In [1]:
```
# import datetime
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datlib.FRED import *
from datlib.plots import *
import pandas_datareader.data as web


#FRED.py
#. . .
def bil_to_mil(series):
    return series* 10**3
# . . .
#fedProject.py
# . . .
data_codes  = {# Assets
               "Total Assets": "WALCL",
               "VIX": "VIXCLS",
               # Liabilities
               "Total Liabilities" : "WLTLECL",
               # Interest Rates
#                "CPI":"CPIAUCSL",
               "Core PCE":"PCEPILFE",
               "Currency in Circulation": "WCURCIR",
#                "VIX": "VIXCLS",
               }

rate_codes = {"Effective Federal Funds Rate (%)": "DFF",
#                "Federal Funds Target Rate (Pre-crisis)":"DFEDTAR",
#                "Federal Funds Upper Target":"DFEDTARU",
#                "Federal Funds Lower Target":"DFEDTARL",
#                "Interest on Reserves (%)": "IOER",
#                "5 Year Forward Rate": "T5YIFR",
               "Unemployment Rate": "UNRATE",
              "$U_N$": "NROU"
}


inflation_target = 2

unemployment_target = 4.5
# Select start and end dates
start = datetime.datetime(2000, 1, 1)
end = datetime.datetime.today()

## year variable automatically adjusts the numper of periods
#   per year in light of data frequency
annual_div = {"Q":4,
              "W":52,
              "M":12}
### choose frequency
freq = "M"
### set periods per year
year = annual_div[freq]
```

In [2]:
```
rate_keys = list(rate_codes.keys())
diffs = ["Diff", "Diff-in-Diff"]

# freq refers to data frequency. Choose "D", "W", "M", "Q", "A"
# a number may also be place in front of a letter. "2D" indicates
#       alternating days

if "data_gathered" not in locals():
    data = gather_data(data_codes, start,
          end = end, freq = freq)
    rate_data = gather_data(rate_codes, start,
          end = end, freq = freq)
    # transform bil to mil
    data["Currency in Circulation"] = data["Currency in Circulation"].mul(1000)
    data.fillna(0, inplace=True)
    log_data = np.log(data)
    log_diff_data = log_data.diff(year)
    log_diff_data[rate_keys] = rate_data[rate_keys]

    # calculate monthly rates as well. This data will be used for ADF and KPSS te
    monthly_log_diff_data = log_data.diff()
    monthly_log_diff_data[rate_keys] = rate_data[rate_keys]

    data = log_diff_data
    monthly_data = monthly_log_diff_data
    data_gathered = True

# use natural rate of unemployment for target
rate_data["$U_N$"] = rate_data["$U_N$"].interpolate(method='linear')
unemployment_target = rate_data["$U_N$"]
```

```
C:\Users\HP\anaconda3\lib\site-packages\pandas\core\internals\blocks.py:402: Ru
ntimeWarning: divide by zero encountered in log
  result = func(self.values, **kwargs)
```

In [3]:
```
for df in [data,monthly_data]:
    df["Currency in Circulation / Total Assets"] = df["Currency in Circulation"].
    df["Inflation Loss"]= df["Core PCE"].sub(inflation_target)
    df["Unemployment Loss"]= df["Unemployment Rate"].sub(unemployment_target)
    df["Inflation Loss Sq"]= df["Inflation Loss"].pow(2)
    df["Inflation Loss Sq"][df["Inflation Loss"] < 0] = df["Inflation Loss Sq"][d
    df["Unemployment Loss Sq"]= df["Unemployment Loss"].pow(2)
    df["Unemployment Loss Sq"][df["Unemployment Loss"] < 0] = df["Unemployment Lo
    df["Loss Function"] = df["Inflation Loss Sq"].sub(df["Unemployment Loss Sq"])
```

In [4]:
```
data={"Data":data,
      "Diff": data.diff(year),
      "Diff-in-Diff": data.diff(year).diff(year),
      }
monthly_data={"Data":monthly_data,
      "Diff": monthly_data.diff(),
      "Diff-in-Diff": monthly_data.diff().diff(),
      }
diffs = list(data.keys())
for key, val in data.items():
    data[key]["Date"] = val.index.astype(str)
```

In [5]:
```
from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.api import VAR
import statsmodels.api as sm
from arch.unitroot import ADF, KPSS
import copy
import pingouin
from scipy.stats import pearsonr
from datlib.ts_tests import *
from statsmodels.tsa.adfvalues import *
import warnings
warnings.simplefilter("ignore")
import statsmodels
from statsmodels.tools.validation import (
    array_like,
    bool_like,
    dict_like,
    float_like,
    int_like,
    string_like,
)

from statsmodels.tools.sm_exceptions import (
    CollinearityWarning,
    InfeasibleTestError,
    InterpolationWarning,
    MissingDataError,
)


from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.api import VAR
import statsmodels.api as sm
from arch.unitroot import ADF, KPSS
import copy
import pingouin
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from datlib.ts_tests import *
from statsmodels.tsa.adfvalues import *
import warnings
warnings.simplefilter("ignore")
import statsmodels
from statsmodels.tools.validation import (
    array_like,
    bool_like,
    dict_like,
    float_like,
    int_like,
    string_like,
)

from statsmodels.tools.sm_exceptions import (
    CollinearityWarning,
    InfeasibleTestError,
    InterpolationWarning,
```
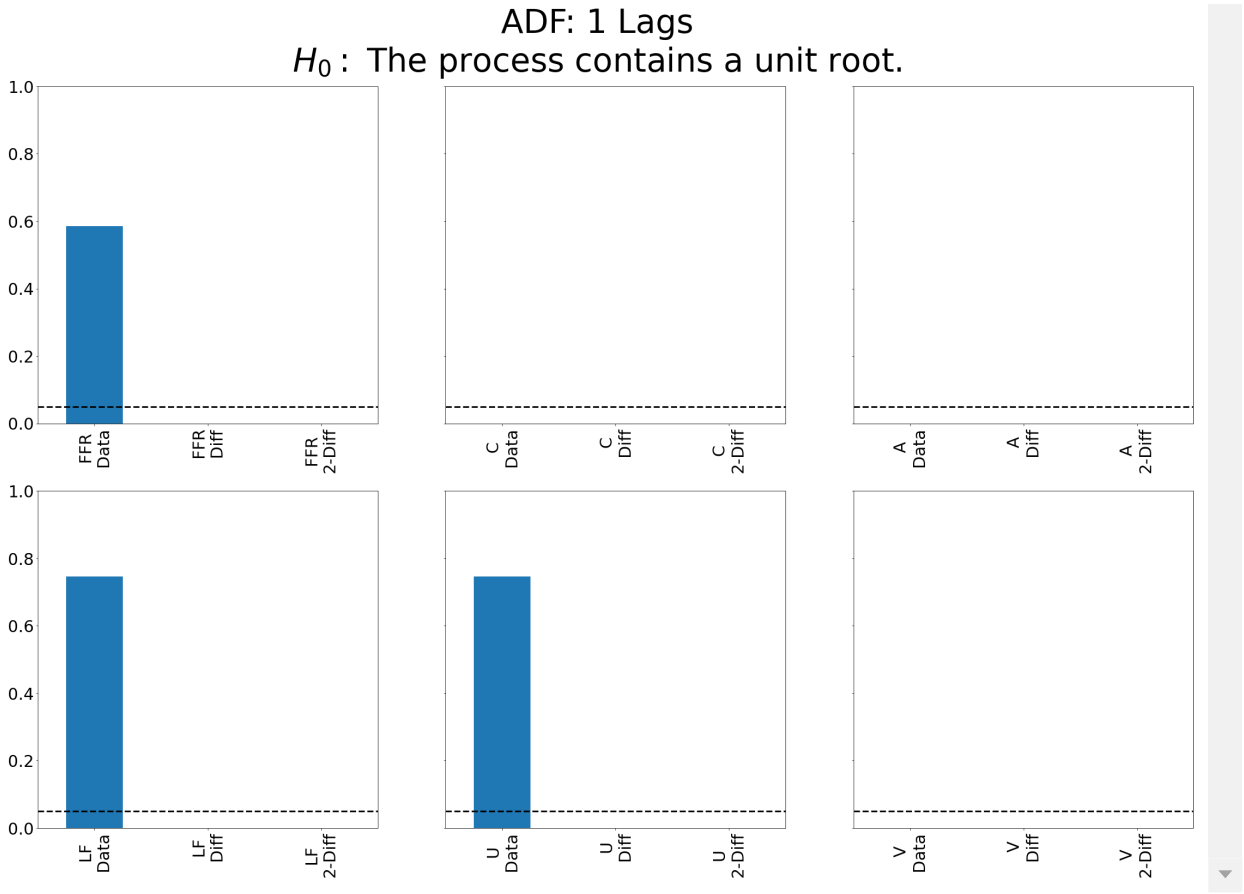
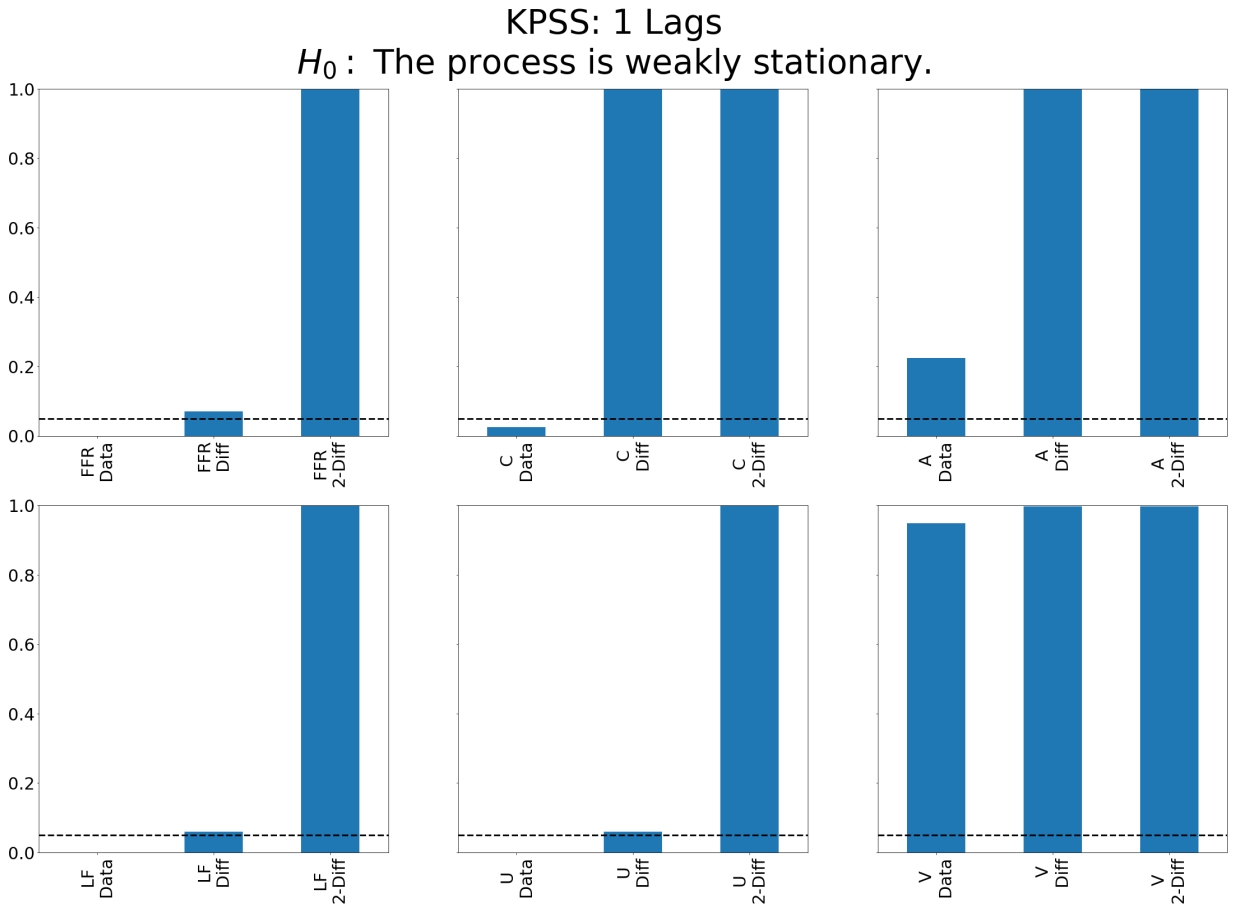

```
    MissingDataError,
)
```

```
C:\Users\HP\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: Fu
tureWarning: pandas.Int64Index is deprecated and will be removed from pandas in
a future version. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
C:\Users\HP\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: Fu
tureWarning: pandas.Float64Index is deprecated and will be removed from pandas
in a future version. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
```

