stocks_data_cleaning

July 8, 2023

1 Stock Trades by Members of the US House of Representatives

This project uses public data about the stock trades made by members of the US House of Representatives. This data is collected and maintained by Timothy Carambat as part of the House Stock Watcher project. The project describes itself as follows:

> With recent and ongoing investigations of incumbent congressional members being investigated for potentially violating the STOCK act. This website compiles this publicly available information in a format that is easier to digest then the original PDF source.
>
> Members of Congress must report periodic reports of their asset transactions. This website is purely for an informative purpose and aid in transparency.
>
> This site does not manipluate or censor any of the information from the original source. All data is transcribed by our community of contributors, which you can join for free by going to our transcription tool. Our moderation team takes great care in ensuring the accuracy of the information.
>
> This site is built and maintained by Timothy Carambat and supported with our contributors.

Some interesting questions to consider for this data set include:

- Is there a difference in stock trading behavior between political parties? For example:
  - does one party trade more often?
  - does one party make larger trades?
  - do the two parties invest in different stocks or sectors? For instance, do Democrats invest in Tesla more than Republicans?
- What congresspeople have made the most trades?
- What companies are most traded by congresspeople?
- Is there evidence of insider trading? For example, Boeing stock dropped sharply in February 2020. Were there a suspiciously-high number of sales of Boeing before the drop?
- When are stocks bought and sold? Is there a day of the week that is most common? Or a month of the year?

1.0.1 Getting the Data

The full data set of stock trade disclosures is available as a CSV or as JSON at https://housestockwatcher.com/api.

This data set does not, however, contain the political affiliation of the congresspeople. If you wish to investigate a question that relies on having this information, you'll need to find another dataset that contains it and perform a merge. *Hint*: Kaggle is a useful source of data sets.

1.0.2 Cleaning and EDA

- Clean the data.
  - Certain fields have "missing" data that isn't labeled as missing. For example, there are fields with the value "–." Do some exploration to find those values and convert them to null values.
  - You may also want to clean up the date columns to enable time-series exploration.
- Understand the data in ways relevant to your question using univariate and bivariate analysis of the data as well as aggregations.

1.0.3 Assessment of Missingness

- Assess the missingness per the requirements in `project03.ipynb`

1.0.4 Hypothesis Test / Permutation Test

Find a hypothesis test or permutation test to perform. You can use the questions at the top of the notebook for inspiration.

2 Summary of Findings

2.0.1 Introduction

The following notebook analyzes publicly available information regarding stock trades made by US House of Representatives members to reach inferences. We first cleaned up the dataset and combined *The 116th U.S. House of Representatives* at https://www.kaggle.com/datasets/aavigan/house-of-representatives-congress-116 which contains information regarding political affiliation of congresspeople. Next, we evaluate the dataset's `owner` column's missingness association.

After that, we began processing the dataset for insights, and try to explore answers to the following questions: - Does one party trade more often? - Does one party make larger trades? - What congresspeople have made the most trades? - What companies are most traded by congresspeople? - When are stocks bought and sold? Is there a day of the week that is most common? Or a month of the year?

2.0.2 Cleaning and EDA

After obtaining the complete dataset of stock trade disclosures from https://housestockwatcher.com/api, we discover that the data need to be cleaned up since they are fairly untidy. To clean it, we did what is shown below: 1. Change `disclosure_date` and `transaction_date` column to `datetime` type. 2. Replace '–' value in `ticker` column with `np.NaN`. 3. Replace '–' value in `owner` column with `np.NaN`. 4. Convert `amount` to a `pd.Categorical` series.

The political affiliation of congressmen is missing from the dataset after it has been cleaned up, therefore we choose to utilize one from **Kaggle** at https://www.kaggle.com/datasets/aavigan/house-of-representatives-congress-116. Due of the distinctions in the names between the two datasets, we combined them using the first and last names of each participant. Then we examine a few rare occurrences and manually resolve them. We were able to successfully integrate stock trade activity with representative political allegiance as an outcome.

Moving on, we process to EDA and find out that: - `owner`, `ticker`, `transaction_date`, and `asset_description` are 4 columns that contain missing data, some of the missingness in `transaction_date` is because of the incorrect value. For example, there are a few cell with value `0009-06-09` which is clearly not a valid date. - `transaction_date` range between `2012-06-19` and `2022-10-21`. - Most of the congresspeople are either from `Democrat` or `Republican`, there is only one house member who is listed as `Independent` regrading their political affiliation.

What congresspeople have made the most trades? & What congresspeople have made the largest amount of trades?

- By plotting the value counts of `representative` column, we have discovered that the representative **Josh Gottheimer** has made the most trades.
- By plotting the value counts of `representative` column, we have discovered that the representative **Kevin Hern** has made the largest amount of trades.

What companies are most traded by congresspeople?

- By plotting the value counts of `ticker` column, we have discovered that the ticker **MSFT**, which is **Microsoft Corp.**, has the most trade transactions.

When are stocks bought and sold? Is there a day of the week that is most common? Or a month of the year?

- By grouping the dateset by weekday of `transaction_date`, such that most of the transactions happened during weekdays, while only a tiny amount of transactions are done in weekend. Among weekdays, **Thurday** seems to have a slightly higher transaction volume.
- By grouping the dataset by month of `transation_date`, we discover that **February** is the month has largest volume of transactions.

2.0.3 Assessment of Missingness

In this section we decided to evaluate the missingness of `owner` column as it has the most missing values across all columns. It has values like `self`, `joint`, `dependent`, and `np.NaN`. We think the missingness of `owner` column could be associated with `type` column. This concept arises from the fact that `type` describes the sort of transaction that is performed; if the type of transaction is not a stock exchange, it is less likely to fall into the `self`, `joint`, or `dependant` categories and end up as an empty value.

In order to validate this assumption, we have to perform a permutation test. To begin with, we determine the test statistic to be **Total Variation Distance (TVD)**, as `type` is a categorical data. Then, we calculate the observed statistic for the original dataset, which is `0.07390`. Afterwards, we shuffle the `owner` column and calculate the simulate statistics. By repeating this prcoess for 5,000 times, we then calculate the p-value for this permutation. As a result, we get a p-value of `0.0` which indicates that none of the simulate statistics has a more extreme result than the observed statistics. In conclusion, we conclude that the missingness of `owner` is **Missing at Random (MAR)**, and it's dependent on `type` column the most.

2.0.4 Hypothesis Test

Which party trade more often?

- **Null hypothesis**: the distribution of trading frequency among congresspeople from different party is the same. The difference between the two observed sample is due to chance.
- **Alternative hypothesis**: the distribution of trading frequency among congresspeople from different party are different.

For the test statistics, we calculate the average trading transactions per month of each party and take the absolute difference between them. The observed statistics is `58.5469`, and we shuffle the `party` column and run the permutation test for 5,000 times. At the end, we get a p-value of `0.8756`, which indicates that majority of the permutation test cases have more extreme result than the observed statistics. Therefore, we **fail to reject** the null hypothesis, the distribution of trading frequency among congresspeople from various parties is probably the same.

Which party make larger trades?

- **Null hypothesis**: the distribution of trading amount among congresspeople from different party is the same. The difference between the two observed samples is due to chance.
- **Alternative hypothesis**: In the US, the distributions of trading amount of the two groups are different.

For the test statistics, we calculate the mean difference of trading amount across the two party. The observed statistics is 11862, and we shuffle the party column and run the permutation test for 5,000 times. At the end, we get a p-value of around 0.03 which falls within the rejecting area of a significant level of 0.05 that indicates the distribution of trading amount among congresspeople from different party might not be the same and Democrat might be having a larger trading amount than the Republican.

