -5283.611135
2024-03-14 10:57:11+00:00 2.848734e+07 -5284.355245
2024-04-13 09:42:59+00:00 3.393681e+07 -14697.377392
2024-04-13 09:48:23+00:00 3.400722e+07 -14675.836169
2024-04-13 09:49:23+00:00 3.413429e+07 -14636.980474
2024-04-13 10:01:59+00:00 3.422011e+07 -14610.750432
2024-04-13 10:21:23+00:00 3.422911e+07 -14608.000282
[12957 rows x 2 columns],
 'uniswap_v3_eth-4-usdc-weth-spot': asset
                                                                      usdc
                                                                                  weth
consensus time
2024-03-14 11:41:47+00:00 2.642002e+06 -283.532436
2024-03-14 11:43:59+00:00 2.640952e+06 -283.798518
2024-03-14 12:23:47+00:00 2.622886e+06 -288.384197
2024-03-14 12:40:23+00:00 2.620937e+06 -288.879822
2024-03-14 13:25:59+00:00 2.618804e+06 -289.422528
2024-04-13 06:45:47+00:00 1.484304e+06 -515.811281
2024-04-13 06:59:11+00:00 1.491348e+06 -513.655788
2024-04-13 07:02:11+00:00 1.492328e+06 -513.355865
2024-04-13 10:12:23+00:00 1.492931e+06 -513.171680
2024-04-13 10:16:23+00:00 1.497931e+06 -511.643648
[1149 rows x 2 columns]}
```

Retrieve Reference Rates to calculate the equivalent USD value for TVL

To normalize pool TVL into USD-denominated terms, we'll leverage the Coin Metrics Reference Rate, which represents a volume-weighted median price across a subset of the asset's most highly-liquid markets.

```
In [16]: ref_rate = client.get_asset_metrics(
    assets=|'usdc','weth'],
    metrics='ReferenceRateUSD',
    start_time=start,
    frequency='Im'
).parallel(max_workers=10,time_increment=relativedelta(days=1)).to_dataframe()

Exporting to dataframe type: 100%|| | 62/62 [00:09<00:00, 6.80it/s]

In [17]: ref_rate = ref_rate.pivot(index='time', columns='asset', values='ReferenceRateUSD')
    ref_rate</pre>
```

```
Out[17]:
                                asset
                                          usdc
                                                        weth
          2024-03-14 10:34:00+00:00 0.999897 3985.438079
          2024-03-14 10:35:00+00:00 0.99994 3982.89304
          2024-03-14 10:36:00+00:00 0.999912 3982.89304
          2024-03-14 10:37:00+00:00 1.000045 3982.89304
          2024-03-14 10:38:00+00:00 1.000003 3982.89304
                                  •••
          2024-04-13 10:30:00+00:00 1.000031 3262.654799
          2024-04-13 10:31:00+00:00 0.999591 3264.797214
          2024-04-13 10:32:00+00:00 1.000048 3265.381434
          2024-04-13 10:33:00+00:00 0.99999 3267.569238
          2024-04-13 10:34:00+00:00 1.000103 3270.443579
         43201 rows × 2 columns
In [18]: # Iterate over each market DataFrame
          for market, df in market_dfs.items():

# Resample the DataFrame to 1-minute intervals
              df_resampled = df.resample('min').last().dropna()
               # Reindex the market DataFrame to the ref_rate DataFrame's index
              aligned_df = df_resampled.reindex(ref_rate.index, method='nearest')
              # Multiply the 'usdc' and 'weth' columns by the corresponding rate
aligned_df['usdc'] = aligned_df['usdc'] * ref_rate['usdc']
aligned_df['weth'] = aligned_df['weth'] * ref_rate['weth']
              # Replace the original DataFrame in the dictionary with the updated one
              market_dfs[market] = aligned_df
In [19]: first_pool_key = list(market_dfs.keys())[0]
          first_pool = market_dfs[first_pool_key]
          first_pool
                                                               weth
                                 time
          2024-03-14 10:34:00+00:00 23458.951944 -14049.646311
          2024-03-14 10:35:00+00:00 23459.955449 -14040.674423
          2024-03-14 10:36:00+00:00 23459.308652 -14040.674423
          2024-03-14 10:37:00+00:00 23462.428113 -14040.674423
          2024-03-14 10:38:00+00:00 23461.427278 -14040.674423
          2024-04-13 10:30:00+00:00 19878.927927 -9995.422358
          2024-04-13 10:31:00+00:00 19870.168805 -10001.985828
          2024-04-13 10:32:00+00:00 19879.251575 -10003.775636
          2024-04-13 10:33:00+00:00 19878.101981 -10010.478162
          2024-04-13 10:34:00+00:00 19880.358821 -10019.283953
         43201 rows x 2 columns
```

Plot USD-denominated TVL for target liquidity pools