In [6]:
```
def run_ts_tests(data_dct, lags, adf_dct = {}, kpss_dct = {}):
    def build_result_dcts():
        for key in keys:
            adf_dct[key] = {}
            kpss_dct[key] = {}
            for diff in diffs:
                adf_dct[key][diff] = {}
                kpss_dct[key][diff] = {}
        return adf_dct, kpss_dct

    diffs = list(data_dct.keys())
    keys = list(data_dct[diffs[0]].keys())
    build_result_dcts()
    for diff in diffs:
        test_data = data_dct[diff][list(rename_dct.values())]
        test_data.dropna().to_csv("TestData"+diff+".csv")
        test_data = test_data.loc[:"2020-02-29"].dropna()
        for key, val in test_data.items():
            adf_dct[key][diff] = ADF(val,
                                     lags = lags,
                                     trend= "c").pvalue
            kpss_dct[key][diff] = KPSS(val,
                                     lags = lags,
                                     trend= "c").pvalue
    return pd.DataFrame(adf_dct), pd.DataFrame(kpss_dct)

def bar_plots(dct, width = 2, length = 3,title = "", title_y = 1):

    fig, ax = plt.subplots(width,
                           length,
                           figsize = (38,25))
    i = 0
    j = 0
    for key, df in dct.items():
        df.plot.bar(ax = ax[j][i],
                              legend = False)
        xtick_labels = ax[j][i].get_xticks()
        ax[j][i].axhline(.05, ls = "--", color = "k", linewidth = 3)
        ax[j][i].set_xticklabels([key + "\n" + diff.replace("Diff-in-Diff","2-Dif
                                  fontsize = 30)
        ax[j][i].set_ylim(0,1)

        if i == 0:
            ax[j][i].set_yticklabels([round(y,2) for y in ax[j][i].get_yticks()],
                                  fontsize = 30)
        else:
            ax[j][i].set_yticklabels(["" for y in ax[j][i].get_yticks()])

        i+=1

        if i == length:
            i = 0
            j += 1
        #     if i == 2 and j == 1:
        #         ax[j][i].set_axis_off()
    fig.suptitle(title, y = title_y, fontsize = 60)
```

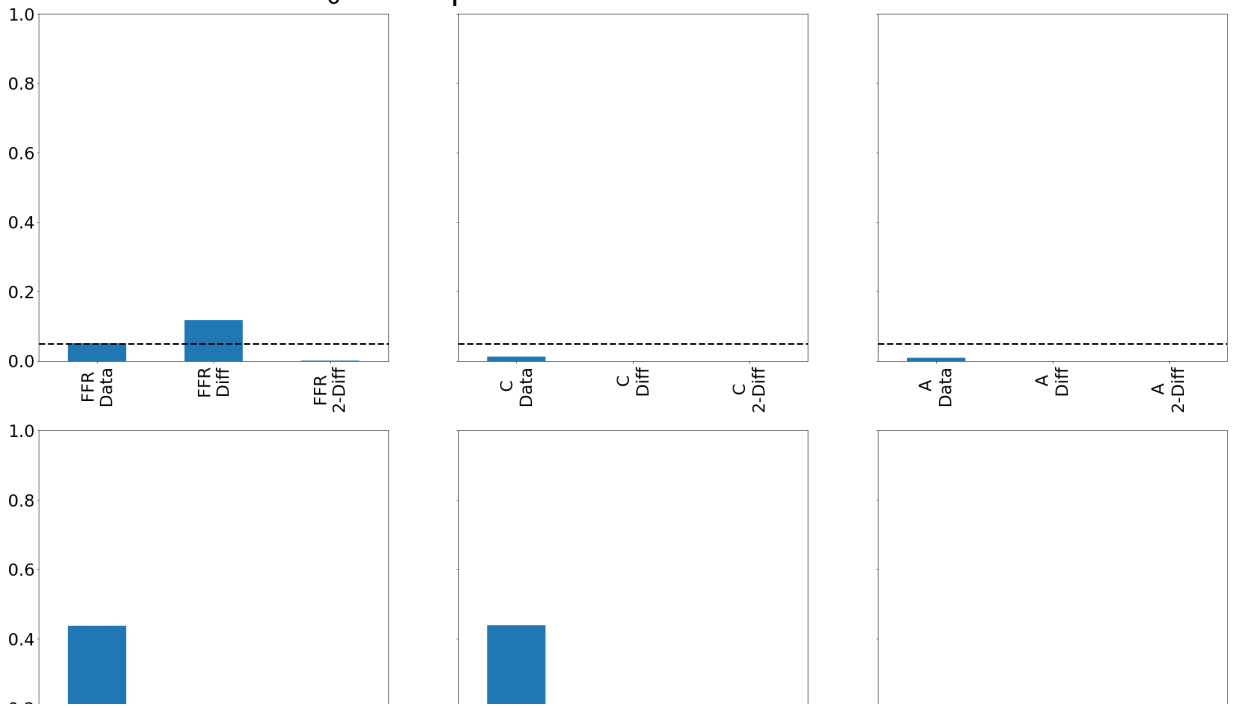
```
    fig.savefig(title.replace(":", "-").replace("$","").replace("\n","") + ".png'



rename_dct = {"Effective":"FFR",
#               "Circulation / Total":"C/A",
              "Circulation":"C",
             "Assets":"A",
              "Function":"LF",
             "Unemployment":"U",
             "VIX" : "V"}
abbrev_keys = list(rename_dct.values())
lags = 1
# lags = year




for diff in diffs:
    # test all variables, include loss fucntion components
    test_vars = ["Effective Federal Funds Rate (%)",
        "Currency in Circulation",
        "Total Assets",
        "Loss Function",
                 "VIX",
        "Unemployment Loss Sq"]
#     adf_data = monthly_data[diff][test_vars]
    for key in test_vars:
        for rename_key in rename_dct:
            if rename_key in key:
                monthly_data[diff].rename(columns={key:rename_dct[rename_key] for
                                inplace = True)

test_data = copy.copy(monthly_data)
for diff in test_data.keys():
    test_data[diff] = test_data[diff][abbrev_keys].dropna().loc[:"2020-02-29"]
for lags in [1,12]:
    adf_df, kpss_df = run_ts_tests(test_data, lags)
    # plot_ADF tests
    # create filler val to get null hypothesis
    val = [i for i in range(10)]
    title = "ADF: " + str(lags) + " Lags\n$H_0:$ "+ ADF(val,
                      lags = lags,
                      trend = "c").null_hypothesis
    title_y = .96
    bar_plots(adf_df, title = title, title_y = title_y)

    # plot KPSS tests
    title = "KPSS: " + str(lags) + " Lags\n$H_0:$ "+  KPSS(val,
                          lags = lags,
                          trend = "c").null_hypothesis
    bar_plots(kpss_df, title = title, title_y = title_y)
```


ADF: 1 Lags
$H_0:$ The process contains a unit root.
1.0
0.8
0.6
0.4
0.2
0.0
FFR Data
FFR Diff
FFR 2-Diff
C Data
C Diff
C 2-Diff
A Data
A Diff
A 2-Diff
LF Data
LF Diff
LF 2-Diff
U Data
U Diff
U 2-Diff
V Data
V Diff
V 2-Diff


KPSS: 1 Lags
$H_0:$ The process is weakly stationary.
1.0
0.8
0.6
0.4
0.2
0.0
FFR Data
FFR Diff
FFR 2-Diff
C Data
C Diff
C 2-Diff
A Data
A Diff
A 2-Diff
LF Data
LF Diff
LF 2-Diff
U Data
U Diff
U 2-Diff
V Data
V Diff
V 2-Diff