3 Code

[2]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures
```

3.0.1 Load transaction dataset

[3]:
```
transactions = pd.read_csv('data/all_transactions.csv')
transactions.head()
```

[3]:
```
   disclosure_year disclosure_date transaction_date  owner ticker  \
0             2021         10/4/21          9/27/21  joint     BP
1             2021         10/4/21          9/13/21  joint    XOM
```

```
2             2021         10/4/21          9/10/21  joint   ILPT
3             2021         10/4/21          9/28/21  joint     PM
4             2021         10/4/21          9/17/21   self    BLK

                                 asset_description         type  \
0                                           BP plc      purchase
1                          Exxon Mobil Corporation      purchase
2  Industrial Logistics Properties Trust - Common…    purchase
3                     Phillip Morris International Inc      purchase
4                                    BlackRock Inc  sale_partial

             amount          representative district  \
0   $1,001 - $15,000      Hon. Virginia Foxx     NC05
1   $1,001 - $15,000      Hon. Virginia Foxx     NC05
2  $15,001 - $50,000      Hon. Virginia Foxx     NC05
3  $15,001 - $50,000      Hon. Virginia Foxx     NC05
4   $1,001 - $15,000  Hon. Alan S. Lowenthal     CA47

                                          ptr_link  cap_gains_over_200_usd
0  https://disclosures-clerk.house.gov/public_dis…                   False
1  https://disclosures-clerk.house.gov/public_dis…                   False
2  https://disclosures-clerk.house.gov/public_dis…                   False
3  https://disclosures-clerk.house.gov/public_dis…                   False
4  https://disclosures-clerk.house.gov/public_dis…                   False
```

[23]:
```
combined.to_csv("data/congress_trading")
```

3.0.2 Cleaning and EDA

[4]:
```
cleaned = transactions.copy()

# convert `disclosure_date`, `transaction_date` to datetime type
cleaned['disclosure_date'] = pd.to_datetime(cleaned['disclosure_date'])
cleaned['transaction_date'] = pd.to_datetime(cleaned['transaction_date'],
 ↪errors='coerce')

# change `ticker` null values
cleaned['ticker'] = cleaned['ticker'].replace('--', np.NaN)

# convert `amount` to categorical type
cleaned['amount'] = pd.Categorical(cleaned['amount'])

cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15674 entries, 0 to 15673
Data columns (total 12 columns):
```

 ```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   disclosure_year         15674 non-null  int64
 1   disclosure_date         15674 non-null  datetime64[ns]
 2   transaction_date        15667 non-null  datetime64[ns]
 3   owner                   9661 non-null   object
 4   ticker                  14378 non-null  object
 5   asset_description       15670 non-null  object
 6   type                    15674 non-null  object
 7   amount                  15674 non-null  category
 8   representative          15674 non-null  object
 9   district                15674 non-null  object
 10  ptr_link                15674 non-null  object
 11  cap_gains_over_200_usd  15674 non-null  bool
dtypes: bool(1), category(1), datetime64[ns](2), int64(1), object(7)
memory usage: 1.2+ MB
```

[5]:
```
cleaned.isna().sum()
```

[5]:
```
disclosure_year              0
disclosure_date              0
transaction_date             7
owner                     6013
ticker                    1296
asset_description            4
type                         0
amount                       0
representative               0
district                     0
ptr_link                     0
cap_gains_over_200_usd       0
dtype: int64
```

3.0.3 Combine with political affliation dataset

[6]:
```
# remove unwanted name suffixs
suffixs = ['Hon\\.', 'Mr\\.', 'Mrs\\.', 'None', 'Aston', 'S\\.', 'W\\.']
cleaned['representative'] = (cleaned['representative']
                             .str.replace('|'.join(suffixs), '', regex=True)
                             .str.strip())

cleaned['representative'].head()
```

[6]:
```
0      Virginia Foxx
1      Virginia Foxx
2      Virginia Foxx
3      Virginia Foxx
```

```
4    Alan  Lowenthal
Name: representative, dtype: object
```

[7]:
```
# split representative name into `first_name` and `last_name` for later merge
cleaned['first_name'] = cleaned['representative'].apply(lambda x: x.split()[0].
 ↪lower())
cleaned['last_name'] = cleaned['representative'].apply(lambda x: x.split()[-1].
 ↪lower())

# fix special cases
cleaned.loc[cleaned['representative'] == 'Neal Patrick Dunn MD, FACS',␣
 ↪'last_name'] = 'dunn'

cleaned['first_name'].head()
```

[7]:
```
0    virginia
1    virginia
2    virginia
3    virginia
4        alan
Name: first_name, dtype: object
```

[8]:
```
# import member table 1
members1 = pd.read_csv('data/us-house.csv')
members1 = members1[['party', 'first_name', 'last_name']]
members1['first_name'] = members1['first_name'].str.lower()
members1['last_name'] = members1['last_name'].str.lower()
members1['party'] = members1['party'].str.capitalize()

members1.head(10)
```

[8]:

	party	first_name	last_name
0	Republican	don	young
1	Republican	jerry	carl
2	Republican	felix	moore
3	Republican	mike	rogers
4	Republican	robert	aderholt
5	Republican	mo	brooks
6	Republican	gary	palmer
7	Democrat	terri	sewell
8	Republican	rick	crawford
9	Republican	french	hill

[9]:
```
# import member table 2
members2 = pd.read_csv('data/house_members.csv')
members2['first_name'] = members2['name'].apply(
    lambda x: x.split('-')[0].lower())
```

```python
members2['last_name'] = members2['name'].apply(
    lambda x: x.split('-')[-1].lower())
members2 = members2.rename(columns={'current_party': 'party'})[
    ['first_name', 'last_name', 'party']]

# unify party values
members2.loc[members2['party'] == 'Democratic', 'party'] = 'Democrat'

members2.head(10)
```

[9]:

	first_name	last_name	party
0	ralph	abraham	Republican
1	alma	adams	Democrat
2	robert	aderholt	Republican
3	pete	aguilar	Democrat
4	rick	allen	Republican
5	colin	allred	Democrat
6	justin	amash	Independent
7	mark	amodei	Republican
8	kelly	armstrong	Republican
9	jodey	arrington	Republican

[10]:

```python
# combine 2 member tables
members = (pd.concat([members1, members2])
           .sort_values(['first_name', 'last_name'])
           .drop_duplicates(subset=['first_name', 'last_name'])
           .reset_index(drop=True))

# fix mismatch names
members.loc[members['first_name'] == 'k', 'first_name'] = 'k.'
members.loc[members['first_name'] == 'raul', 'first_name'] = 'raúl'
members.loc[members['first_name'] == 'wm', 'first_name'] = 'wm.'
members.loc[members['first_name'] == 'ro', 'first_name'] = 'rohit'
members.loc[members['first_name'] == 'cynthia', 'first_name'] = 'cindy'
members.loc[members['last_name'] == 'allen', 'first_name'] = 'richard'
members.loc[members['last_name'] == 'steube', 'first_name'] = 'greg'
members.loc[members['last_name'] == 'banks', 'first_name'] = 'james'
members.loc[(members['first_name'] == 'j') & (
    members['last_name'] == 'hill'), 'first_name'] = 'james'
members.loc[(members['first_name'] == 'mike') & (
    members['last_name'] == 'garcia'), 'first_name'] = 'michael'
members.loc[members['last_name'] == 'crenshaw', 'first_name'] = 'daniel'
members.loc[members['last_name'] == 'taylor', 'first_name'] = 'nicholas'
members.loc[members['last_name'] == 'gallagher', 'first_name'] = 'michael'
members.loc[(members['first_name'] == 'gregory') & (
    members['last_name'] == 'murphy'), 'first_name'] = 'greg'
members.loc[members['first_name'] == 'ashley', 'last_name'] = 'arenholz'
```

```python
members.loc[members['last_name'] == 'buck', 'first_name'] = 'kenneth'
members.loc[members['last_name'] == 'costa', 'first_name'] = 'james'
members.loc[members['last_name'] == 'hagedorn', 'first_name'] = 'james'

# drop duplicate rows
members = members.drop_duplicates(subset=['first_name', 'last_name'])

# output cleaned representative table
members.to_csv('data/cleaned_members.csv', index=False)

members.shape
members
```

[10]:

```
          party first_name   last_name
0    Republican          a    ferguson
1      Democrat          a    mceachin
2      Democrat       abby  finkenauer
3      Democrat    abigail  spanberger
4    Republican       adam   kinzinger
..          …          …          …
543    Democrat        wm.        clay
544    Democrat    xochitl       small
545  Republican      young         kim
546    Democrat     yvette      clarke
547    Democrat        zoe     lofgren

[547 rows x 3 columns]
```

[11]:
```python
# transaction table with member info table
combined = cleaned.merge(members, how='left', on=['first_name', 'last_name'])

combined.loc[combined['party'].isna(), 'representative'].unique()
```

[11]: `array([], dtype=object)`

[28]:
```python
combined.to_csv("data/congress_trading.csv")
```

[27]:
```python
combined
```

[27]:

```
       disclosure_year disclosure_date transaction_date  owner ticker  \
0                 2021      2021-10-04       2021-09-27  joint     BP
1                 2021      2021-10-04       2021-09-13  joint    XOM
2                 2021      2021-10-04       2021-09-10  joint   ILPT
3                 2021      2021-10-04       2021-09-28  joint     PM
4                 2021      2021-10-04       2021-09-17   self    BLK
…                  …             …              …     …    …
15669             2020      2020-06-10       2020-04-09     --    SWK
```

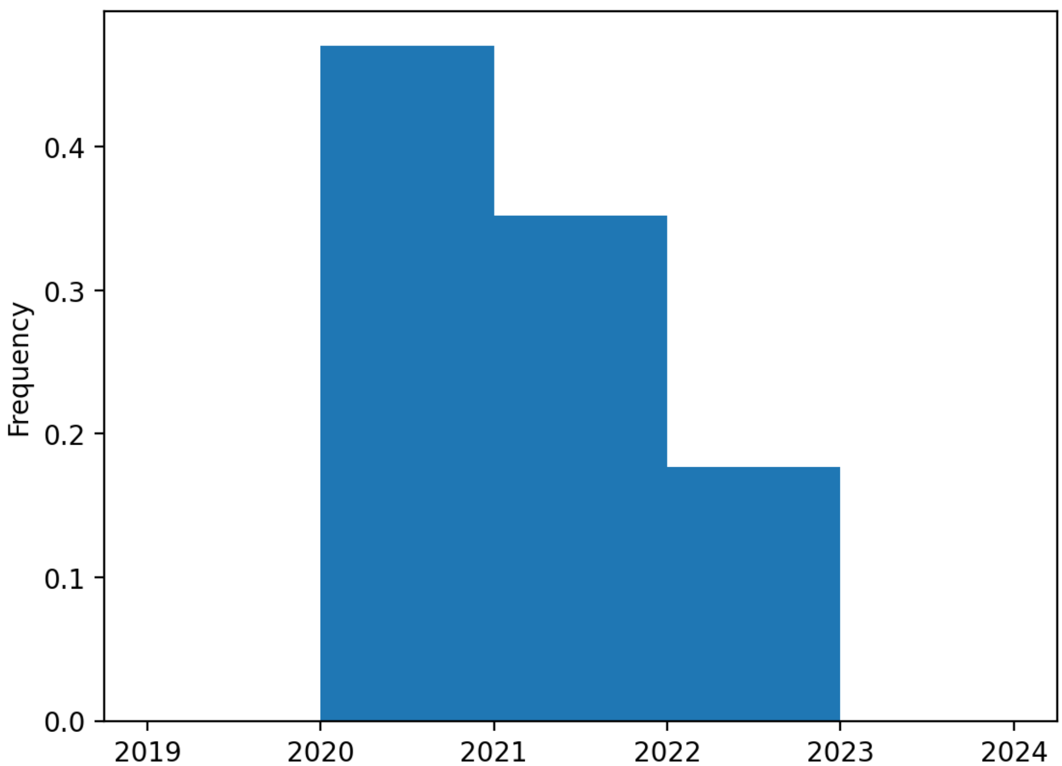
```
15670            2020      2020-06-10       2020-04-09    --    USB
15671            2020      2020-06-10       2020-03-13    NaN   BMY
15672            2020      2020-06-10       2020-03-13    NaN   LLY
15673            2020      2020-06-10       2020-03-13    NaN   DIS

                                      asset_description         type  \
0                                                BP plc      purchase
1                             Exxon Mobil Corporation      purchase
2      Industrial Logistics Properties Trust - Common…      purchase
3                       Phillip Morris International Inc      purchase
4                                         BlackRock Inc  sale_partial
…                                                   …           …
15669                        Stanley Black & Decker, Inc.  sale_partial
15670                                   U.S. Bancorp  sale_partial
15671                        Bristol-Myers Squibb Company     sale_full
15672                             Eli Lilly and Company     sale_full
15673                               Walt Disney Company     sale_full

                          amount       representative district  \
0              $1,001 - $15,000        Virginia Foxx     NC05
1              $1,001 - $15,000        Virginia Foxx     NC05
2             $15,001 - $50,000        Virginia Foxx     NC05
3             $15,001 - $50,000        Virginia Foxx     NC05
4              $1,001 - $15,000      Alan  Lowenthal     CA47
…                             …                  …       …
15669          $1,001 - $15,000        Ed Perlmutter     CO07
15670          $1,001 - $15,000        Ed Perlmutter     CO07
15671      $100,001 - $250,000  Nicholas Van Taylor     TX03
15672    $500,001 - $1,000,000  Nicholas Van Taylor     TX03
15673      $250,001 - $500,000  Nicholas Van Taylor     TX03

                                               ptr_link  \
0      https://disclosures-clerk.house.gov/public_dis…
1      https://disclosures-clerk.house.gov/public_dis…
2      https://disclosures-clerk.house.gov/public_dis…
3      https://disclosures-clerk.house.gov/public_dis…
4      https://disclosures-clerk.house.gov/public_dis…
…                                                   …
15669  https://disclosures-clerk.house.gov/public_dis…
15670  https://disclosures-clerk.house.gov/public_dis…
15671  https://disclosures-clerk.house.gov/public_dis…
15672  https://disclosures-clerk.house.gov/public_dis…
15673  https://disclosures-clerk.house.gov/public_dis…

       cap_gains_over_200_usd first_name   last_name       party
0                       False   virginia        foxx  Republican
1                       False   virginia        foxx  Republican
```

```
2                        False   virginia        foxx  Republican
3                        False   virginia        foxx  Republican
4                        False       alan   lowenthal    Democrat
…                        …         …        …          …
15669                    False         ed  perlmutter    Democrat
15670                    False         ed  perlmutter    Democrat
15671                    False   nicholas      taylor  Republican
15672                    False   nicholas      taylor  Republican
15673                    False   nicholas      taylor  Republican