```
In [20]: def generate_area_figure(df, layout, columns, diverging_colors=False):
              traces = []
              for series in columns:
                 {\tt traces.append(}
                     go.Scatter(
                         x=df.index,
                          y=df[series],
                         name=series,
fill='tozeroy' # Ensures filling to the zero line on the y-axis
             return go.Figure(data=traces, layout=layout)
In [21]: market_to_contract = contract_to_market.reset_index().set_index('market')
          # Plotting for each market
         for market, data in market_dfs.items():
             address = market_to_contract.loc[market, 'contract_address']
              print(f'{market}
             print(f'{address}')
             print(f'USDC: https://atlas.coinmetrics.io/address-details?asset=usdc&address={address}')
             print(f'WETH: https://atlas.coinmetrics.io/address-details?asset=weth&address={address}')
              layout = qo.Layout(
                  title=f'{market.upper()}<br>Liquidity Pool TVL',
                  xaxis=dict(
                     title=
                      gridcolor='white',
                      gridwidth=2,
                      zerolinecolor='white',
                     zerolinewidth=2,
```

```
color='white'
),
yaxis=dict(
    title='<br/>br>TVL Value (USD)',
    gridcolor='white',
    gridwidth=2,
    zerolinecolor='white',
    zerolinewidth=2,
    color='white'
),
showlegend=True,
plot_bgcolor='#49494a',
paper_bgcolor='#49494a',
font=dict(color='white'),
width=1000,
height=600
)

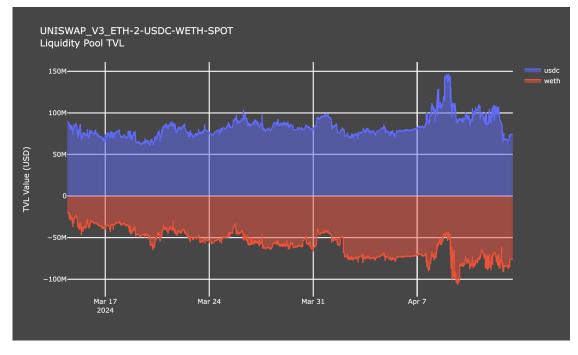
fig = generate_area_figure(
    df=data,
    layout=layout,
    columns=data.columns,
    diverging_colors=True
)

fig.show()
```

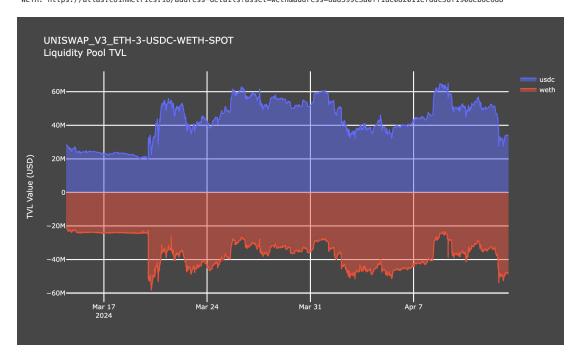
uniswap_v3_eth-1-usdc-weth-spot e0554a476a092703abdb3ef35c80e0d76d32939f USDC: https://atlas.coinmetrics.io/address-details?asset=usdc&address=e0554a476a092703abdb3ef35c80e0d76d32939f WETH: https://atlas.coinmetrics.io/address-details?asset=weth&address=e0554a476a092703abdb3ef35c80e0d76d32939f



uniswap_v3_eth-2-usdc-weth-spot 88e6a0c2ddd26feeb64f039a2c41296fcb3f5640 USDC: https://atlas.coinmetrics.io/address-details?asset=usdc&address=88e6a0c2ddd26feeb64f039a2c41296fcb3f5640 WETH: https://atlas.coinmetrics.io/address-details?asset=weth&address=88e6a0c2ddd26feeb64f039a2c41296fcb3f5640



 $USDC: \ https://atlas.coinmetrics.io/address-details?asset=usdc\&address=8ad599c3a0ff1de082011efddc58f1908eb6e6d8 \\ WETH: \ https://atlas.coinmetrics.io/address-details?asset=weth\&address=8ad599c3a0ff1de082011efddc58f1908eb6e6d8 \\ WETH: \ https://atlas.coinmetrics.io/address=8ad599c3a0ff1de082011efddc58f1908eb6e6d8 \\ WETH: \ https://atlas.coinmetrics.io/address=8ad590c3a0ff1de082011efddc58f1908eb6e6d8 \\ WETH: \ https://atlas.coinmetrics.coinmetrics.io/address=8ad590c3a0ff1de082011efddc58f1908eb6e6$



uniswap_v3_eth-4-usdc-weth-spot 7bea39867e4169dbe237d55c8242a8f2fcdcc387

 $\label{local-bound} \begin{tabular}{ll} USDC: $https://atlas.coinmetrics.io/address-details?asset=usdc&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $WETH: $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address-details?asset=weth&address=7bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address=3bea39867e4169dbe237d55c8242a8f2fcdcc387 $https://atlas.coinmetrics.io/address=3bea39867e4169dbe237d55c84$