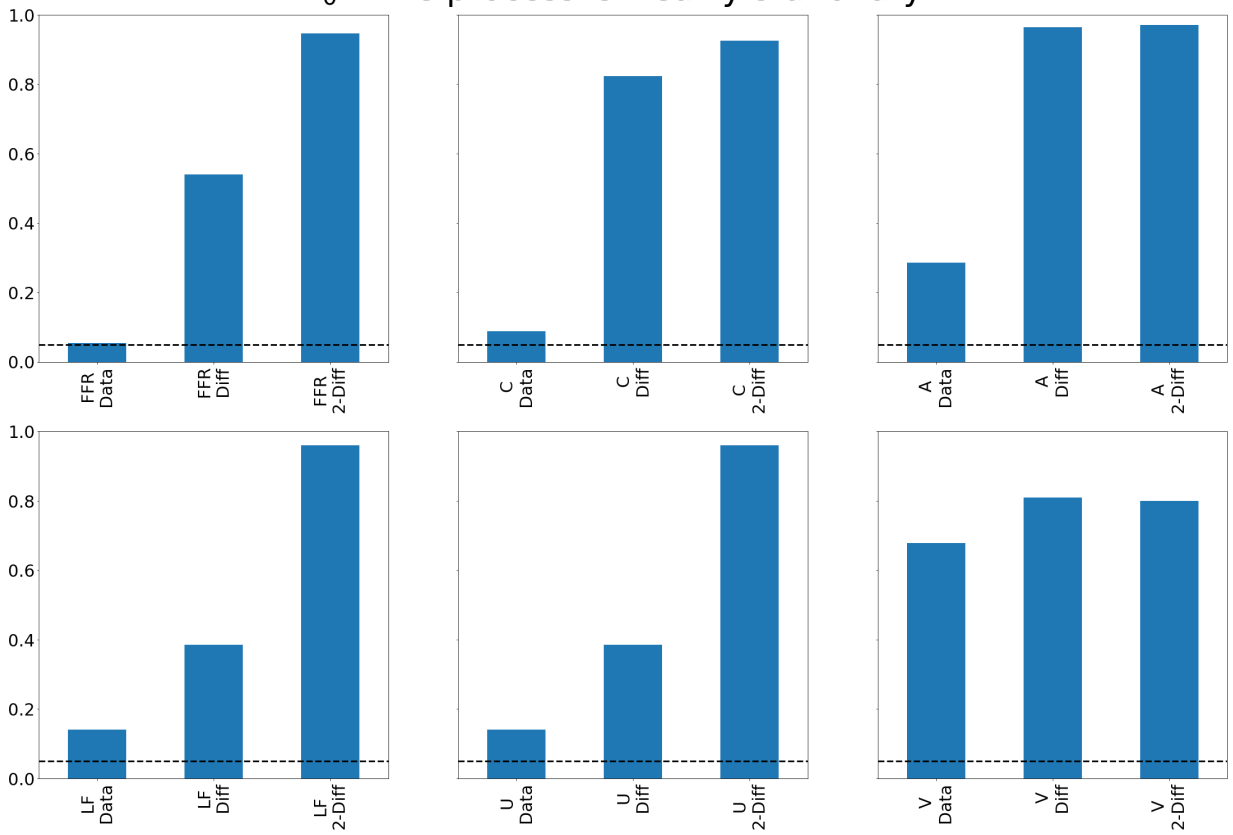
ADF: 12 Lags

$H_0:$ The process contains a unit root.

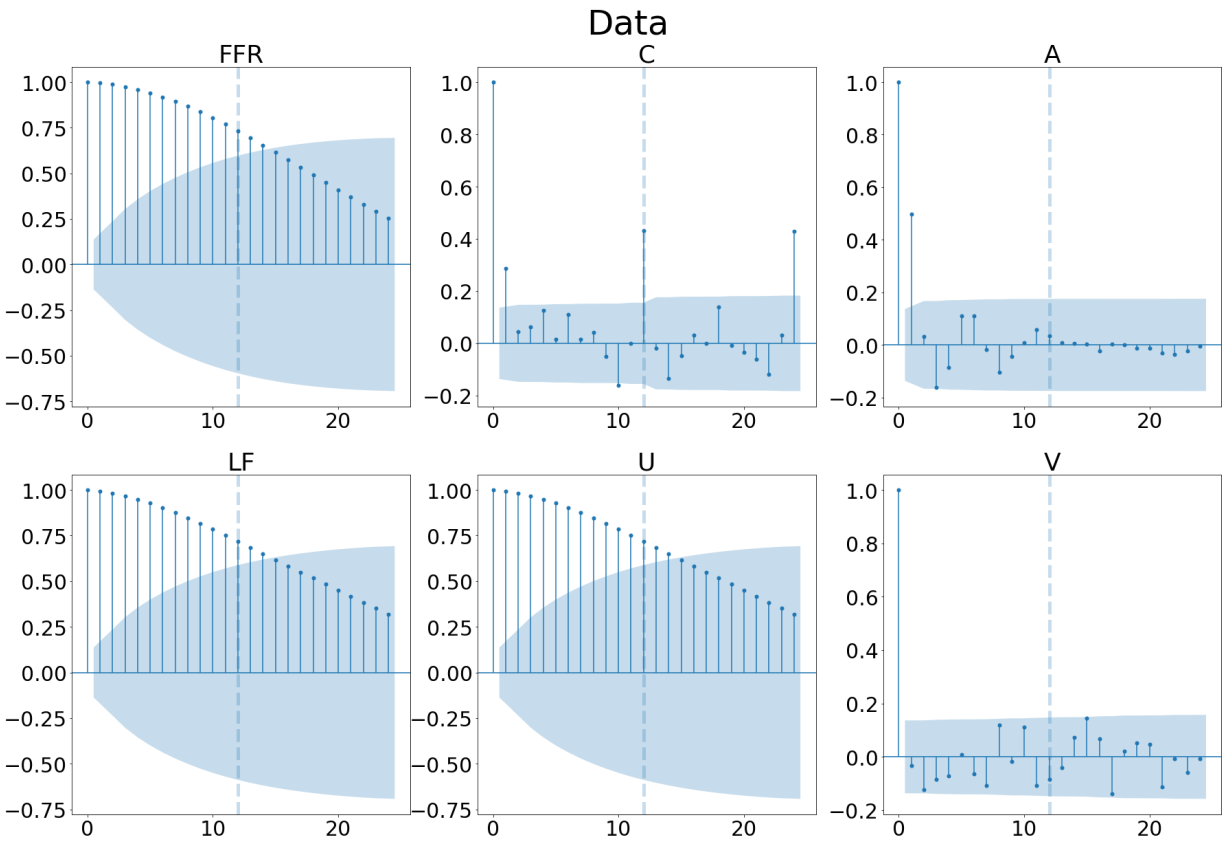


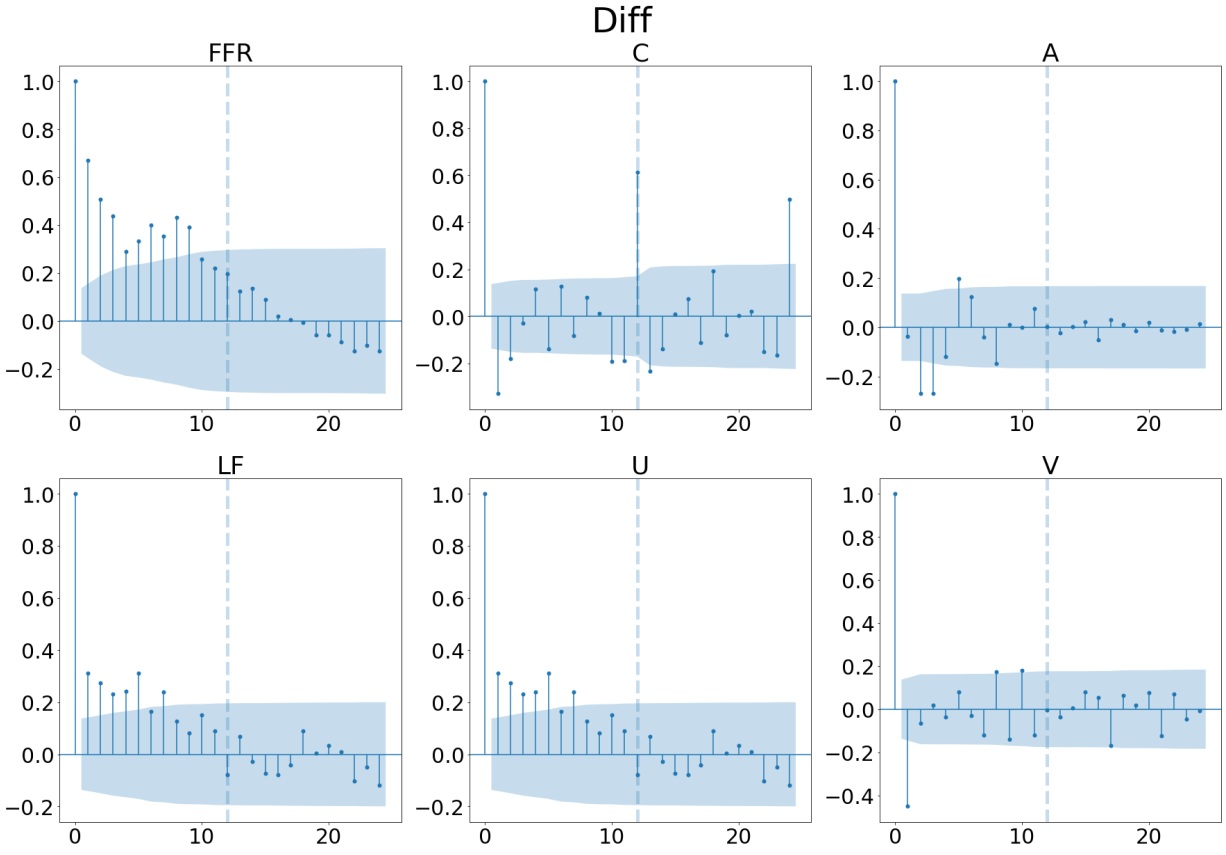
KPSS: 12 Lags

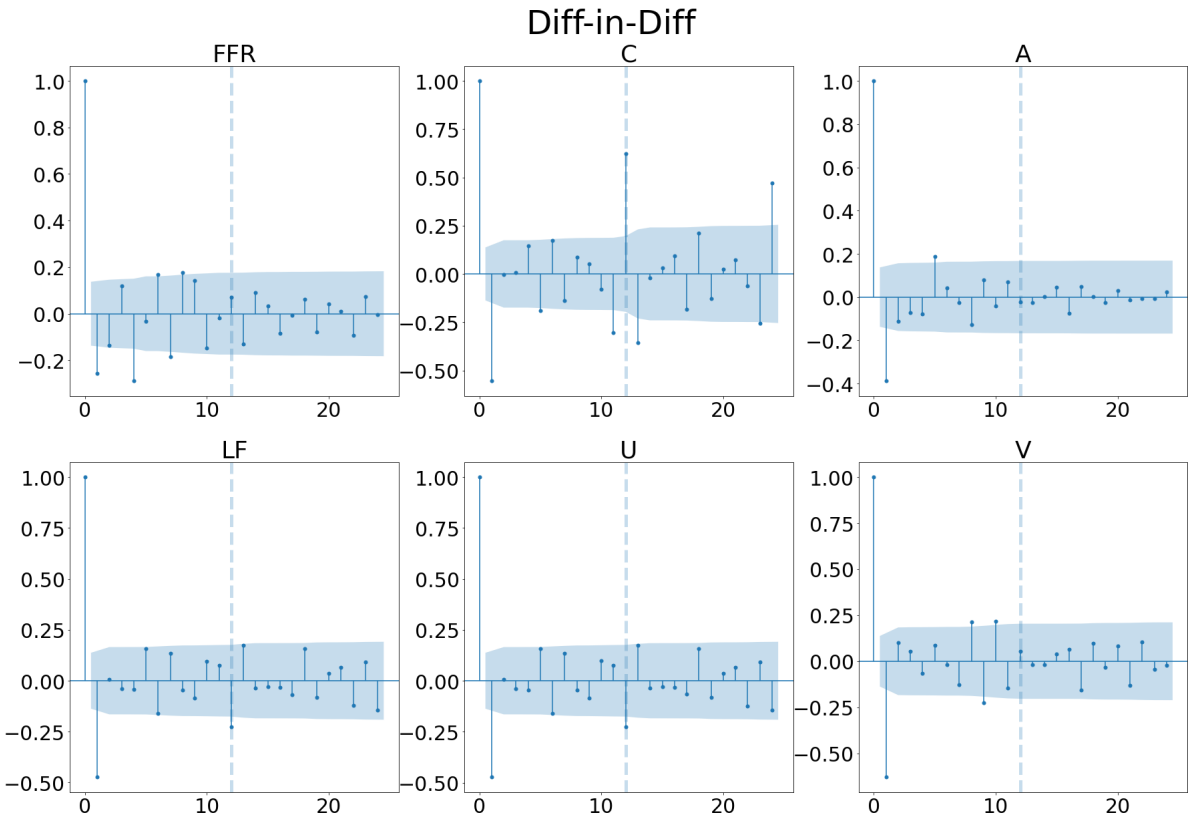
$H_0:$ The process is weakly stationary.