[15674 rows x 15 columns]
```

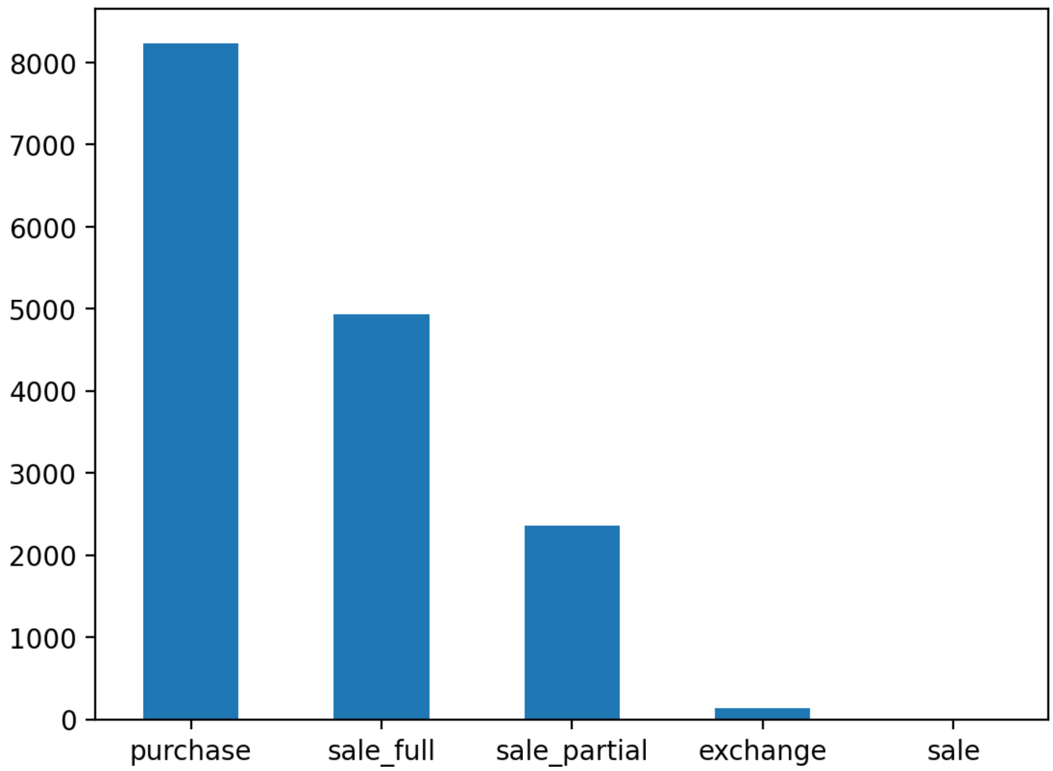
[13]:
```
transactions.shape
```

[13]:
```
(15674, 12)
```

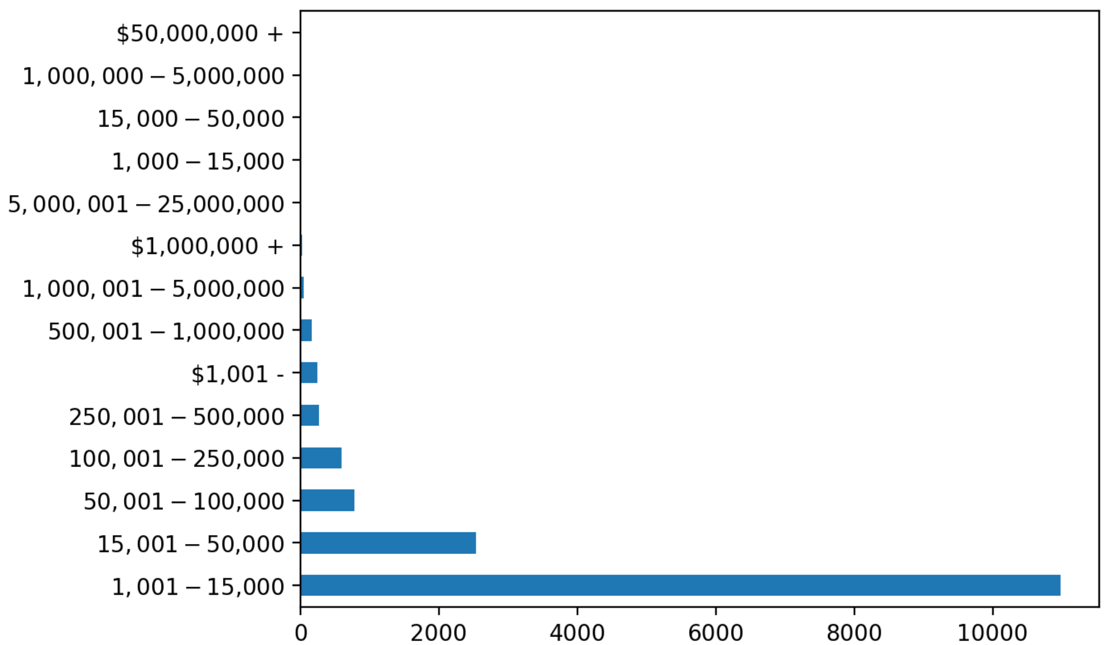
[13]:
```
combined['disclosure_year'].plot(kind='hist', density=True,␣
↪bins=range(2019,2025,1));
```



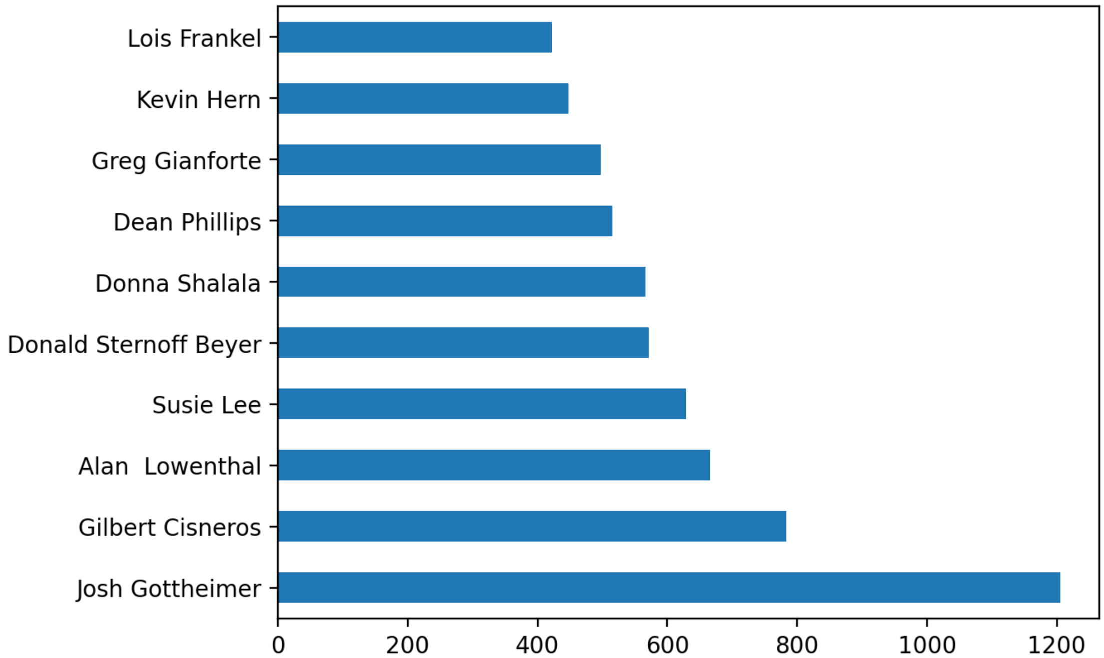
[14]:
```
combined['type'].value_counts().plot(kind='bar')
plt.xticks(rotation=0);
```



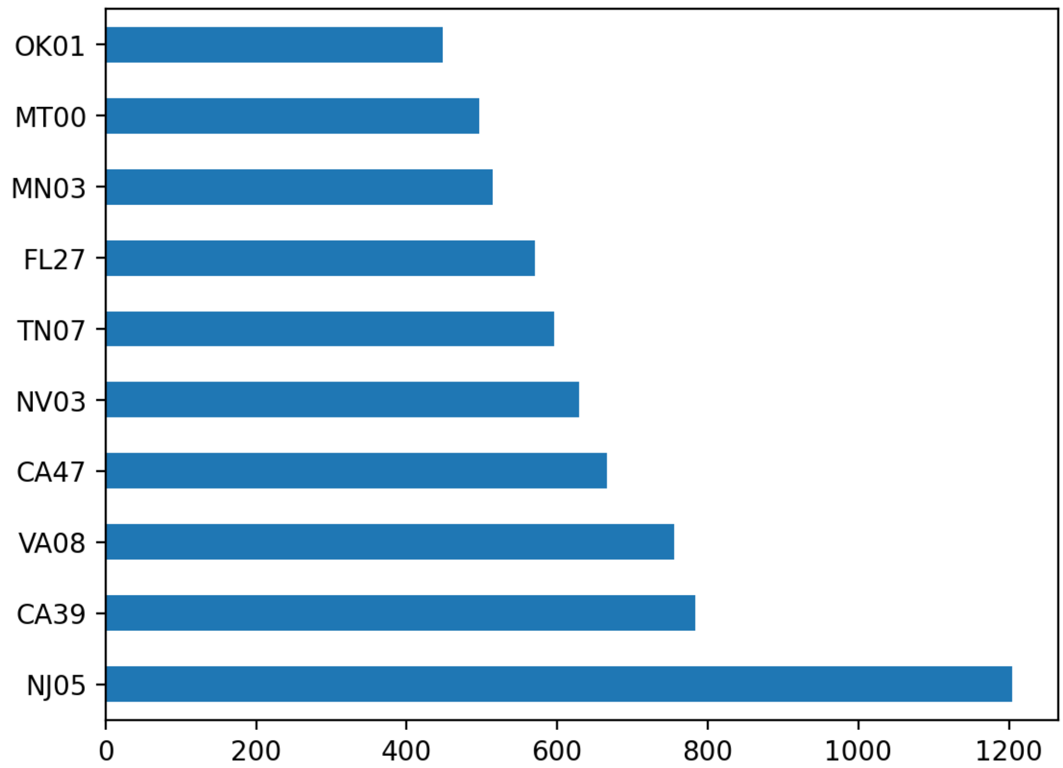
[15]:
```
combined['amount'].value_counts().plot(kind='barh');
```



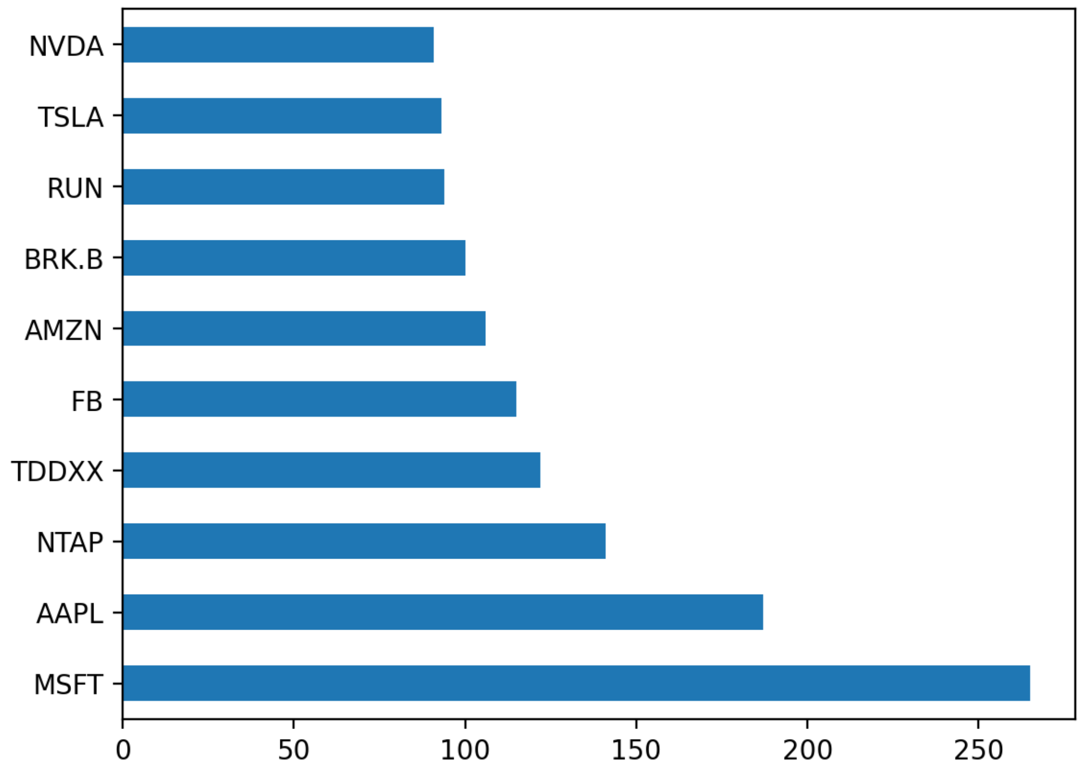
[16]:
```
combined['representative'].value_counts().head(10).plot(kind='barh');
```



[17]:
```
combined['district'].value_counts().head(10).plot(kind='barh');
```



[18]:
```
combined['ticker'].value_counts().head(10).plot(kind='barh');
```



3.0.4 Assessment of Missingness

[19]:
```
# find columns having missing datas
combined.isna().sum()
```

[19]:
```
disclosure_year            0
disclosure_date            0
transaction_date           7