In [7]:
```
from statsmodels.graphics.tsaplots import plot_acf
plt.rcParams.update({"font.size":30})
width, length = 3,2

for diff in diffs:
    fig,ax = plt.subplots(length, width,figsize = (30,20))
    i, j = 0, 0
    for key, val in test_data[diff].items():
        a = ax[i][j]
        a.axvline(12, ls = "--", linewidth = 5, color = "C0", alpha = .25)
        plot_acf(val, title = key, ax = a)

        j+=1

        if j == width:
            j = 0
            i += 1
    fig.suptitle(diff, fontsize = 50, y = .94)
```




Diff
FFR
C
A
LF
U
V


Diff-in-Diff
FFR
C
A
LF
U
V

In [8]:
```
from datlib.DAG import *
from collections import OrderedDict
from linearmodels.system import SUR
from matplotlib.backends.backend_pdf import PdfPages
from scipy import stats


# plt.rcParams.update({"font.size":20})
# pd.to_datetime(data['Date'])
# data.set_index("Date")
# diff = "Diff"

sig_vals = [.05, .01, .001]


def add_lags(data, lags=12 / year):
    for key in data:
        for i in range(1, lags + 1):
            new_key = key +" Lag" * i
            data[new_key] = var_data[key].shift(year * i)

def rename_vars(rename_data, rename_dct):
    for key in rename_data:
        for rename_key in rename_dct:
            if rename_key in key:
                rename_data.rename(columns={key:rename_dct[rename_key]}, inplace



# only estimate twice differenced data since a some variables fail to reject the
diffs = ["Diff", "Diff-in-Diff"]
reg_dict = {}
lags = int(round(12 / year,0))

for diff in diffs:

    ## Use return_type = "pdag" to allow for endogeneity
    ##  "dag" disallows this sort ambiguity
    reg_dict[diff] = {}
    # only test the aggregated data, since the hypothesis is that:
        # 1) currency and total assets are indicate relative provision of liquidi
        # 2) loss function variables are targeted together

    plot_vars =  ["Effective Federal Funds Rate (%)",
                                        "Currency in Circulation",
                                        "Total Assets",
                                        "Loss Function",
                  "VIX"]
    sig = sigs = [0.1, 0.2, 0.3]
    variants = ["orig", "stable", "parallel"]
    ci_test = "pearsonr"


    # for plot_vars in plot_vars_dct:
    i = ""
    reg_dict[diff][i] = {}
```

```
    df = data[diff]
    var_data = df[plot_vars]
    rename_vars(var_data, rename_dct)
    add_lags(var_data, lags)
    var_data.dropna(inplace=True)
    start_end_list = [(str(var_data.index[0])[:10],"2008-09-30"),
                      ("2010-01-31", "2020-02-29")]
    #                       ("2008-10-31", "2020-02-29"),
    #                        (str(var_data.index[0])[:10],"2020-02-29")]

    # slice dfs by date range, house in dfs {}
    dfs = {}
    for start,end in start_end_list:
        dfs[start +" to " + end] =  var_data.loc[start:end].copy()

    # use dates (key) to track dates for which hypotheses are tested
    for dates, select_df in dfs.items():
        for return_type in ["pdag"]:
            edges = {}
            dag_df = {}
            fig, ax = plt.subplots(3,3,figsize = (20,20))
            fig.suptitle("DAG Estimates\n"+diff.replace(" ", "") + "\n" + return_
                         fontsize = 45)

            fig_sur, ax_sur = plt.subplots(3,3,figsize = (20,20))
            fig_sur.suptitle("SUR Estimates\n"+diff.replace(" ", "") + "\n" + ret
                         fontsize = 45)
            fig_var, ax_var = plt.subplots(3,3,figsize = (20,20))
            fig_var.suptitle("VAR Estimates\n"+diff.replace(" ", "") + "\n" + ret
                         fontsize = 45)

            for x in range(len(sigs)):
                sig = sigs[x]
                edges[sig] = {}
                dag_df[sig] = {}
                for y in range(len(variants)):
                    variant = variants[y]
                    a = ax[y][x]

                    constant = False if diff == "Diff-in-Diff" else True
                    keys = [k for k in select_df if "Lag" not in k]
                    dag_df[sig][variant] = select_df[keys].dropna()
                    # construct dag, save directed edges
                    edges[sig][variant] = DAG(dag_df[sig][variant], variant, ci_t
                    # construct graphs with PC labels
                    graph_DAG(edges[sig][variant],
                              dag_df[sig][variant],
                              title = "",
                              fig = fig,
                              ax = a)
                    if x == 0:
                        a.set_ylabel(variant, fontsize = 30)
                    if y == len(variants) - 1:
                        a.set_xlabel("$p \leq$ "+ str(sig), fontsize = 30)
                    a = ax_sur[y][x]
#                     identify sink nodes in directed dag edges, use info to dete
#                      additional graphs with marginal effects from SUR and VAR c
```

```
                    sink_source = identify_sink_nodes(edges[sig][variant])
                    filename = i + " " + diff + "DAGOLS " + dates + " " + variant
                    DAG_OLS(dag_df[sig][variant], sink_source, filename, a, diff,
                    if x == 0:
                        a.set_ylabel(variant, fontsize = 30)
                    if y == len(variants) - 1:
                        a.set_xlabel("$p \leq$ "+ str(sig), fontsize = 30)

                    a = ax_var[y][x]

    #                   filename = i + " " + diff + "DAGVAR " + dates
                    DAG_VAR(select_df.dropna(), sink_source, filename, a, diff, c
                    if x == 0:
                        a.set_ylabel(variant, fontsize = 30)
                    if y == len(variants) - 1:
                        a.set_xlabel("$p \leq$ "+ str(sig), fontsize = 30)
```

```
Working for n conditional variables: 3:                    3/3 [00:00<00:00,
100%                                                        4.75it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    48.01it/s]

Working for n conditional variables: 3:                    3/3 [00:00<00:00,
100%                                                        9.88it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    16.00it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    16.00it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    14.22it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    12.80it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    16.00it/s]

Working for n conditional variables:                       3/3 [00:00<00:00,
3: 100%                                                    14.22it/s]
```

Working for n conditional variables: 3: 100% 3/3 [00:01<00:00, 2.49it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 7.21it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 3.21it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 7.49it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 6.80it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 4.97it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 7.34it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 7.60it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 5.30it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 18.29it/s]

Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 48.00it/s]

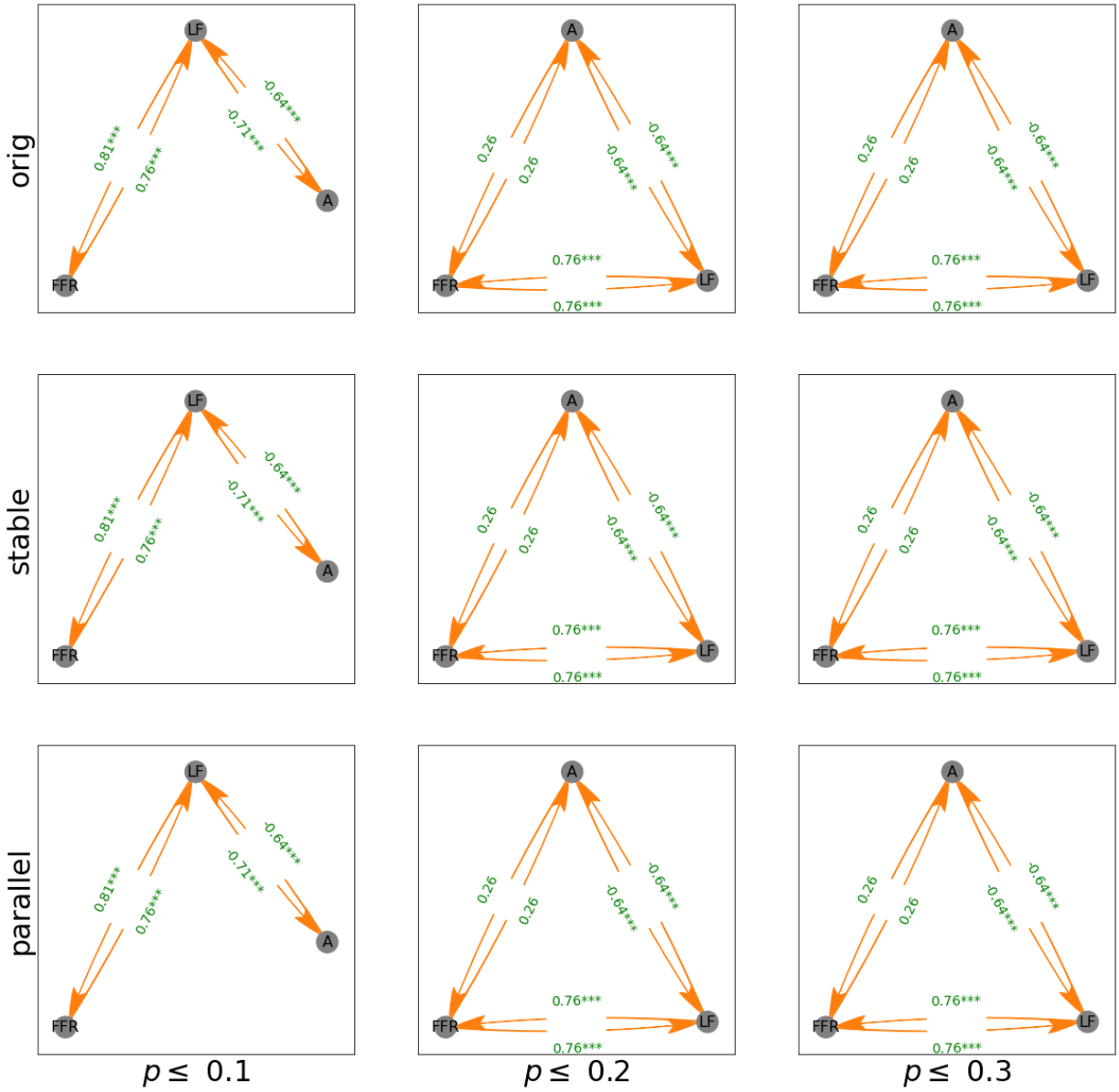
Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 27.43it/s]

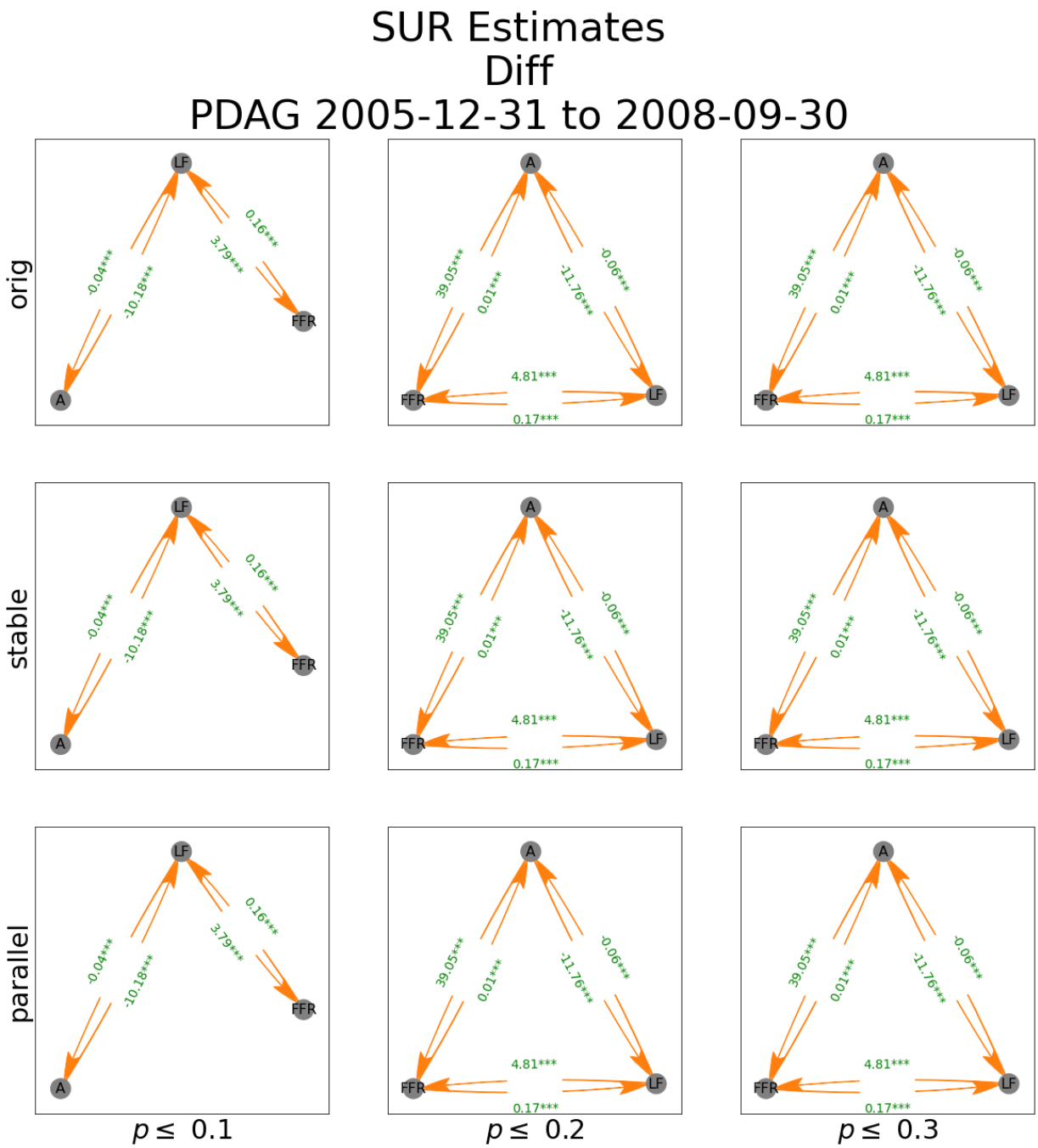
Working for n conditional variables: 3: 100% 3/3 [00:00<00:00, 27.43it/s]

Working for n conditional variables: 3/3 [00:00<00:00,

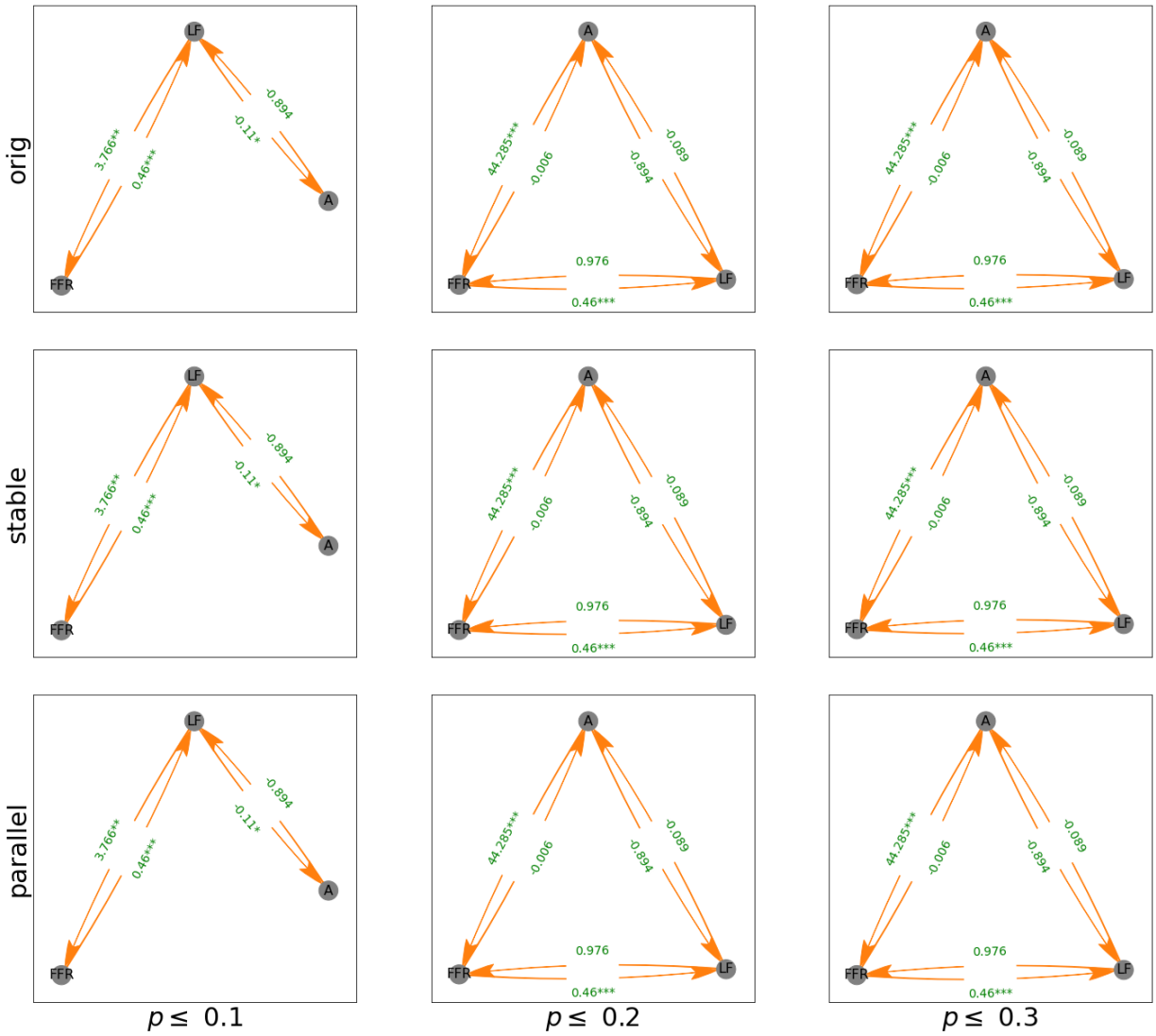
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 18.29it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 32.01it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 16.00it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 10.17it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 18.29it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 12.80it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 9.85it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 8.53it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 9.14it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 7.53it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 10.32it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 6.53it/s]
Working for n conditional variables: 3: 100%	3/3 [00:00<00:00, 6.49it/s]

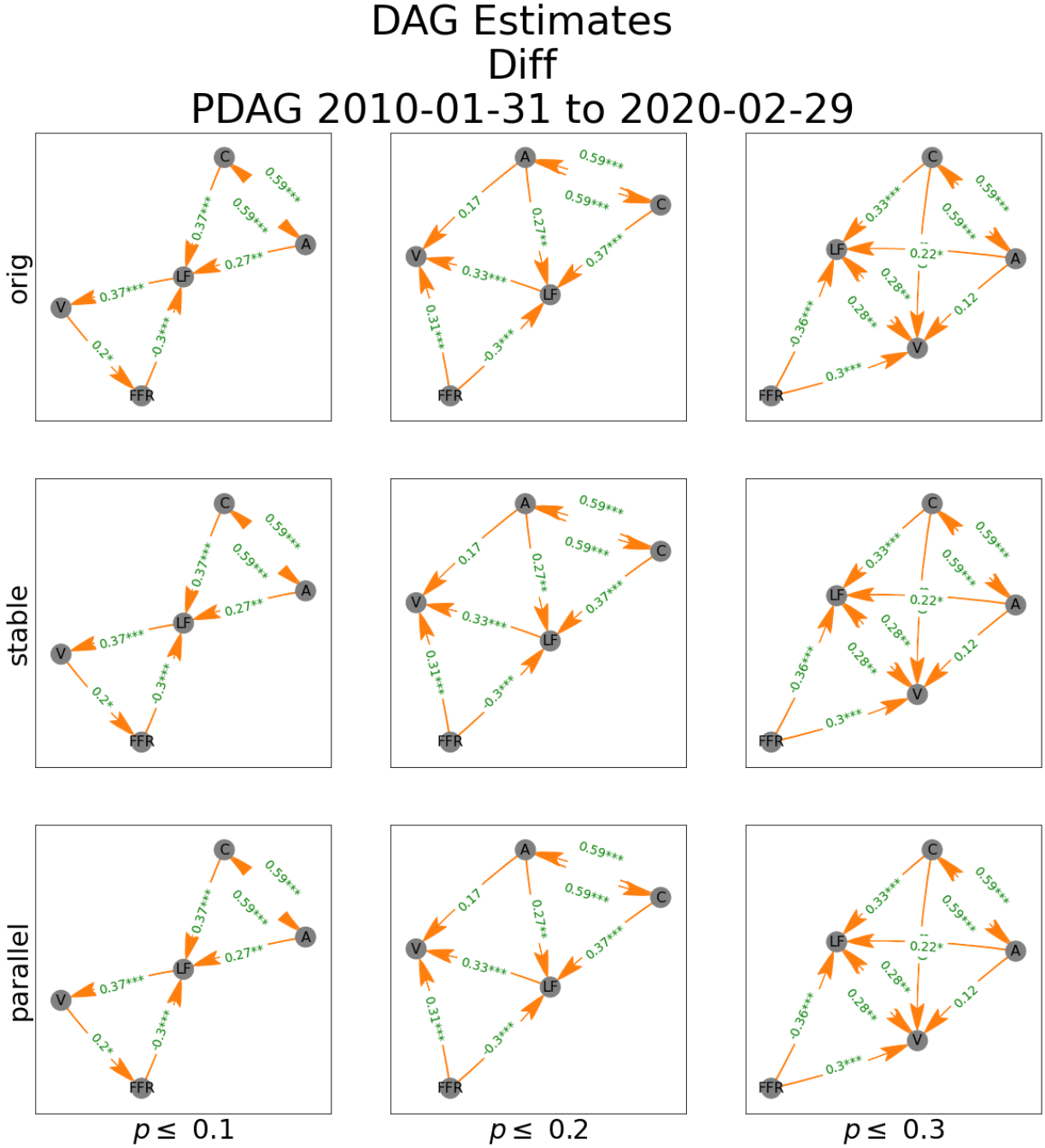
DAG Estimates
Diff
PDAG 2005-12-31 to 2008-09-30