owner                   6013
ticker                  1296
asset_description          4
type                       0
amount                     0
representative             0
district                   0
ptr_link                   0
cap_gains_over_200_usd     0
first_name                 0
last_name                  0
party                      0
dtype: int64
```

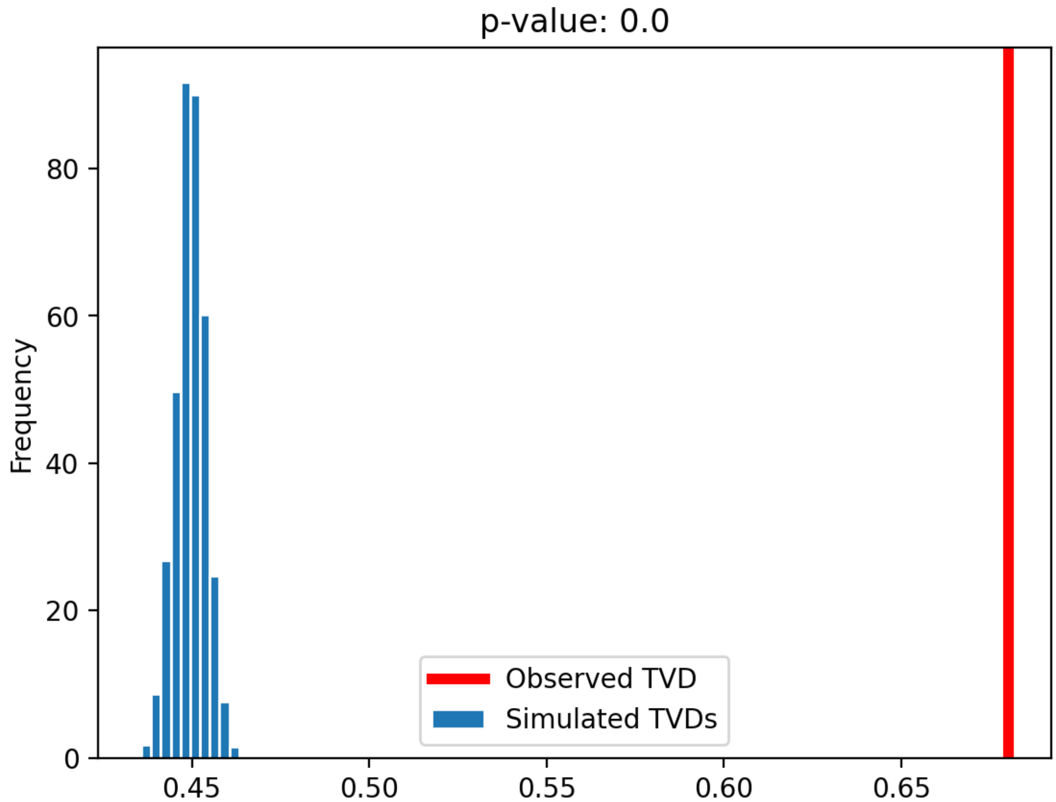
[20]:
```
combined['owner'] = combined['owner'].replace('--', np.NaN)
```

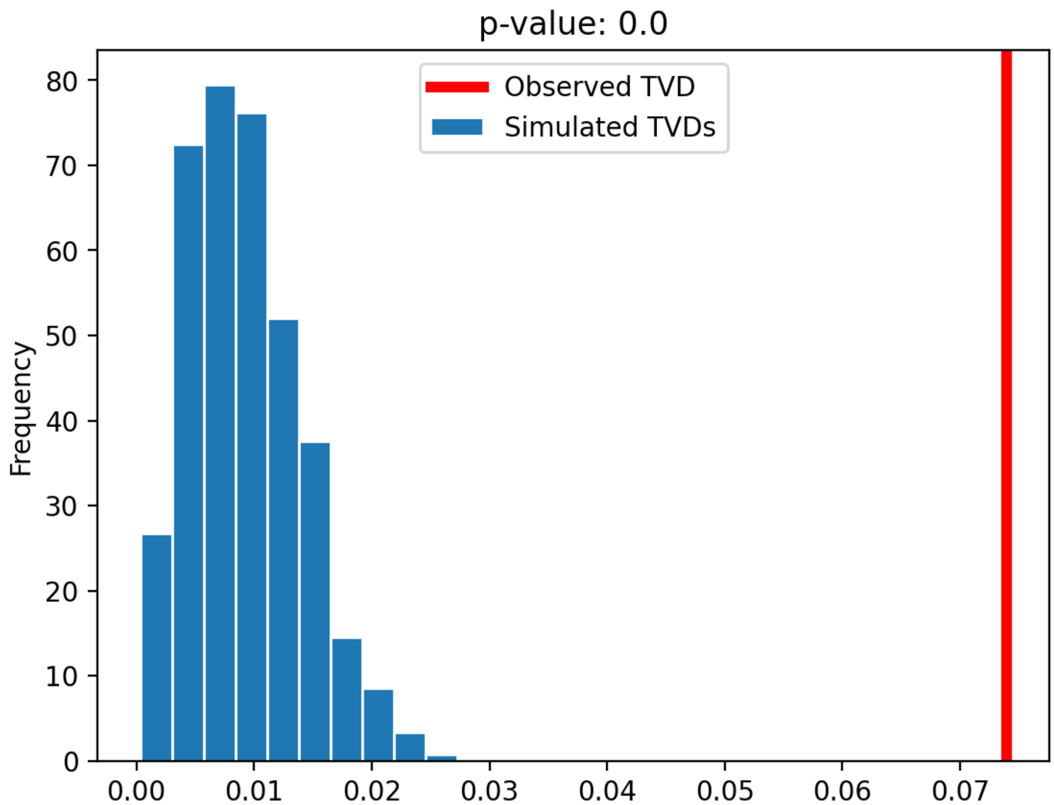
- two columns we have to take closer look is owner and ticker in which having the most missingness
  - assess whether owner is MAR or MCAR
  - assess whether ticker is MAR or MCAR

[21]:
```
def calc_tvd(df, missing_col, col):
    dist = (
        df
        .assign(**{f'{missing_col}_null': df[missing_col].isna()})
        .pivot_table(index=col, columns=f'{missing_col}_null', aggfunc='size',␣
 ↪fill_value=0)
    )
    dist = dist / dist.sum()
    return dist.diff(axis=1).iloc[:, -1].abs().sum() / 2