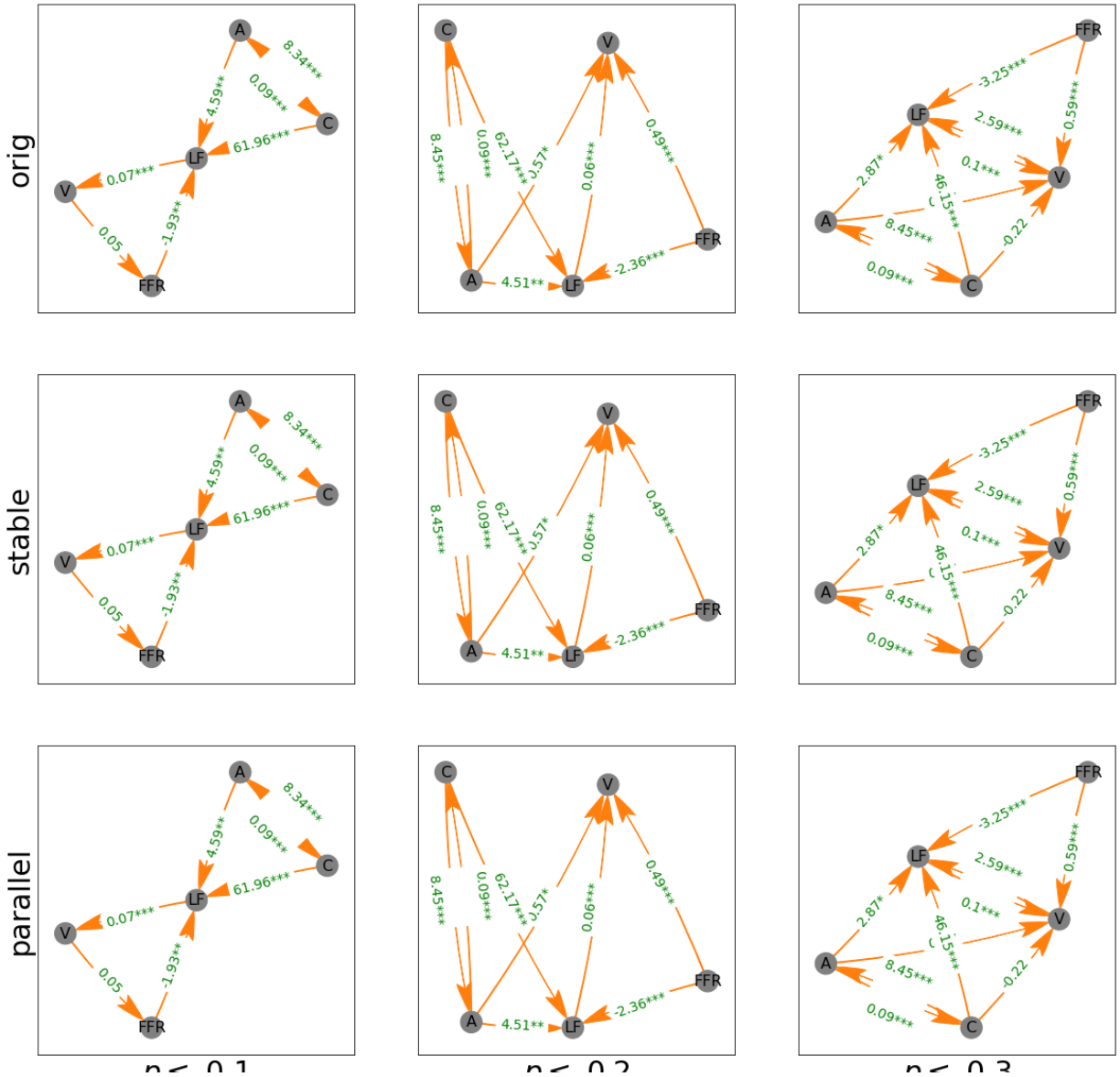

SUR Estimates
Diff
PDAG 2005-12-31 to 2008-09-30
orig
stable
parallel
LF
A
FFR
0.16***
3.79***
-0.04***
-10.18***
39.05***
0.01***
-11.76***
-0.06***
4.81***
0.17***
p ≤ 0.1
p ≤ 0.2
p ≤ 0.3

VAR Estimates
Diff
PDAG 2005-12-31 to 2008-09-30

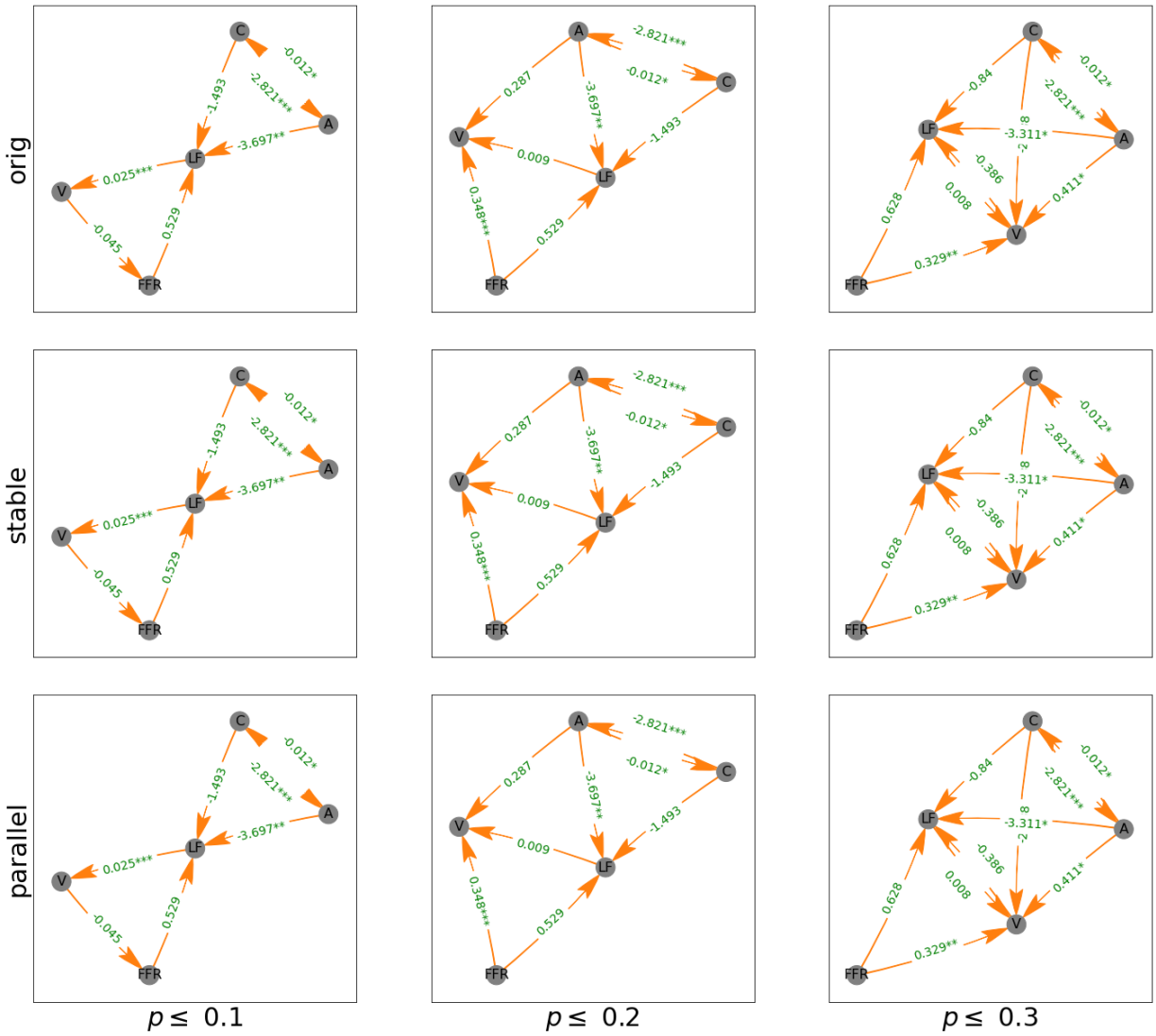


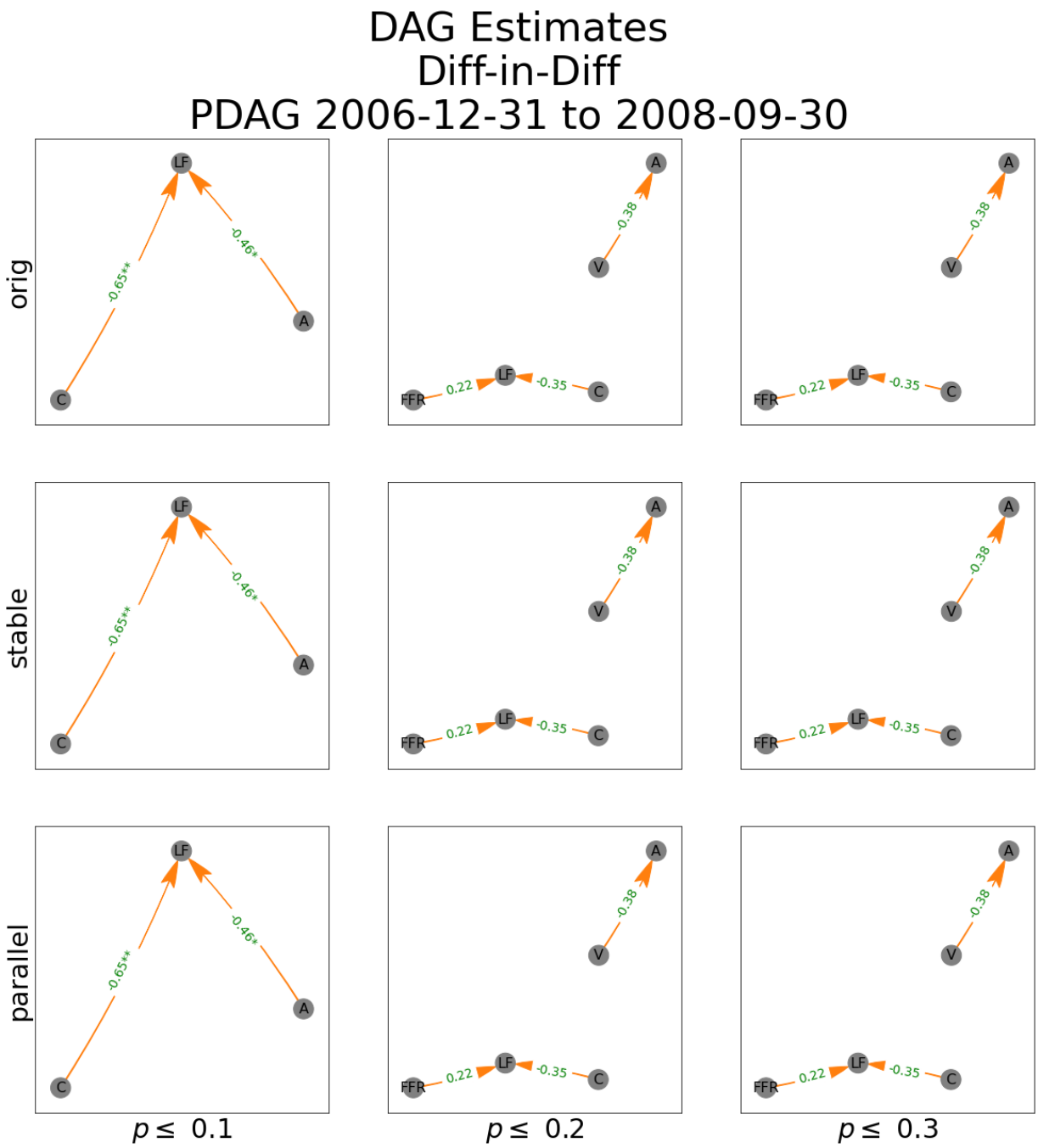

DAG Estimates
Diff
PDAG 2010-01-31 to 2020-02-29
orig
stable
parallel
$p \leq 0.1$
$p \leq 0.2$
$p \leq 0.3$

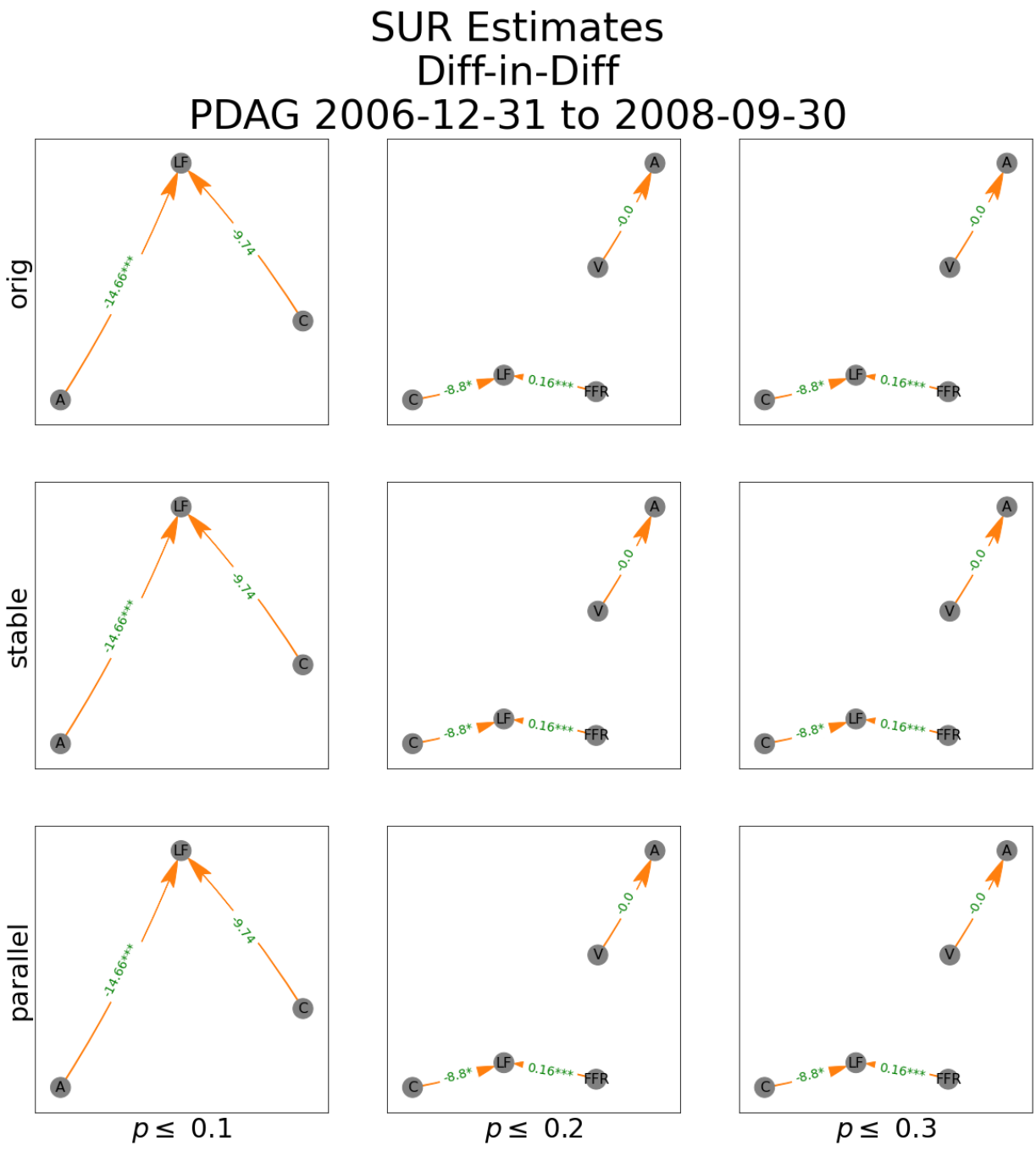
SUR Estimates
Diff
PDAG 2010-01-31 to 2020-02-29



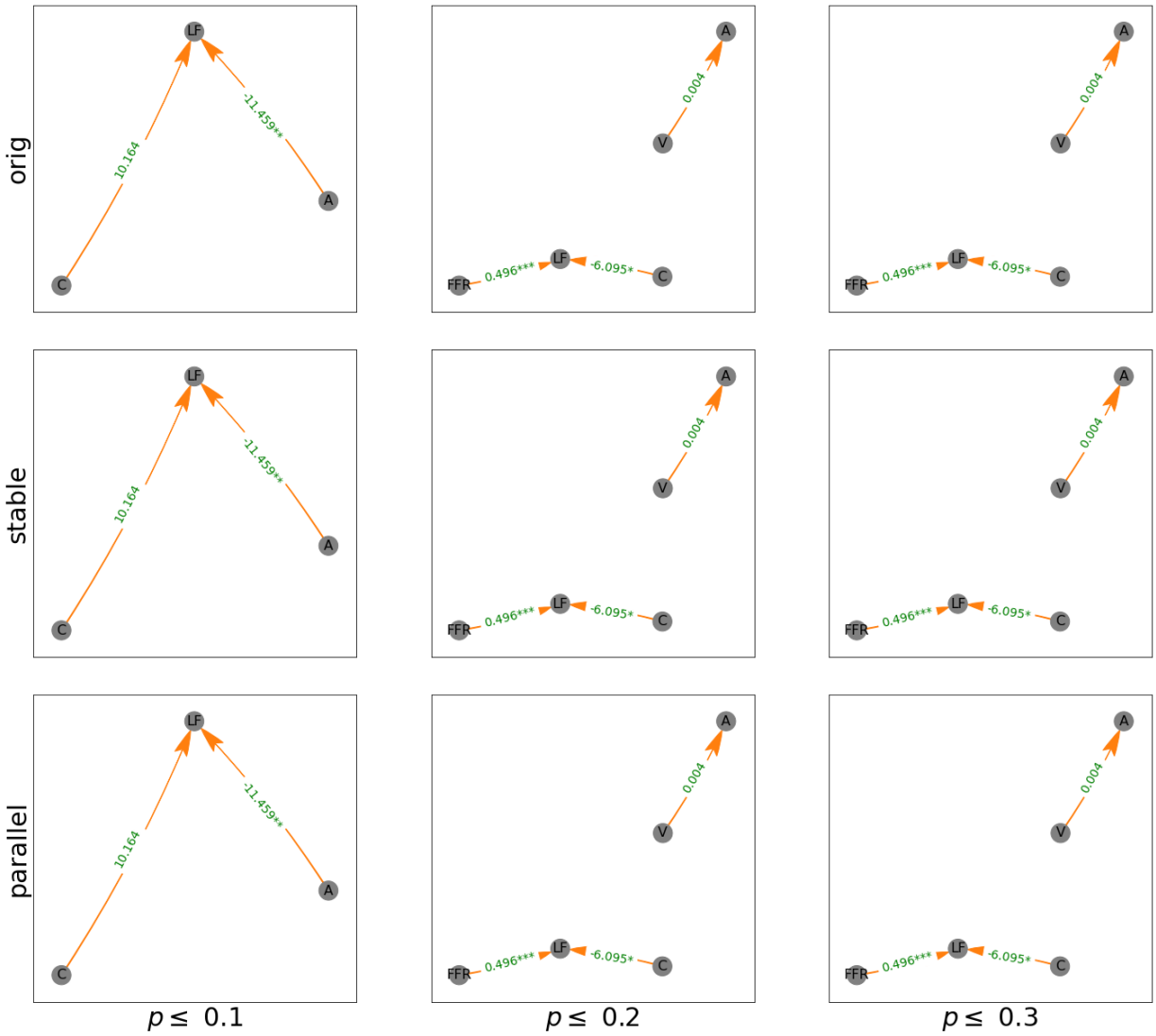
VAR Estimates
Diff
PDAG 2010-01-31 to 2020-02-29