def missingness_perm_test(df, missing_col, col):
    shuffled = df.copy()
    shuffled[f'{missing_col}_null'] = shuffled[missing_col].isna()

    obs_tvd = calc_tvd(df, missing_col, col)

    n_repetitions = 1000
    tvds = []
    for _ in range(n_repetitions):

        # Shuffling genders and assigning back to the DataFrame
        shuffled[col] = np.random.permutation(shuffled[col])

        # Computing and storing TVD
        tvd = calc_tvd(shuffled, missing_col, col)
        tvds.append(tvd)

    tvds = np.array(tvds)
    pval = np.mean(tvds >= obs_tvd)

    # Draw the p-value graph
    pd.Series(tvds).plot(kind='hist', density=True, ec='w', bins=10,␣
 ↪title=f'p-value: {pval}', label='Simulated TVDs')
    plt.axvline(x=obs_tvd, color='red', linewidth=4, label='Observed TVD')
    plt.legend()
    plt.show()

    return pval
```

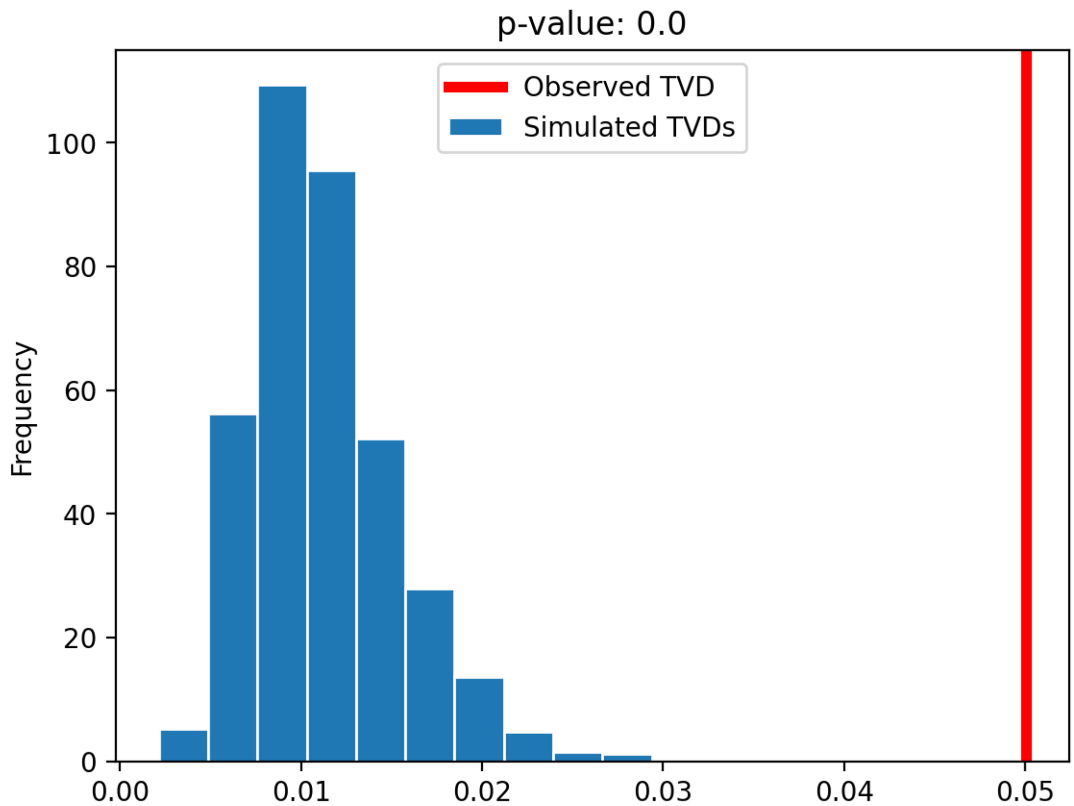
determine the relationship of owner missingness with col [type, amount, representative]

[22]:
```
p_val = []
for col in combined.columns[5:8]:
    p_val.append(missingness_perm_test(combined, 'owner', col))
p_val
# we determined the missing values in owner are MAR
```





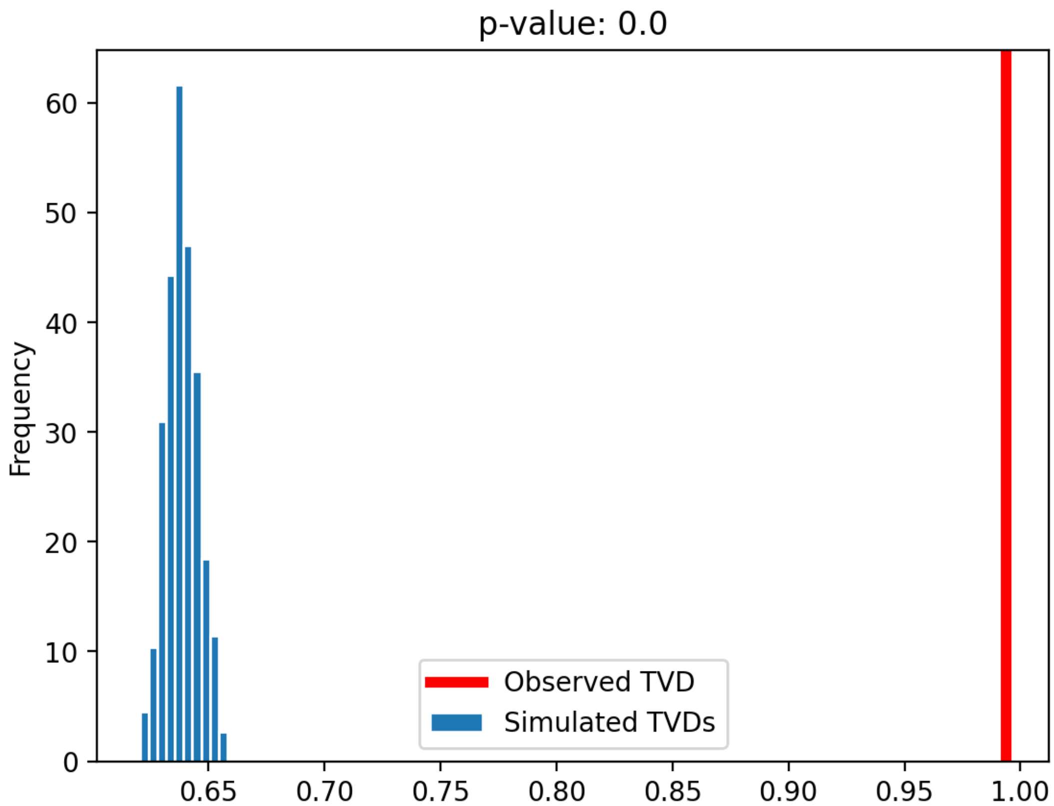
p-value: 0.0
Observed TVD
Simulated TVDs
Frequency
0
10
20
30
40
50
60
70
80
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07

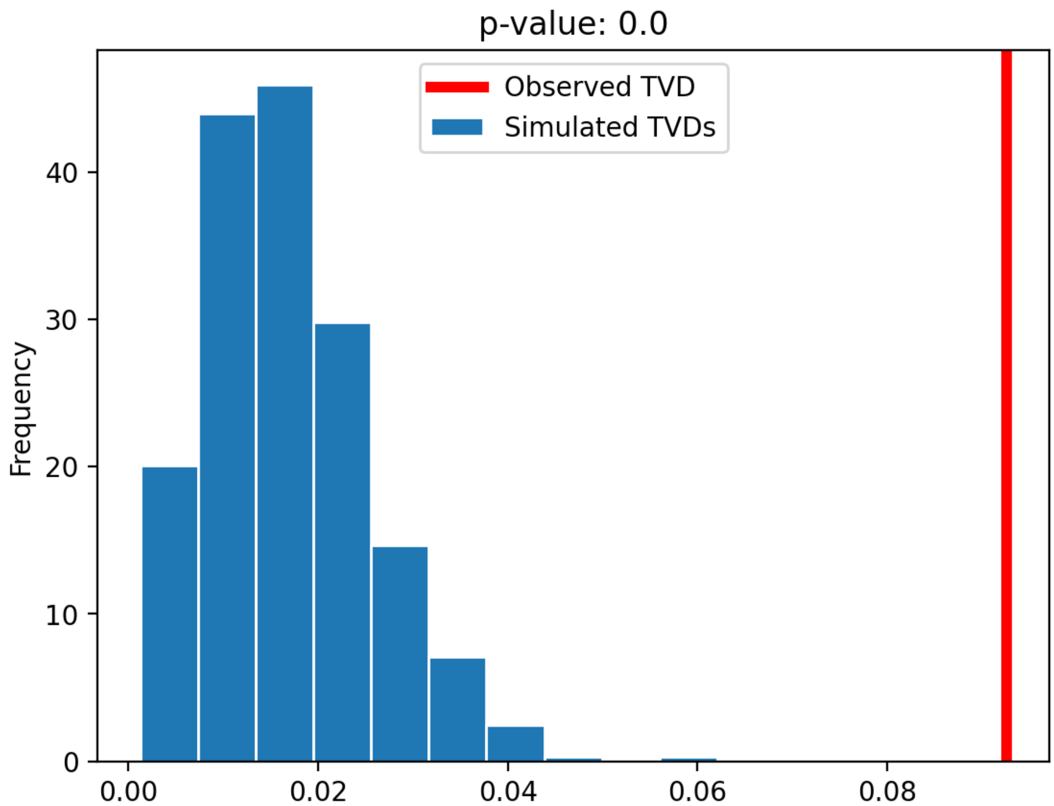


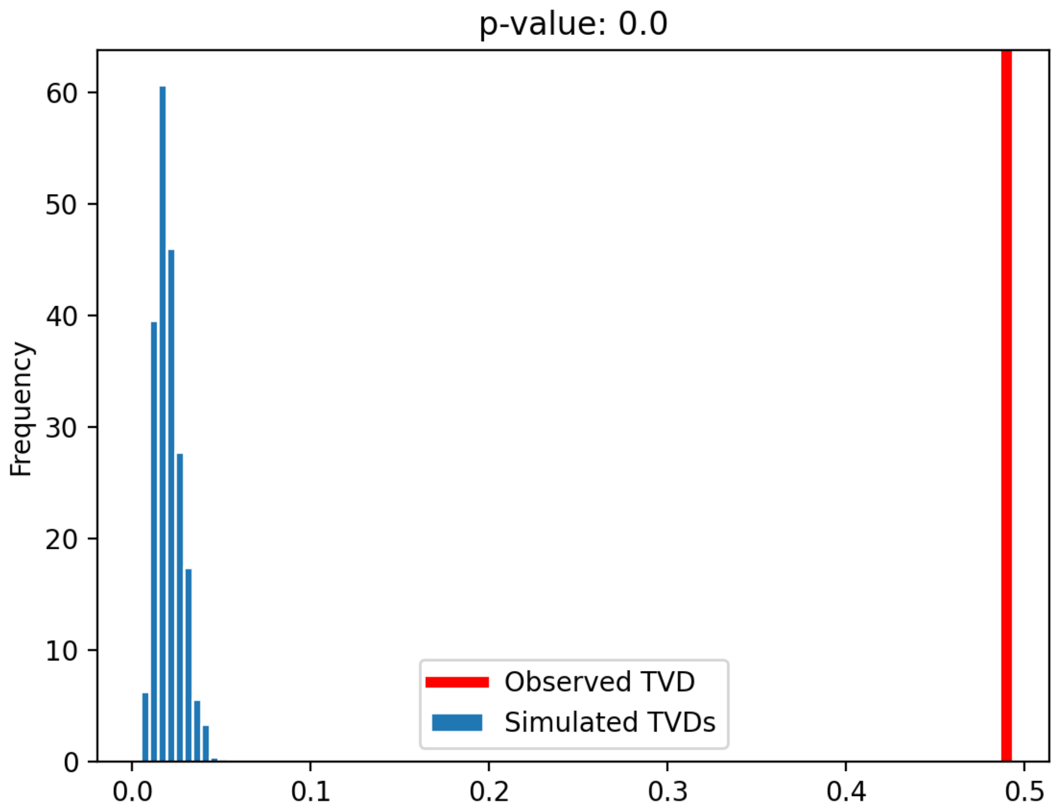
[22]: [0.0, 0.0, 0.0]

determine the relationship of ticker missingness with col [type, amount, representative]

[23]:
```
p_vals = []
for col in combined.columns[5:8]:
    p_vals.append(missingness_perm_test(combined, 'ticker', col))
p_vals
# we determined the missing values in ticker are MAR
```


p-value: 0.0
Frequency
Observed TVD
Simulated TVDs
0
10
20
30
40
50
60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00


p-value: 0.0
Observed TVD
Simulated TVDs
Frequency
0
10
20
30
40
0.00
0.02
0.04
0.06
0.08



[23]: [0.0, 0.0, 0.0]

So we conclude that the missingness of `owner` is **MAR**, and it's dependent on `type` column the most.

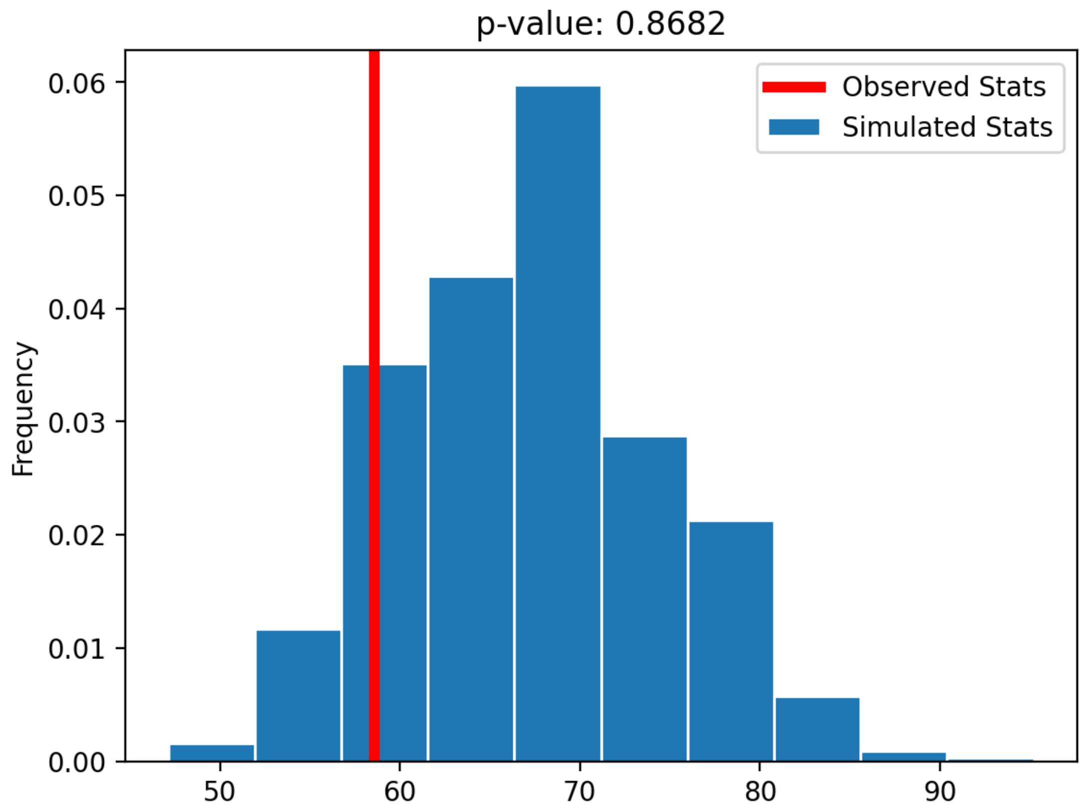
3.0.5 Hypothesis Test / Permutation Test

Which party trade more often?

- **Null hypothesis**: the distribution of trading frequency among congresspeople from different party is the same. The difference between the two observed sample is due to chance.
- **Alternative hypothesis**: the distribution of trading frequency among congresspeople from different party are different.

[24]:
```
df = combined.assign(transaction_year=combined['transaction_date'].dt.year,
                     transaction_month=combined['transaction_date'].dt.month)
df = (
    df
    .groupby(['transaction_year', 'transaction_month',␣
 ↪'party'])[['representative']]
    .count()
    .reset_index()
```

```
)
democrat_stats = df.loc[df['party'] == 'Democrat', 'representative'].sum() /␣
↪(df['party'] == 'Democrat').sum()
republican_stats =  df.loc[df['party'] == 'Republican', 'representative'].sum()␣
↪/ (df['party'] == 'Republican').sum()

obs_stats = abs(democrat_stats - republican_stats)

shuffled = combined.assign(transaction_year=combined['transaction_date'].dt.
↪year,
                           transaction_month=combined['transaction_date'].dt.
↪month)

n_repetitions = 5000
stats = []
for _ in range(n_repetitions):

    # Shuffling genders and assigning back to the DataFrame
    shuffled['party'] = np.random.permutation(shuffled['party'])

    # Computing and storing TVD
    pivoted = (
        shuffled
        .groupby(['transaction_year', 'transaction_month',␣
↪'party'])[['representative']]
        .count()
        .reset_index()
    )

    democrat_stats = pivoted.loc[pivoted['party'] == 'Democrat',␣
↪'representative'].sum() / (pivoted['party'] == 'Democrat').sum()
    republican_stats =  pivoted.loc[pivoted['party'] == 'Republican',␣
↪'representative'].sum() / (pivoted['party'] == 'Republican').sum()
    stats.append(abs(democrat_stats - republican_stats))

stats = np.array(stats)
pval = np.mean(stats >= obs_stats)

pd.Series(stats).plot(kind='hist', density=True, ec='w', bins=10,␣
↪title=f'p-value: {pval}', label='Simulated Stats')
plt.axvline(x=obs_stats, color='red', linewidth=4, label='Observed Stats')
plt.legend();
```



Conclusion The p-value of the permutation test is `0.8722`, which is way larger the the `0.05`. Thus, we **fail to reject** the null hypothesis, which means that distribution of trading frequency among congresspeople from different party may be the same.

Which party make larger trades?

- **Null hypothesis**: the distribution of trading amount among congresspeople from different party is the same. The difference between the two observed samples is due to chance.
- **Alternative hypothesis**: In the US, the distributions of trading amount of the two groups are different.

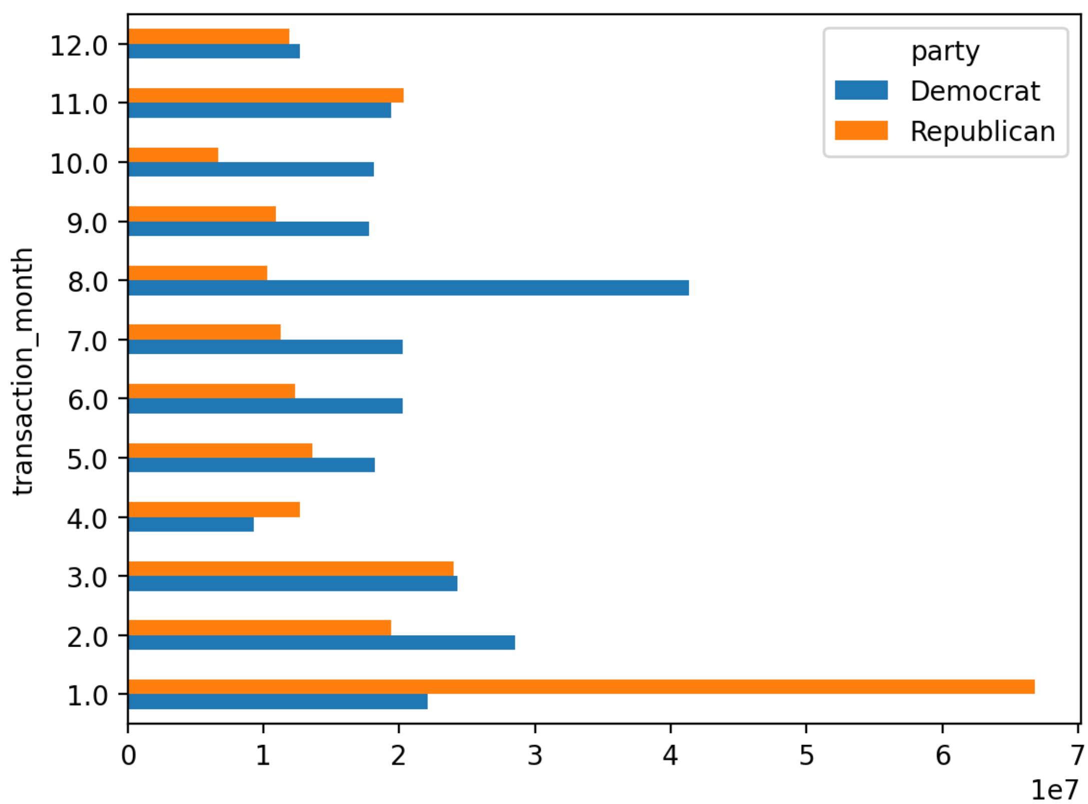
[14]:
```
cb_copy = combined.copy()
cb_copy['amount'] = cb_copy['amount'].str.split(' - ')




def transform(df):
    return int(df['amount'][0].strip('$').replace(',','').replace(' -','').
 ↪replace(' +',''))
```

```
cb_copy['amount'] = cb_copy.apply(transform, axis = 1)
```

[18]:
```
cb_copy = cb_copy.assign(transaction_year=combined['transaction_date'].dt.year,
                         transaction_month=combined['transaction_date'].dt.month)
cb_copy

cb_copy.to_csv("data/Congress_Trading_Behavior.csv")
```

[27]:
```
total_trade = pd.pivot_table(cb_copy, values='amount',␣
 ↪index='transaction_month', columns='party',aggfunc='sum').
 ↪drop(columns='Independent')
total_trade.plot(kind='barh')
```

[27]: <AxesSubplot:ylabel='transaction_month'>

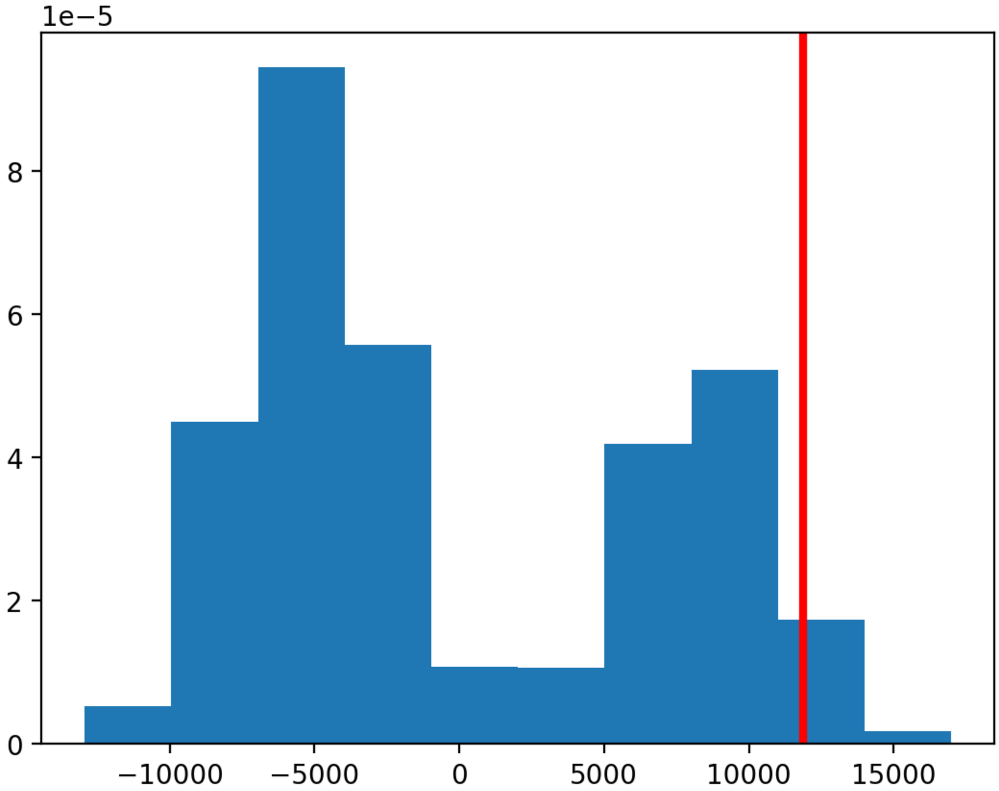


[28]:
```
distr = cb_copy[['party','amount']]
distr = distr[distr['party'] != 'Independent']

obs_diff = distr.groupby('party').mean().diff().iloc[-1][0]

n_repetitions = 5000
```

```
differences = []
for _ in range(n_repetitions):

    shuffled_party= (
        distr['party']
        .sample(frac=1)
        .reset_index(drop=True)
    )

    shuffled = (
        distr
        .assign(**{'shuffled_party': shuffled_party})
    )

    # Step 3: Compute the test statistic
    group_means = (
        shuffled
        .groupby('shuffled_party')
        .mean()
        .loc[:, 'amount']
    )
    difference = group_means.diff().iloc[-1]

    # Step 4: Store the result
    differences.append(difference)

pval = (np.array(differences) >= obs_diff).mean()
print('obs', obs_diff,'pval', pval)
plt.hist(differences, density=True)
plt.axvline(x=obs_diff, color='red', linewidth=3, label='P-value')
```

```
obs 11862.298356514457 pval 0.0318
```

[28]:
```
<matplotlib.lines.Line2D at 0x7fb3a35bdb80>
```



Null hypothesis we reject the null and conclude there might be chance of two group having difference trading amount

What congresspeople have made the most trades (amount)?

- Kevin Hern with trade amount of $ 68733447 in total

[29]:
```
cb_copy.groupby('representative')['amount'].sum().idxmax()
```

[29]: 'Kevin Hern'

What companies are most traded by congresspeople?

- Microsoft (MSFT)

[30]:
```
cb_copy.groupby('ticker')['representative'].count().idxmax()
```

[30]: 'MSFT'

When are stocks bought and sold? Is there a day of the week that is most common? Or a month of the year? Thursday, Feburary

[31]:
```
def to_weekday(x):
    day = x.weekday()
    if day == 0:
        return 'Monday'
    elif day == 1:
        return 'Tuesday'
    elif day == 2:
        return 'Wednesday'
    elif day == 3:
        return 'Thursday'
    elif day == 4:
        return 'Friday'
    elif day == 5:
        return 'Saturday'
    else:
        return 'Sunday'

df = combined.assign(weekday=combined['transaction_date'].apply(to_weekday))
df.groupby('weekday').count().rename(columns={'transaction_date':␣
 ↪'count'})['count'].idxmax()
```

[31]:
```
'Thursday'
```

[32]:
```
df = combined.assign(month=combined['transaction_date'].dt.month)
df.groupby('month').count().rename(columns={'transaction_date':␣
 ↪'count'})['count'].idxmax()
```

[32]:
```
2.0
```