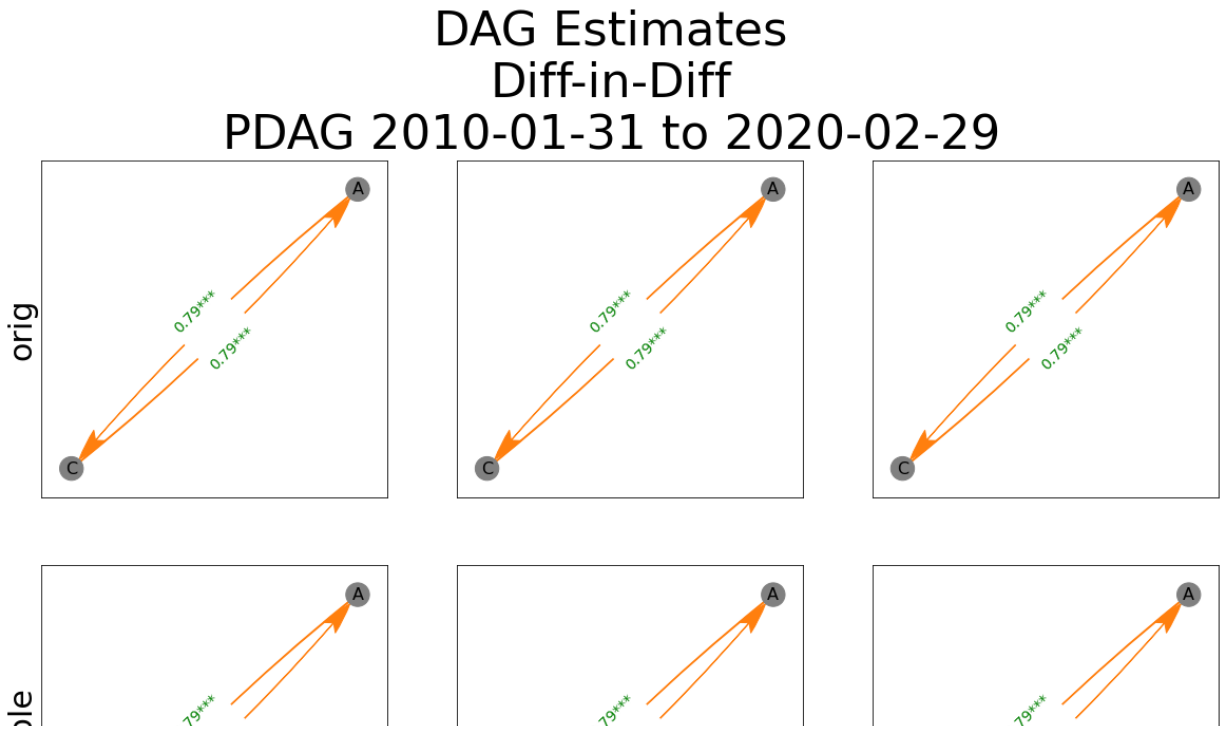


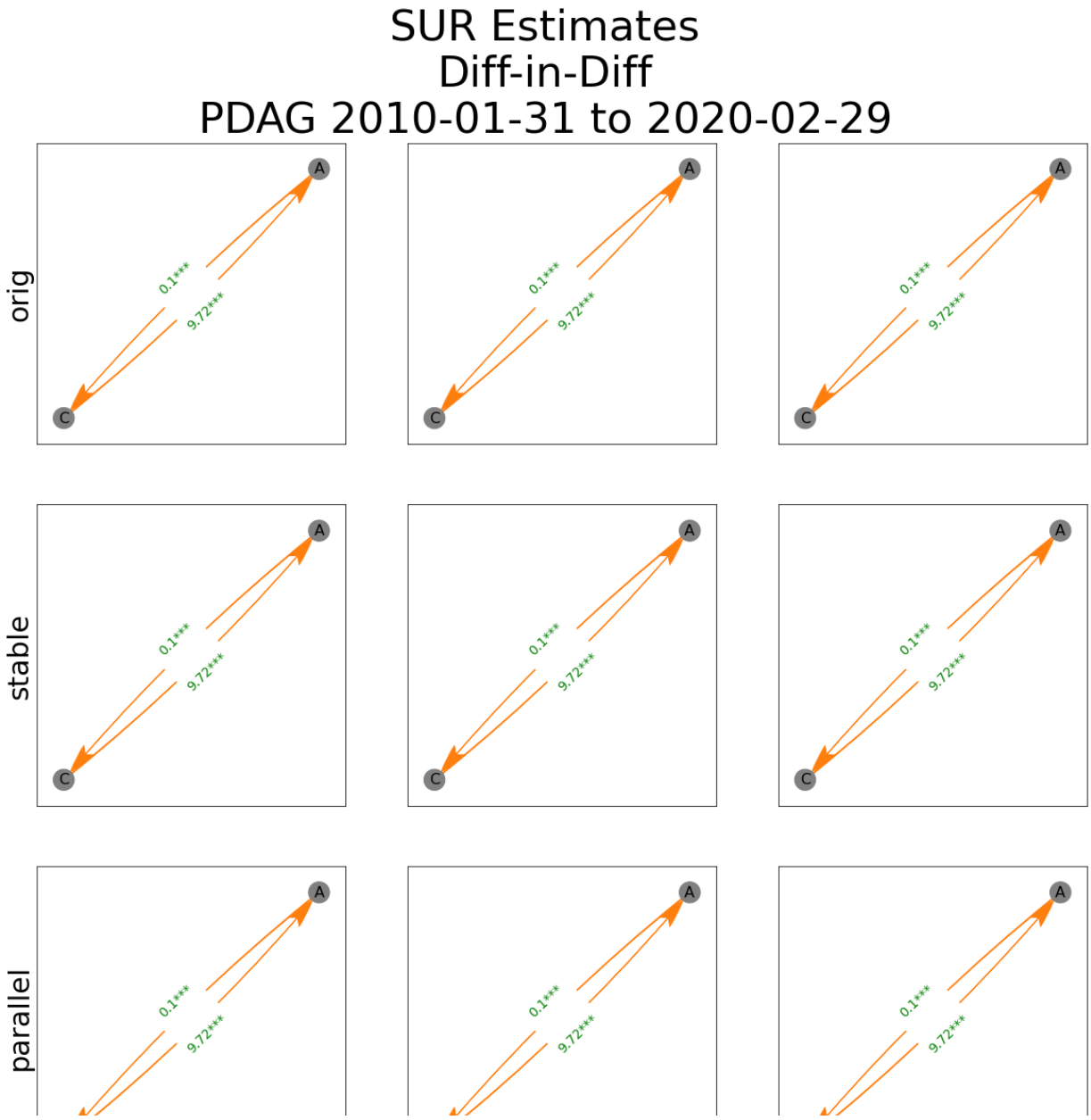

DAG Estimates
Diff-in-Diff
PDAG 2006-12-31 to 2008-09-30
orig
stable
parallel
LF
C
A
V
FFR
-0.65**
-0.46*
-0.38
0.22
-0.35
$p \leq$ 0.1
$p \leq$ 0.2
$p \leq$ 0.3

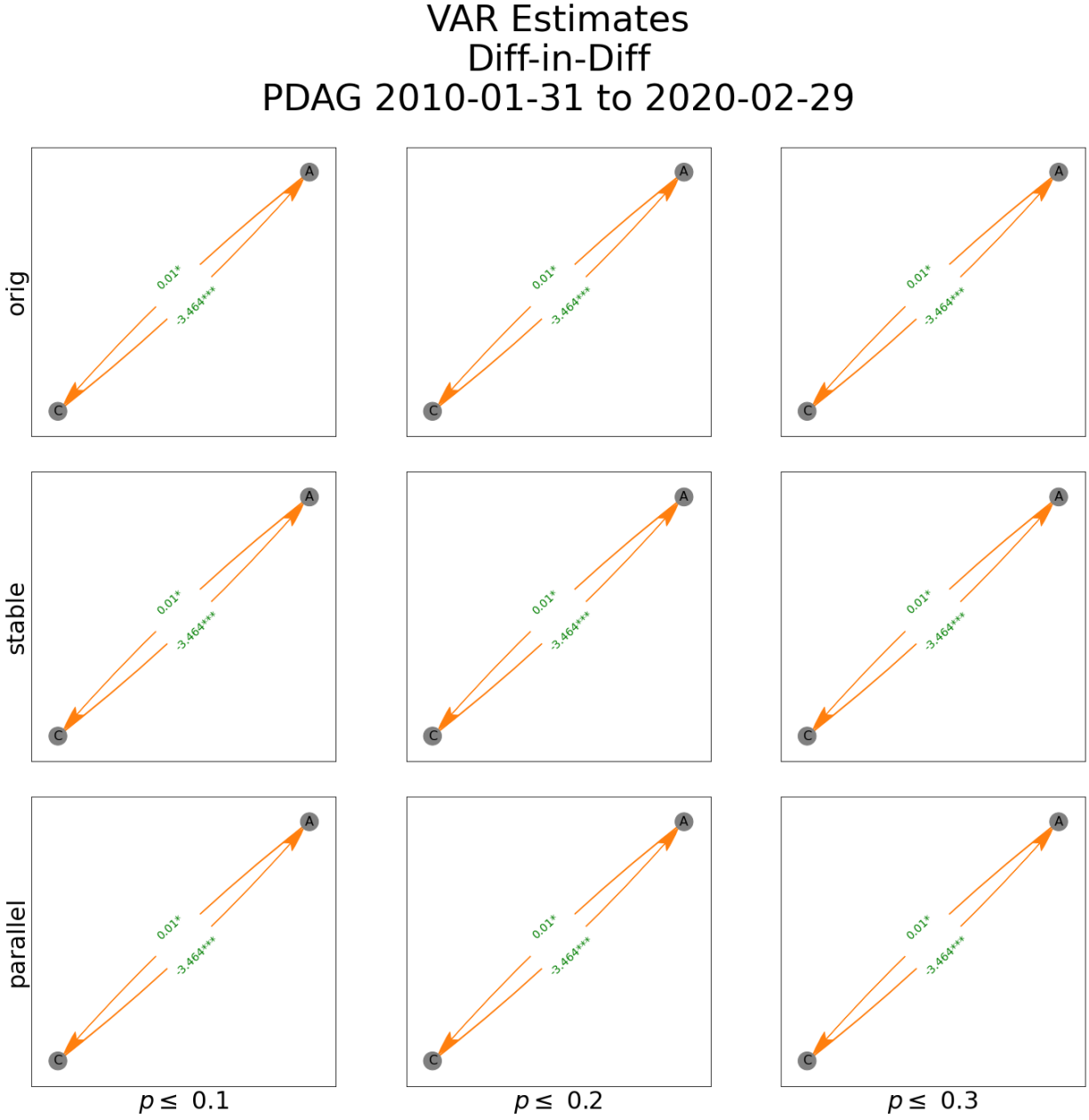

SUR Estimates
Diff-in-Diff
PDAG 2006-12-31 to 2008-09-30
orig
stable
parallel
LF
A
C
V
FFR
-14.66***
-9.74
-0.0
-8.8*
0.16***
p ≤ 0.1
p ≤ 0.2
p ≤ 0.3

VAR Estimates
Diff-in-Diff
PDAG 2006-12-31 to 2008-09-30




DAG Estimates
Diff-in-Diff
PDAG 2010-01-31 to 2020-02-29
orig
A
C
0.79***
0.79***


SUR Estimates
Diff-in-Diff
PDAG 2010-01-31 to 2020-02-29
orig
stable
parallel
A
C
0.1***
9.72***


VAR Estimates
Diff-in-Diff
PDAG 2010-01-31 to 2020-02-29
orig
stable
parallel
A
C
0.01*
-3.464***
$p \leq$ 0.1
$p \leq$ 0.2
$p \leq$ 0.3

In [ ]: