EDA, Missingness and Hypothesis Analysis of Congressmember Stock Trades

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Summary of Findings

Introduction

This dataset primarily contains information relating to stock trades made by members of the US congress. The majority of the data is categorical which had great impact on how to approach analysis. This analysis is primarily focused in inquiring further about how party affilition is related to various other variables part of transactions.

Cleaning and EDA

It was observed that the owner variable had many values missing and the missingness mechanism was to be further explored. Cleaning involved converting the dates formating to timestamps, making sure to replace user nan values with appropriate nan values for analysis. The data cleaning also involved manual cleanup of representative names in order to merge with a second dataset that contained party affiliation which was not part of the original dataset. EDA revealed that the two biggest stocks held amongst both republicans and democrats was Apple and Microsoft, further exploration showed that republicans tended to trade older technology and traditional energy companies compared to democrats who traded newer technology, solar energy and large holdings companies. Within the data set it was observed that democrats traded about 63% of the trades and republicans made up 36% of the trades, further more when analysing the amount traded by party it was found that democrats engaged in many more high usd value trades that were at or exceeded $500,000.

Assessment of Missingness

It was found that the Owner variable may be NMAR, but MAR permutation testing showed that the missingness of owner is in fact MAR dependent on amount, type, and party variables.

Hypothesis Test

When hypothesizing about the proportion of trades based on party affiliation, a null hypothesis in which party affiliates traded at equal proportions was rejected in favor of a alternative hypothesis that democrats tend to initiate more trades than republicans.

Code

In [207]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
import requests
import bs4
```

Cleaning and EDA

Load the data and take an initial look

In [208]:
```
raw_data = pd.read_csv('all_transactions.csv')
raw_data.head()
```

Out[208]:

	disclosure_year	disclosure_date	transaction_date	owner	ticker	asset_description	
0	2021	10/04/2021	2021-09-27	joint	BP	BP plc	pu
1	2021	10/04/2021	2021-09-13	joint	XOM	Exxon Mobil Corporation	pu
2	2021	10/04/2021	2021-09-10	joint	ILPT	Industrial Logistics Properties Trust - Common...	pu
3	2021	10/04/2021	2021-09-28	joint	PM	Phillip Morris International Inc	pu
4	2021	10/04/2021	2021-09-17	self	BLK	BlackRock Inc	sale

Okay merging political party on names might be a good idea, let's get clean up names column by removing 'Hon.' from all names, also by deafult if there was no value in csv is was loaded into dataframe with np.nan float but some values were loaded with '--' so let's change those to np.nan floats across all columns and rows and lets check to make sure all columns have appropriate data

In [299]:
```
raw_data = pd.read_csv('all_transactions.csv')
#raw_data

raw_data['representative'] = raw_data['representative']
    .apply(lambda x: x.replace('Hon. ',''))
#raw_data[:50]

raw_data_nan = raw_data.replace('--',np.nan)
#raw_data_nan['ticker'].value_counts()
```

The transaction_date has a different format to where we can't just easily convert it to timestamp so we let's make a helper function to prep is to that we can call to_datetime on cleaned series

In [210]:
```
def convert_date(x):
    return x[5:7] + '/' + x[8:] + '/' + x[0:4]
```

Convert the transaction and discolse dates to timestamps

In [211]:
```
raw_data_nan['disclosure_date'] = pd.to_datetime(
    raw_data_nan['disclosure_date'])


raw_data_nan['transaction_date'] = raw_data_nan['transaction_date']
    .apply(convert_date)
raw_data_nan['transaction_date'] = pd.to_datetime(
    raw_data_nan['transaction_date'])
raw_data_nan
#raw_data_nan['transaction_date'] = pd.to_datetime(raw_data_nan['tra
#raw_data_nan
```

...	...	...	...	...	...	.
14269	2020	2020-06-10	2020-04-09	NaN	SWK	Stanley Black Decker, Inc
14270	2020	2020-06-10	2020-04-09	NaN	USB	U.S. Bancor
14271	2020	2020-06-10	2020-03-13	NaN	BMY	Bristol-Myer Squibb Compan
14272	2020	2020-06-10	2020-03-13	NaN	LLY	Eli Lilly an Compan
14273	2020	2020-06-10	2020-03-13	NaN	DIS	Walt Disne Compan

14274 rows × 12 columns

Let's go over a couple columns and check values to make sure different forms of nans aren't showing up

In [216]:
```
print(raw_data_nan['disclosure_year'].value_counts())
print('sum:', raw_data_nan['disclosure_year'].value_counts().sum())
```

```
2020    7379
2021    5520
2022    1375
Name: disclosure_year, dtype: int64
sum: 14274
```

Overall data types, leaving disclosure year as int seems fine because it can be used as a broad categorial variable, more refined data with months and days have been converted to datetimes, the rest are fine as strings in cludeing amount. The amount has a coarse granularity because it only captures ranges no a specific monetary amount so we will have to use it as a categorical variable. We could extract days and months for further accuracy if we want.

In [217]:
```
raw_data_nan.dtypes
```

Out[217]:
```
disclosure_year                    int64
disclosure_date           datetime64[ns]
transaction_date          datetime64[ns]
owner                             object
ticker                            object
asset_description                 object
type                              object
amount                            object
representative                    object
district                          object
ptr_link                          object
cap_gains_over_200_usd              bool
dtype: object
```

Verify datetime data type

In [218]:
```
raw_data_nan['disclosure_date'][0]
```

Out[218]:
```
Timestamp('2021-10-04 00:00:00')
```

In [219]:
```
raw_data_nan
```

...	...	...	...	...	...	.
14269	2020	2020-06-10	2020-04-09	NaN	SWK	Stanley Black Decker, Inc
14270	2020	2020-06-10	2020-04-09	NaN	USB	U.S. Bancor
14271	2020	2020-06-10	2020-03-13	NaN	BMY	Bristol-Myer Squibb Compan
14272	2020	2020-06-10	2020-03-13	NaN	LLY	Eli Lilly an Compan
14273	2020	2020-06-10	2020-03-13	NaN	DIS	Walt Disne Compan

Just going to check values to make sure nothing weird appears, or variation of nan value

In [220]:
```
raw_data_nan['disclosure_year'].value_counts()
```

Out[220]:
```
2020    7379
2021    5520
2022    1375
Name: disclosure_year, dtype: int64
```

In [221]:
```
raw_data_nan['disclosure_date'].value_counts()
```

Out[221]:
```
2020-04-27    581
2020-04-16    272
2021-03-16    199
2020-06-15    165
2021-10-08    163
             ... 
2020-08-11      1
2020-12-24      1
2021-11-23      1
2021-05-27      1
2022-04-27      1
Name: disclosure_date, Length: 606, dtype: int64
```

In [222]:
```
raw_data_nan['transaction_date'].value_counts()
```

Out[222]:
```
2020-03-18    292
2019-06-24    204
2021-02-16    194
2020-11-13    133
2020-02-20    129
             ... 
2020-06-21      1
2019-11-04      1
2019-10-03      1
2019-10-30      1
2020-03-28      1
Name: transaction_date, Length: 790, dtype: int64
```

In [229]:
```
print(raw_data_nan['owner'].value_counts())
print((raw_data_nan['owner'].astype(str) == 'nan').sum()
      + (raw_data_nan['owner'].astype(str) != 'nan').sum())
(raw_data_nan['owner'].astype(str) == 'nan').sum()
```

```
joint        4418
self         2799
dependent     388
Name: owner, dtype: int64
14274
```

Out[229]:
```
6669
```

A significant amount of owner types are still nan, this could be looked at for missingness analysis

In [300]:
```
print(raw_data_nan['ticker'].value_counts())
(raw_data_nan['ticker'].astype(str) == 'nan').sum()
```

```
MSFT     239
AAPL     173
NTAP     124
TDDXX    122
FB       106
        ... 
GME        1
PB         1
PSB        1
QRTEA      1
LSFYX      1
Name: ticker, Length: 2072, dtype: int64
```

Out[300]:
```
1147
```

there are around 1,000 nan's here in tickers... I'm thinking maybe they didn't invest particularly in stock but some sort of investment that doesn't have a ticker?

In [232]:
```
print(raw_data_nan['asset_description'].value_counts())
(raw_data_nan['asset_description'].astype(str) == 'nan').sum()
```

```
Microsoft Corporation                            191
BLF FedFund                                      119
Apple Inc.                                       113
Sunrun Inc.                                       93
Apple Inc                                         61
                                                ... 
Proctor & Gamble Company                           1
Prudential Financial                               1
Reata Pharmaceuticals, Inc - Class A stock         1
Republic Services                                  1
GrubHub Inc.                                       1
Name: asset_description, Length: 5000, dtype: int64
```

Out[232]:
```
4
```

```
only 4 missing here
```

In [233]:
```
print(raw_data_nan['type'].value_counts())
raw_data_nan['type'].value_counts().sum()
```

```
purchase        7428
sale_full       4563
sale_partial    2155
exchange         128
Name: type, dtype: int64
```

Out[233]:
```
14274
```

```
All types are present
```

In [234]:
```
print(raw_data_nan['amount'].value_counts())
raw_data_nan['amount'].value_counts().sum()
```

```
$1,001 - $15,000            10054
$15,001 - $50,000            2258
$50,001 - $100,000            722
$100,001 - $250,000           545
$1,001 -                      242
$250,001 - $500,000           227
$500,001 - $1,000,000         142
$1,000,001 - $5,000,000        38
$1,000,000 +                   28
$5,000,001 - $25,000,000        9
$1,000 - $15,000                4
$15,000 - $50,000               3
$50,000,000 +                   1
$1,000,000 - $5,000,000         1
Name: amount, dtype: int64
```

Out[234]:
```
14274
```

Hmmm, not sure how to interperet $1,001 - , but all amounts are present

I tried to webscrape because the site that hosts the data convenietnly had all formated names and party affiliation in one place but the get request never seemed to return the html I was looking for, bummer.

In [51]:
```
raw_get = requests.get('https://housestockwatcher.com/summary_by_rep
raw_get.text
#stock_party_soup = bs4.BeautifulSoup(raw_get.text)
#stock_party_soup
```

Out[51]:
'<!doctype html><html lang="en"><head><meta charset="utf-8"/><meta
name="viewport" content="width=device-width,initial-scale=1"/><meta
http-equiv="X-UA-Compatible" content="IE=edge,chrome=1"/><meta cont
ent="width=device-width,initial-scale=1,shrink-to-fit=no" name="vie
wport"/><meta name="title" content="House Stock Watcher - See What
Your Representative Is Trading"><meta name="description" content="U
pdated Daily - See the stock trades US Representatives are making a
s they are reported. Get notifications when new reports are uploade
d. Get insight now!"><meta property="og:type" content="website"><me
ta property="og:url" content="https://housestockwatcher.com"><meta
property="og:title" content="House Stock Watcher - See What Your Re
presentative Is Trading"><meta property="og:description" content="U
pdated Daily - See the stock trades US Representatives are making a
s they are reported. Get notifications when new reports are uploade
d. Get insight now!"><meta property="og:image" content="https://hou
sestockwatcher.com/promo1.png"><meta property="twitter:card" conten
t="summary_large_image"><meta property="twitter:url" content="http
s://housestockwatcher.com/"><meta property="twitter:title" content
="House Stock Watcher - See What Your Representative Is Trading"><m
eta property="twitter:description" content="Updated Daily - See the
stock trades US Representatives are making as they are reported. Ge
t notifications when new reports are uploaded. Get insight now!"><m
eta property="twitter:image" content="https://housestockwatcher.co
m/promo1.png"><title>House Stock Watcher - See What Your Representa
tive Is Trading</title><link rel="shortcut icon" href="/favicon.pn
g"/><link rel="apple-touch-icon" sizes="76x76" href="/apple-icon.pn
g"/><link rel="manifest" href="/manifest.json"/><link rel="styleshe
et" href="/tailwind.min.css"/><link href="https://unpkg.com/tailwin
dcss@^2/dist/tailwind.min.css" rel="stylesheet"><script async src
="https://www.googletagmanager.com/gtag/js?id=G-Z63X8GDP3C"></scrip
t><script>function gtag(){dataLayer.push(arguments)}window.dataLaye
r=window.dataLayer||[],gtag("js",new Date),gtag("config","G-Z63X8GD
P3C")</script><script async src="https://pagead2.googlesyndication.
com/pagead/js/adsbygoogle.js?client=ca-pub-2466331850146937" crosso
rigin="anonymous"></script><link href="/static/css/2.15bea899.chun
k.css" rel="stylesheet"><link href="/static/css/main.ce686fcf.chun
k.css" rel="stylesheet"></head><body class="text-blueGray-700 antia
liased"><noscript>You need to enable JavaScript to run this app.</n
oscript><div id="root"></div><script>!function(e){function t(t){for
(var n,f,l=t[0],a=t[1],c=t[2],p=0,s=[];p<l.length;p++)f=l[p],Objec
t.prototype.hasOwnProperty.call(o,f)&&o[f]&&s.push(o[f][0]),o[f]=0;
for(n in a)Object.prototype.hasOwnProperty.call(a,n)&&(e[n]=a[n]);f
or(i&&i(t);s.length;)s.shift()();return u.push.apply(u,c||[]),r()}f
unction r(){for(var e,t=0;t<u.length;t++){for(var r=u[t],n=!0,l=1;l
<r.length;l++){var a=r[l];0!==o[a]&&(n=!1)}n&&(u.splice(t--,1),e=f
(f.s=r[0]))}return e}var n={},o={1:0},u=[];function f(t){if(n[t])re
turn n[t].exports;var r=n[t]={i:t,l:!1,exports:{}};return e[t].call
(r.exports,r,r.exports,f),r.l=!0,r.exports}f.m=e,f.c=n,f.d=function
(e,t,r){f.o(e,t)||Object.defineProperty(e,t,{enumerable:!0,get:
r})},f.r=function(e){"undefined"!=typeof Symbol&&Symbol.toStringTag
&&Object.defineProperty(e,Symbol.toStringTag,{value:"Module"}),Obje
ct.defineProperty(e,"__esModule",{value:!0})},f.t=function(e,t){if

```
(1&t&&(e=f(e)),8&t)return e;if(4&t&&"object"==typeof e&&e&&e.__esMo
dule)return e;var r=Object.create(null);if(f.r(r),Object.defineProp
erty(r,"default",{enumerable:!0,value:e}),2&t&&"string"!=typeof e)f
or(var n in e)f.d(r,n,function(t){return e[t]}.bind(null,n));return
r},f.n=function(e){var t=e&&e.__esModule?function(){return e.defaul
t}:function(){return e};return f.d(t,"a",t),t},f.o=function(e,t){re
turn Object.prototype.hasOwnProperty.call(e,t)},f.p="/";var l=this
["webpackJsonphouse-stock-watcher-frontend"]=this["webpackJsonphous
e-stock-watcher-frontend"]||[],a=l.push.bind(l);l.push=t,l=l.slice
();for(var c=0;c<l.length;c++)t(l[c]);var i=a;r()}([])</script><scr
ipt src="/static/js/2.d782ad26.chunk.js"></script><script src="/sta
tic/js/main.8db78f46.chunk.js"></script></body></html>'
```

Now that raw data is all cleaned up lets merge with our political party dataset which has congressmember names and party affiliation. I was able to copy and paste the text from this website https://ballotpedia.org/List_of_current_members_of_the_U.S._Congress (https://ballotpedia.org/List_of_current_members_of_the_U.S._Congress)

right into google sheets and then generate a csv but I still had to clean up around 90 names manually. Some had middle initals, some former members were not included and there were some that had titles like Mr. Mrs. and Dr. This process took quite a while and actually made me appreciate/respect the data cleaning process more.

In [303]:
```
congress_party = pd.read_csv('congress_parties.csv')
congress_party.shape

congress_party = pd.read_csv('congress_parties.csv')
#split name so we can extract last name
congress_party['last_name'] = congress_party['full_name']
    .apply(str.split,' ')
#extract last name and set it to new column
congress_party['last_name'] = congress_party['last_name']
    .apply(lambda x: x[-1])
print(congress_party['last_name'].nunique())
congress_party.nunique()


#merge and then verify all names have been mapped to political party
merged = raw_data_nan.merge(congress_party,left_on = 'representative
                            right_on='full_name', how='left')
merged.groupby('party').count().sum()#[merged['full_name'].astype(st
```

```
502
```

Out[303]:
```
disclosure_year          14274
disclosure_date          14274
transaction_date         14274
owner                     7605
ticker                   13127
asset_description        14270
type                     14274
amount                   14274
representative           14274
district                 14274
ptr_link                 14274
cap_gains_over_200_usd   14274
full_name                14274
last_name                14274
dtype: int64
```

In [305]:
```
merged['ticker'].value_counts().sum()
```

Out[305]:
```
13127
```

```
About 1000 tickers missing, maybe
```

While it says there are 502 unique congress members part of the data set there is actually a bit less, when manually cleaning name mappings I noticed some transactions had different names for the same people, for example same person but one identidy might have mr. or a middle initail while another just has first and last name. When looking at value counts we see they all add up to the original size of the data set except for owner which has a significant amount of values missign almost half and asset description missing 4. For our missingness question we will probably be inquiring further about the mechanism behind the owner data missing.

Now that we have our merged and cleaned dataset let's perform some univariate analysis and take a look into some of the individual columns

In [236]:
```
raw_data_nan
```

Out[236]:

	disclosure_year	disclosure_date	transaction_date	owner	ticker	asset_description
0	2021	2021-10-04	2021-09-27	joint	BP	BP plc
1	2021	2021-10-04	2021-09-13	joint	XOM	Exxon Mobil Corporation
2	2021	2021-10-04	2021-09-10	joint	ILPT	Industrial Logistics Properties Trust - Common...
3	2021	2021-10-04	2021-09-28	joint	PM	Phillip Morris International Inc
4	2021	2021-10-04	2021-09-17	self	BLK	BlackRock Inc
...	...	...	...	...	...	...
14269	2020	2020-06-10	2020-04-09	NaN	SWK	Stanley Black & Decker, Inc.
14270	2020	2020-06-10	2020-04-09	NaN	USB	U.S. Bancorp
14271	2020	2020-06-10	2020-03-13	NaN	BMY	Bristol-Myers Squibb Company
14272	2020	2020-06-10	2020-03-13	NaN	LLY	Eli Lilly and Company
14273	2020	2020-06-10	2020-03-13	NaN	DIS	Walt Disney Company

14274 rows × 12 columns

```
Let's take a quick look at the range of the year in which data was
gathered
```

In [237]:
```
raw_data_nan['disclosure_year'].value_counts()
```

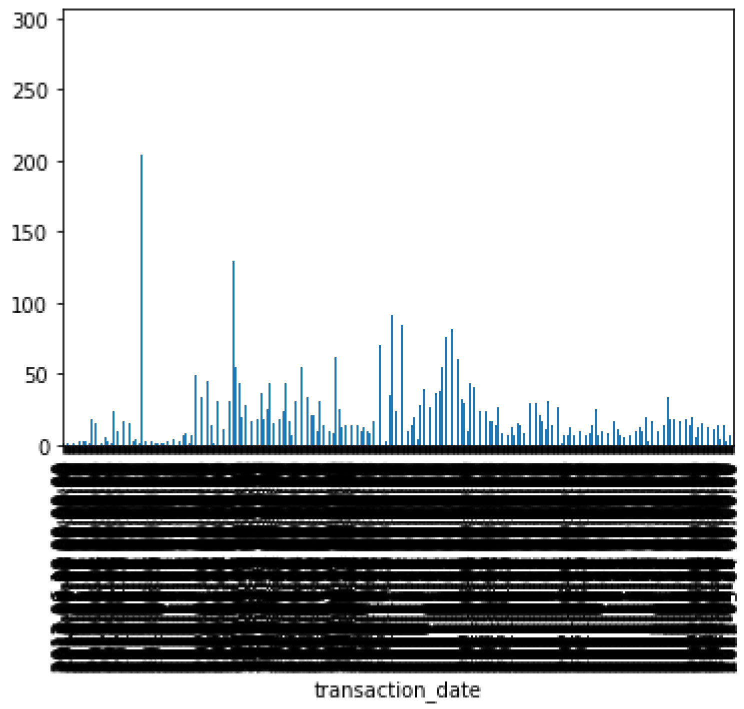
Out[237]:
```
2020    7379
2021    5520
2022    1375
Name: disclosure_year, dtype: int64
```

The years are quite relavent and given the turbulence of the markets over the last recent year this should be an interesting analysis

lets look at the volume of trades by date

In [251]:
```
date_group = raw_data_nan.groupby('transaction_date').count()

date_group['disclosure_year'].plot(kind='bar')
#date_group.plot(kind='bar', x='transaction_year')
```

Out[251]:
```
<AxesSubplot:xlabel='transaction_date'>
```



Well that doesn't look pretty at all, even with the messed up x axis we can kind of see some huge spikes this may be because the transaction dates were not properly recorded? It's weird that there is a massive spike early on and seemingly nothing around the massive spike. I should probably create a column that contains the month, but lets try the years instead

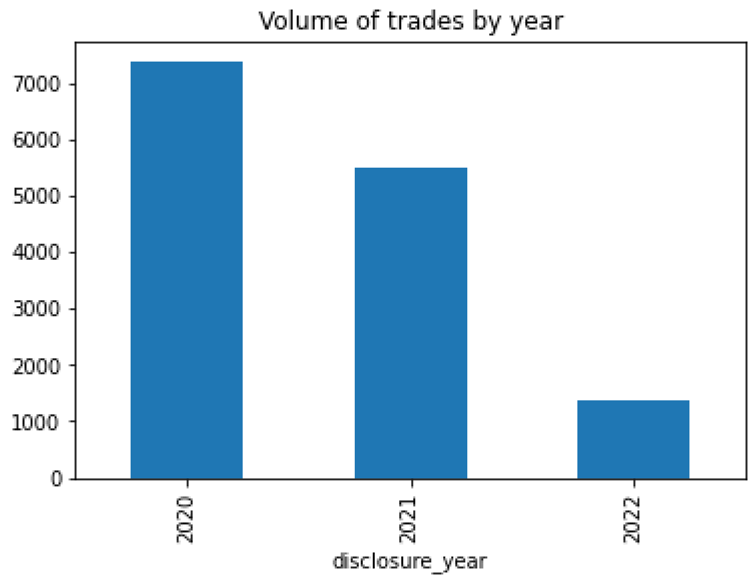
In [270]:
```
date_group = raw_data_nan.groupby('transaction_date').count()
date_group['disclosure_date'].sort_values(ascending = False)[:20]
```

Out[270]:
```
transaction_date
2020-03-18    292
2019-06-24    204
2021-02-16    194
2020-11-13    133
2020-04-02    129
2020-02-20    129
2021-02-11    124
2020-10-22     98
2020-11-05     91
2020-03-23     90
2020-11-19     84
2021-02-05     81
2020-04-29     77
2020-01-13     76
2021-01-28     75
2020-08-07     71
2020-10-16     70
2020-03-27     70
2021-01-15     69
2021-02-17     69
Name: disclosure_date, dtype: int64
```

We can sort of get some sense of the months now

In [254]:
```
date_group = raw_data_nan.groupby('disclosure_year').count()

date_group['disclosure_date'].plot(kind='bar',
                                   title='Volume of trades by year')
```

Out[254]:
```
<AxesSubplot:title={'center':'Volume of trades by year'}, xlabel='d
isclosure_year'>
```



```
Okay this is pretty interesting we se that there were way more trades
in 2020 and 2021 compared to 2022, maybe congressmembers knew
something about the direction the economy was heading? 2022 has been a
bloodbath so it makes sense why there is less trade compared to the
booming markets of 2020 and 2021, later we'll look at whether they
were selling or buying.
```

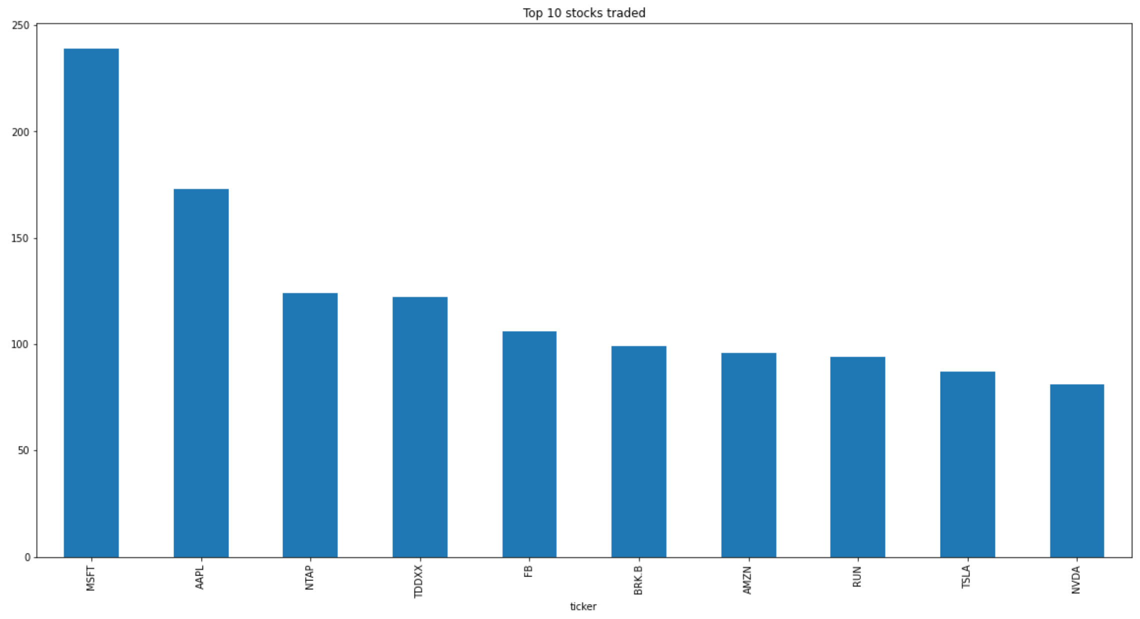
```
we can take a quick look at the hottest stocks congressmembers were
trading, lets look at the top 10
```

In [291]:

```python
group_stocks = raw_data_nan.groupby('ticker').count()
    .sort_values(by='disclosure_year',ascending=False)
plt.figure(figsize=(20, 10))
group_stocks['disclosure_year'][:10].plot(kind='bar',
                                          title= 'Top 10 stocks trad
```

Out[291]:

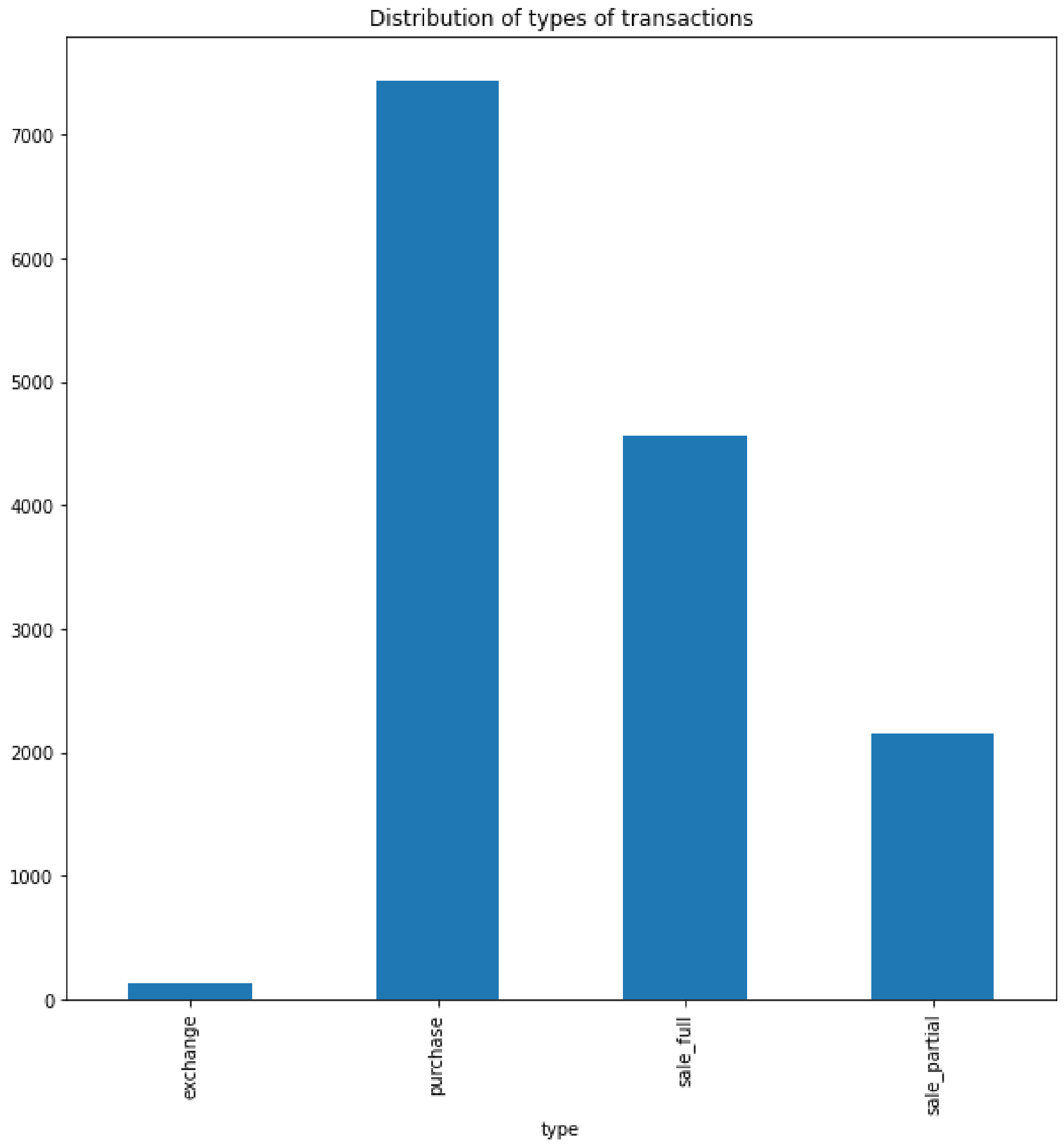
```
<AxesSubplot:title={'center':'Top 10 stocks traded'}, xlabel='ticke
r'>
```



lets take a look at the distribution of types transactions

In [290]:
```
group_types = raw_data_nan.groupby('type').count()
plt.figure(figsize=(10, 10))
group_types['disclosure_year'].plot(kind='bar',
                                    title= 'Distribution of types of
```

Out[290]:
```
<AxesSubplot:title={'center':'Distribution of types of transaction
s'}, xlabel='type'>
```



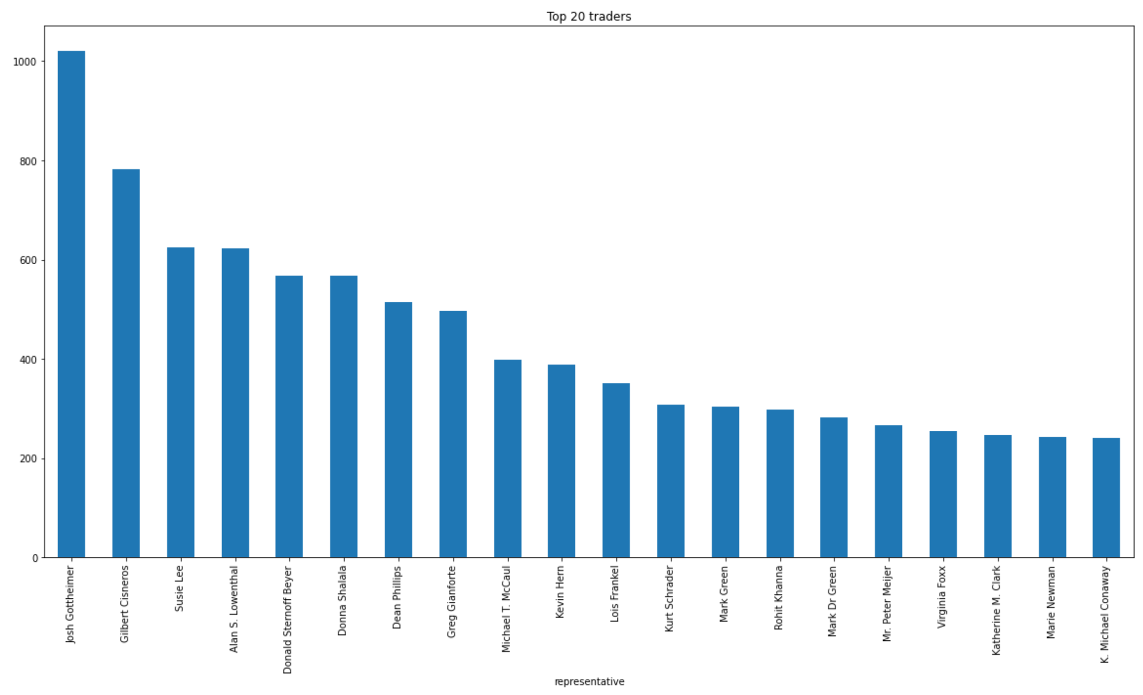
```
Let's check real quick to see who is making the most trades!
```

In [286]:

```
group_rep = raw_data_nan.groupby('representative').count()
    .sort_values(by='disclosure_year',ascending=False)
plt.figure(figsize=(20, 10))
group_rep['disclosure_year'][:20].plot(kind='bar',
                                       title= 'Top 20 traders')
```

Out[286]:

```
<AxesSubplot:title={'center':'Top 20 traders'}, xlabel='representat
ive'>
```

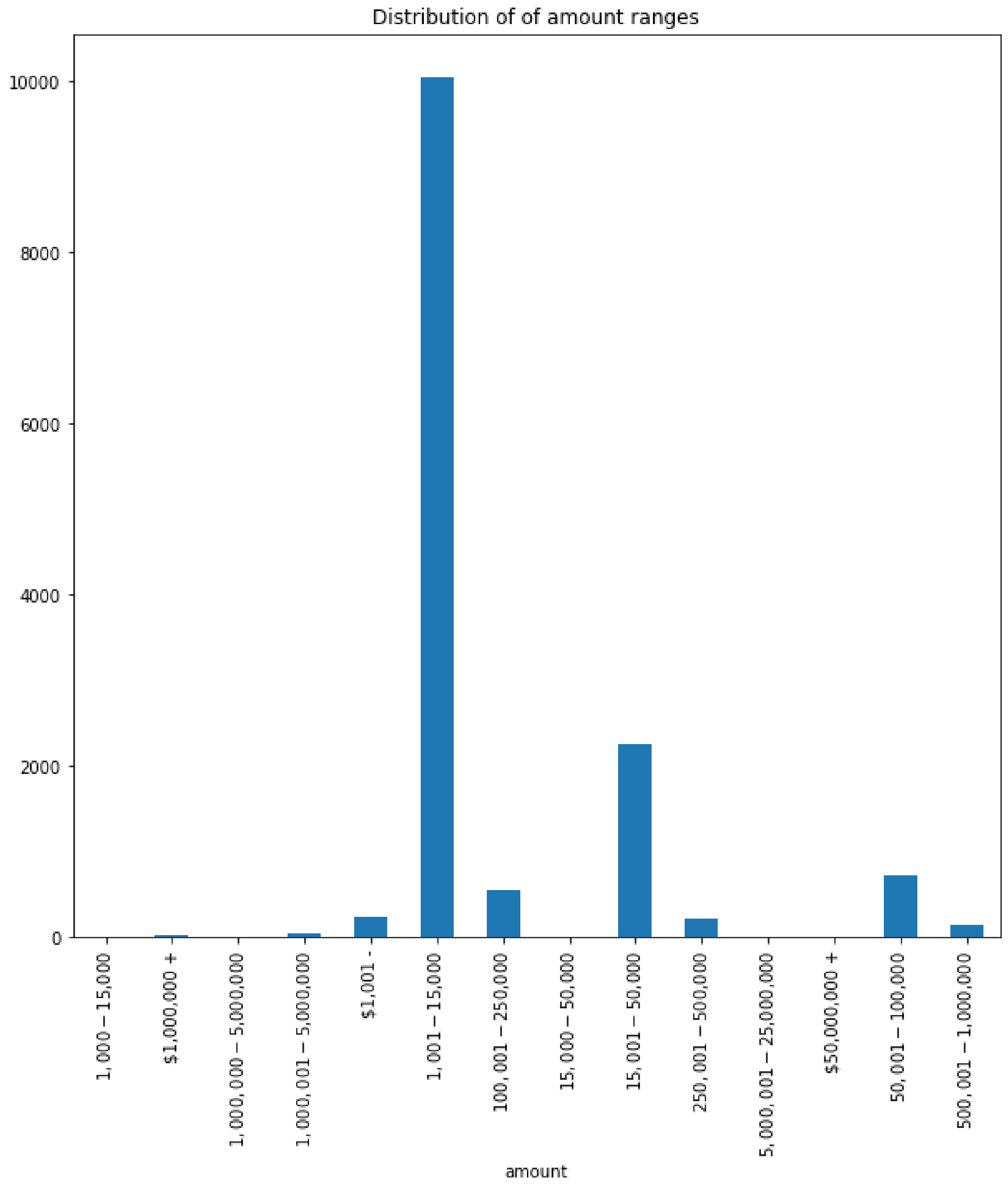


```
Okay we have some names but maybe in bivariate analysis we can explore
how these names relate to party affiliation
and look at proportion
```

before we dive into bivariate and aggregate analyasis based on party affiliation let's look at distribution of amount ranges

In [283]:
```
group_amount = raw_data_nan.groupby('amount').count()
plt.figure(figsize=(10, 10))
group_amount['disclosure_year'].plot(kind='bar',
                                     title= 'Distribution of of amoun
```

Out[283]:
```
<AxesSubplot:title={'center':'Distribution of of amount ranges'}, x
label='amount'>
```



We see most trades were in $1,000 to $15,000 but there were a couple that were above $50,000 let's check real quick how many.

In [280]:
```
group_amount = raw_data_nan.groupby('amount').count()
group_amount['owner']
```

Out[280]:
```
amount
$1,000 - $15,000                1
$1,000,000 +                   28
$1,000,000 - $5,000,000         0
$1,000,001 - $5,000,000        34
$1,001 -                      232
$1,001 - $15,000             5201
$100,001 - $250,000           272
$15,000 - $50,000               1
$15,001 - $50,000            1216
$250,001 - $500,000           136
$5,000,001 - $25,000,000        8
$50,000,000 +                   1
$50,001 - $100,000            373
$500,001 - $1,000,000         102
Name: owner, dtype: int64
```

In [279]:
```
28 + 34 +272 + 136+8+1+373+102
```

Out[279]:
```
954
```

As a proportion of all trades these high value trades account for ...

In [281]:
```
(28 + 34 +272 + 136+8+1+373+102) / group_amount['owner'].sum()
```

Out[281]:
```
0.12544378698224853
```

To explore bivariate distributions we'll mainly plot conditional plots based on part affiliation and pivot tables will be nice too let's use out merged data set

In [289]:
```
merged.head()
```

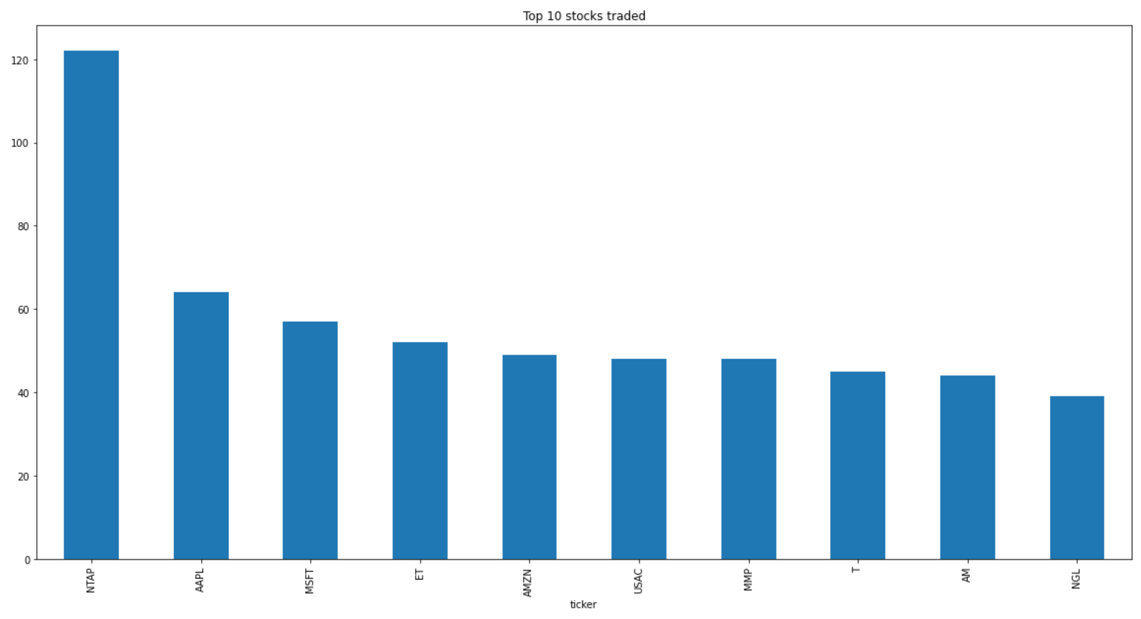
Out[289]:

	disclosure_year	disclosure_date	transaction_date	owner	ticker	asset_description	
0	2021	10/04/2021	2021-09-27	joint	BP	BP plc	pu
1	2021	10/04/2021	2021-09-13	joint	XOM	Exxon Mobil Corporation	pu
2	2021	10/04/2021	2021-09-10	joint	ILPT	Industrial Logistics Properties Trust - Common...	pu
3	2021	10/04/2021	2021-09-28	joint	PM	Phillip Morris International Inc	pu
4	2021	10/04/2021	2021-09-17	self	BLK	BlackRock Inc	sale

```
lets revisit the top 10 stocks based on party affiliation
```

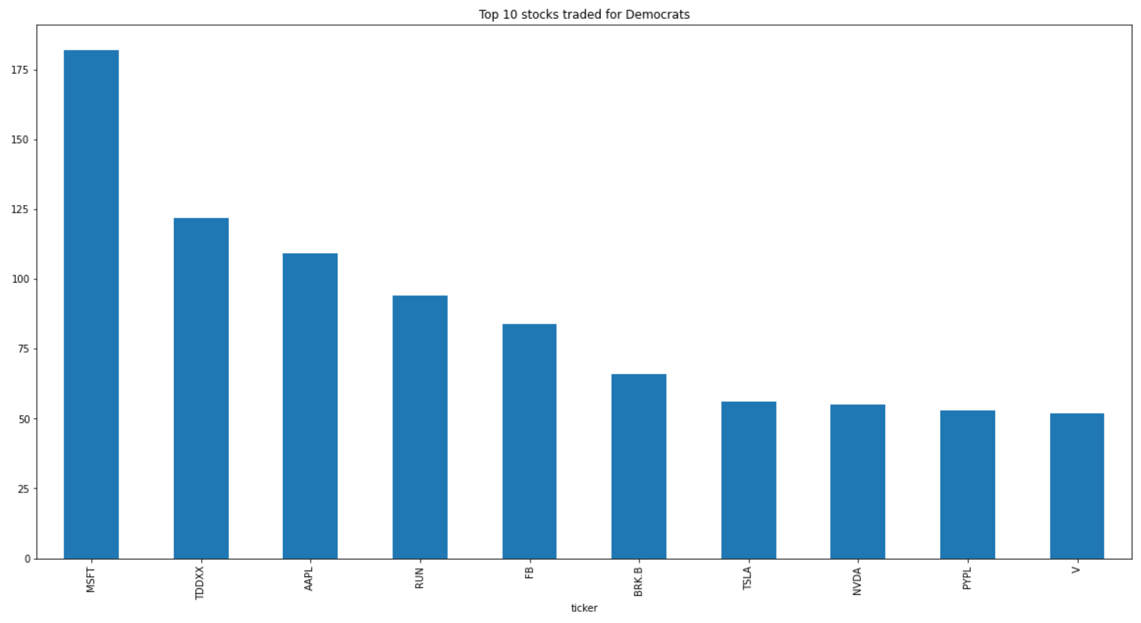
In [306]:
```
group_stocks = merged[merged['party'] == 'Republican']
    .groupby('ticker').count().sort_values(by='disclosure_year',
                                           ascending=False)
plt.figure(figsize=(20, 10))
group_stocks['disclosure_year'][:10].plot(kind='bar',
                                          title= 'Top 10 stocks trad
```

Out[306]:
```
<AxesSubplot:title={'center':'Top 10 stocks traded'}, xlabel='ticke
r'>
```



In [308]:
```
group_stocks = merged[merged['party'] == 'Democratic']
    .groupby('ticker').count().sort_values(by='disclosure_year',asce
plt.figure(figsize=(20, 10))
group_stocks['disclosure_year'][:10].plot(kind='bar',
                                          title= 'Top 10 stocks trad
```

Out[308]:
```
<AxesSubplot:title={'center':'Top 10 stocks traded for Democrats'},
xlabel='ticker'>
```



This is pretty intersting among the top 10 only apple and microsoft are shared amongst the top 10 stocks, We see for republicans there are sort of older well established tech and traditional energy while democrats are trading new tech,solar energy, and blackrock + berkshire

```
Let's see which party makes more trades
```

In [ ]:
```
merged.sort_values(by='pivot_table(index='')
```

In [331]:
```
group_rep = raw_data_nan.groupby('representative').count()
    .sort_values(by='disclosure_year',ascending=False)
all_trades = pd.DataFrame(group_rep['disclosure_year'])
    .merge(congress_party,left_index = True, right_on='full_name', h
all_trades.groupby('party')['disclosure_year'].sum() / raw_data_nan.
```

Out[331]:
```
party
Democratic    0.638434
Republican    0.361566
Name: disclosure_year, dtype: float64
```

In [ ]:
```
merged.pivot_table(index='party',columns='')
```

```
Okay so we observe from the data that Democrats tend to trade more,
how extreme is this value, could this be due to chance? I think I'll
hypothesis test if the distribution of trades comes from a null
distribution of 50% / 50% from each party, we will visit this later
```

```
Lets look at the type of trades congressmembers make based on party
affiliation
```

In [333]:
```
types = merged.pivot_table(index='party',columns = 'type',
                           values='representative',aggfunc='count')
types
```

Out[333]:

type	exchange	purchase	sale_full	sale_partial
party				
Democratic	57	4373	2925	1758
Republican	71	3055	1638	397

```
We can clearly see much more buying and much more selling from
democrats but lets dig a bit deeper
```

```
Okay this is interesting, let's extend this to also see the types of
trades within years as proportions
```

In [385]:
```
types = merged.pivot_table(index='party',columns = ['type','disclosu
                                   ,values='representative',aggfunc='count')
types / types.sum(axis=0)
```

Out[385]:

type	exchange			purchase			sale_full	
disclosure_year	2020	2021	2022	2020	2021	2022	2020	2021
party								
Democratic	0.43956	0.518519	0.3	0.601844	0.583416	0.543417	0.713609	0.548747
Republican	0.56044	0.481481	0.7	0.398156	0.416584	0.456583	0.286391	0.451253

We can see that the majority of purchases were conducted in 2020 and 2021 amongst both parties and that democratic congress members participated in much more selling activity both full and partialy. Okay we can see they participate in more raw number of trades but what about the actual amount of money?

In [388]:
```
types = merged.pivot_table(columns='party',index = ['type','amount']
                                        ,values='representative',aggfunc='count')
types
```

Out[388]:

	party	Democratic	Republican
type	**amount**		
exchange	1, 000, 001−**5,000,000**	NaN	1.0
	$1,001 -	1.0	NaN
	1, 001−**15,000**	44.0	17.0
	100, 001−**250,000**	1.0	9.0
	15, 001−**50,000**	6.0	15.0
	250, 001−**500,000**	2.0	7.0
	50, 001−**100,000**	3.0	21.0
	500, 001−**1,000,000**	NaN	1.0
purchase	**$1,000,000 +**	9.0	NaN
	1, 000, 001−**5,000,000**	17.0	2.0
	$1,001 -	88.0	5.0
	1, 001−**15,000**	3567.0	1626.0
	100, 001−**250,000**	47.0	230.0
	15, 001−**50,000**	461.0	814.0
	250, 001−**500,000**	36.0	59.0
	5, 000, 001−**25,000,000**	4.0	NaN
	50, 001−**100,000**	90.0	301.0
	500, 001−**1,000,000**	54.0	18.0
sale_full	1, 000−**15,000**	NaN	3.0
	$1,000,000 +	12.0	1.0
	1, 000, 000−**5,000,000**	NaN	1.0
	1, 000, 001−**5,000,000**	11.0	4.0
	$1,001 -	21.0	1.0
	1, 001−**15,000**	2267.0	826.0
	100, 001−**250,000**	62.0	156.0
	15, 000−**50,000**	NaN	2.0
	15, 001−**50,000**	369.0	415.0
	250, 001−**500,000**	52.0	58.0
	5, 000, 001−**25,000,000**	2.0	1.0
	$50,000,000 +	NaN	1.0
	50, 001−**100,000**	102.0	144.0
	500, 001−**1,000,000**	27.0	25.0

	party	Democratic	Republican
type	amount		
sale_partial	1, 000−15,000	NaN	1.0
	$1,000,000 +	6.0	NaN
	1, 000, 001−5,000,000	3.0	NaN
	$1,001 -	126.0	NaN
	1, 001−15,000	1472.0	235.0
	100, 001−250,000	20.0	20.0
	15, 000−50,000	NaN	1.0
	15, 001−50,000	80.0	98.0
	250, 001−500,000	10.0	3.0
	5, 000, 001−25,000,000	2.0	NaN
	50, 001−100,000	23.0	38.0
	500, 001−1,000,000	16.0	1.0

There are some baffling findings, when looking at the $500,000+ trades we clearly see that democrats engage in far more high value trades compared to republicans aside from the one republican trade for more than $50,000,000.
Due to the coarse granularity of the amount variable it is definitely a limiting factor in unlocking this particular data set but it is still better than nothing.

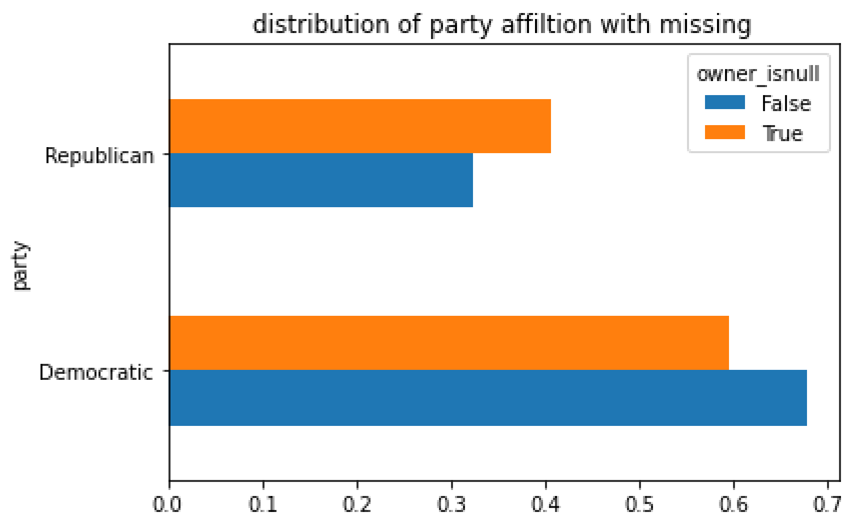
Assessment of Missingness

During the EDA phase I noticed that the owner columns had almost half of it's values missing. Thinking about it, it could potentially be NMAR maybe if the transaction would appear shady based on a certian value it could look bad for the congressmember, so they just don't report it at all. But we should conduct an appropriate MAR test to see if there is actually dependence on other columns, it could very well be the case the maybe party affiliation, type of trade, or amount of trade could be valid variables that influence whether the owner variable is missing so we'll conduct some MAR tests.Given the categorical nature of most columns, we will mostly use tvd as the test statistic. We will use 0.01 significance level.

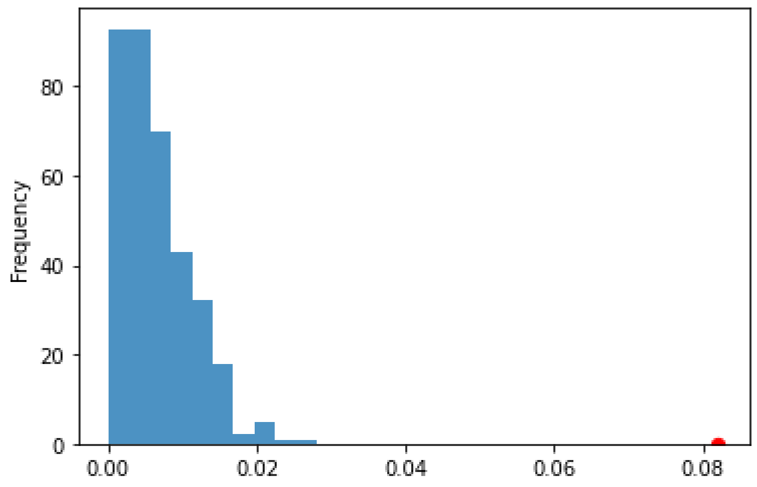
In [372]:

```
merged['owner_isnull'] = merged['owner'].isna()


emp_distributions = (
    merged
    .pivot_table(columns='owner_isnull', index='party',
                 aggfunc='size')
    .fillna(0)
    .apply(lambda x:x / x.sum())
)

emp_distributions.plot(kind='barh', title='distribution of party aff

observed_tvd = np.sum(np.abs(emp_distributions.diff(axis=1)
                             .iloc[:,-1])) / 2
print('observed tvd: ', observed_tvd)


n_repetitions = 500

merged_type = merged.copy()[['party', 'owner_isnull']]
tvds = []
for _ in range(n_repetitions):

    shuffled_types = (
        merged_type['party']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )

    shuffled = (
        merged_type
        .assign(**{'Shuffled Types': shuffled_types})
    )

    # compute the tvd
    shuffed_emp_distributions = (
        shuffled
        .pivot_table(columns='owner_isnull', index='Shuffled Types',
                     values=None, aggfunc='size')
        .fillna(0)
        .apply(lambda x:x/x.sum())
    )

    tvd = np.sum(np.abs(shuffed_emp_distributions.diff(axis=1).iloc[
    # add it to the list of results

    tvds.append(tvd)
```

```
observed tvd:  0.08209972663413961
```



In [373]:
```
pd.Series(tvds).plot(kind='hist', density=True, alpha=0.8)
plt.scatter(observed_tvd, 0, color='red', s=40);
```

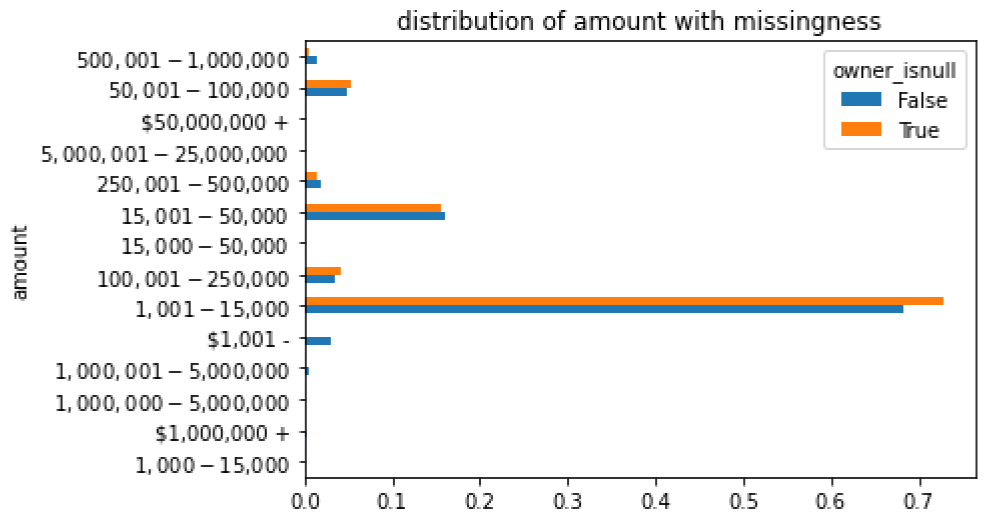


In [374]:
```
pval = np.mean(tvds >= observed_tvd)
pval
```

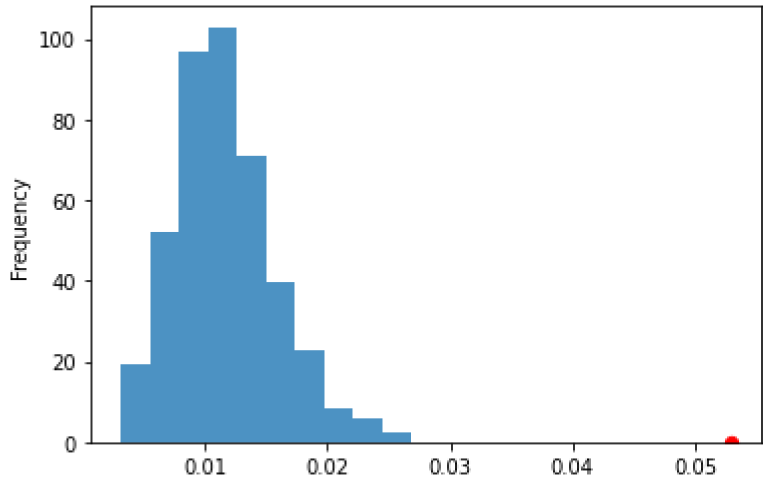
Out[374]:
```
0.0
```

In [375]:
```
merged['owner_isnull'] = merged['owner'].isna()


emp_distributions = (
    merged
    .pivot_table(columns='owner_isnull', index='amount',
                 aggfunc='size')
    .fillna(0)
    .apply(lambda x:x / x.sum())
)

emp_distributions.plot(kind='barh',
                       title='distribution of amount with missingnes

observed_tvd = np.sum(np.abs(emp_distributions.diff(axis=1).iloc[:,-
print('observed tvd: ', observed_tvd)

n_repetitions = 500

payments_type = merged.copy()[['amount', 'owner_isnull']]
tvds = []
for _ in range(n_repetitions):

    shuffled_types = (
        payments_type['amount']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )

    shuffled = (
        payments_type
        .assign(**{'Shuffled Types': shuffled_types})
    )

    # compute the tvd
    shuffed_emp_distributions = (
        shuffled
        .pivot_table(columns='owner_isnull', index='Shuffled Types',
                     values=None, aggfunc='size')
        .fillna(0)
        .apply(lambda x:x/x.sum())
    )

    tvd = np.sum(np.abs(shuffed_emp_distributions.diff(axis=1).iloc[
    # add it to the list of results

    tvds.append(tvd)
```

```
observed tvd:  0.05289456382573785
```



In [376]:
```
pd.Series(tvds).plot(kind='hist', density=True, alpha=0.8)
plt.scatter(observed_tvd, 0, color='red', s=40);
```



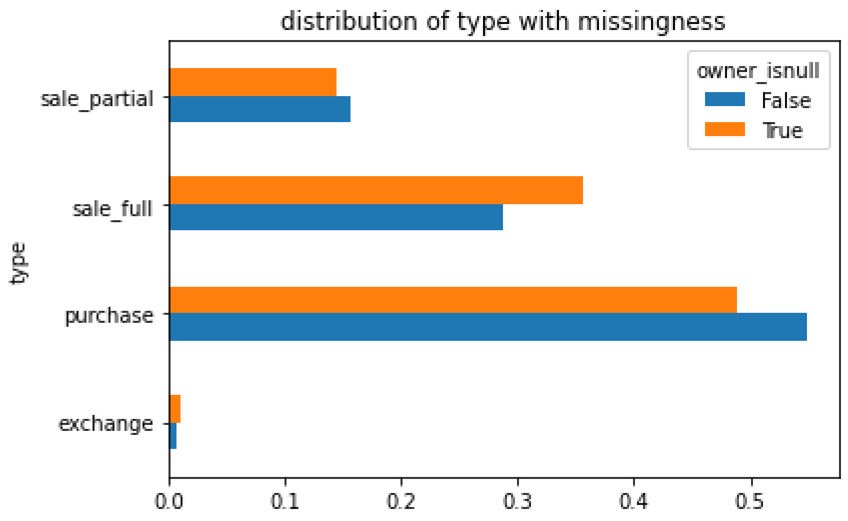
In [377]:
```
pval = np.mean(tvds >= observed_tvd)
pval
```

Out[377]:
```
0.0
```

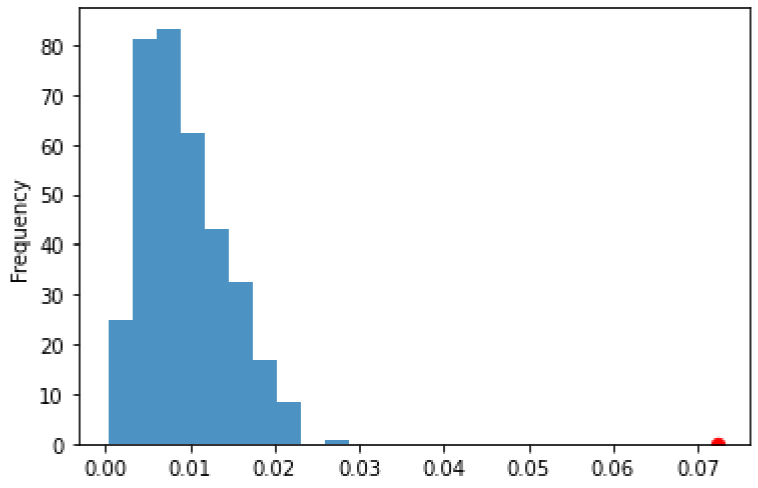
In [381]:

```
merged['owner_isnull'] = merged['owner'].isna()


emp_distributions = (
    merged
    .pivot_table(columns='owner_isnull', index='type', aggfunc='size
    .fillna(0)
    .apply(lambda x:x / x.sum())
)

emp_distributions.plot(kind='barh',
                       title='distribution of type with missingness'

observed_tvd = np.sum(np.abs(emp_distributions.diff(axis=1)
                             .iloc[:,-1])) / 2
print('observed_tvd', observed_tvd)

n_repetitions = 500

merged_type = merged.copy()[['type', 'owner_isnull']]
tvds = []
for _ in range(n_repetitions):

    shuffled_types = (
        merged_type['type']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )

    shuffled = (
        merged_type
        .assign(**{'Shuffled Types': shuffled_types})
    )

    # compute the tvd
    shuffed_emp_distributions = (
        shuffled
        .pivot_table(columns='owner_isnull', index='Shuffled Types',
                     values=None, aggfunc='size')
        .fillna(0)
        .apply(lambda x:x/x.sum())
    )

    tvd = np.sum(np.abs(shuffed_emp_distributions.diff(axis=1).iloc[
    # add it to the list of results

    tvds.append(tvd)
```

```
observed_tvd 0.07241542383242788
```



In [382]:
```
pd.Series(tvds).plot(kind='hist', density=True, alpha=0.8)
plt.scatter(observed_tvd, 0, color='red', s=40);
```



In [383]:
```
pval = np.mean(tvds >= observed_tvd)
pval
```

Out[383]:
```
0.0
```

Even with significane level of 0.01 we see from all three MAR permutation tests that the observed total variation distance among variables party, amount, and type are all much greater than the repective null distribution generated by permutation tests. In all three cases the null hypothesis that these tvd's come from the same distribution is rejected in favor of alternative hypothesis that they come from different distributions. Because these tvd's do not come from the same distributions that means there is a MAR dependence of owner on these variables. After obtaining MAR dependence varification from permutation testing we can think how intuitevey these variables migh influence the probability that the owner column is missing. In terms of party it could be due to that fact that one party or the other might tend to report less or more often, for amount maybe the amount a very large transaction might have a higher probability to report owner because it could appear shady or might not want to diclose the ownership of the position based on size. For the type it could be maybe that buys or sells are over or under reported so as not to appear to buy or sell in a motivated fashion in which the ownership could hint at the scope of those involved.

Hypothesis Testing

```
Let's further explore the distribution behind the proportion of trades
made between party affiliations, the test statistic of interest is the
signed difference between the proportions, we'll use democrats - rep,
my proposed null hypothesis is a world in which I would think both
parties of interest would have an equal interest in trading so the
proportion of trades from democrats is around 50% and the proportion
of trades from republicans is around 50% we might expect our test
statistic to be close to zero under our null. My alternative
hypothesis is that we live in a world where democrats are more
interested in trading, so the proportion of trades from democrats is
above 50% and republicans trade less that 50% of the time yeilding a
test statistic that is positive because, dem % - rep % would expect
higher number of dem % trades. We will use 0.01 significance level.
```

In [339]:
```
observed = all_trades.groupby('party')['disclosure_year'].sum() / ra
observed = observed[0] - observed[1]
observed
```

Out[339]:
```
0.2768670309653916
```

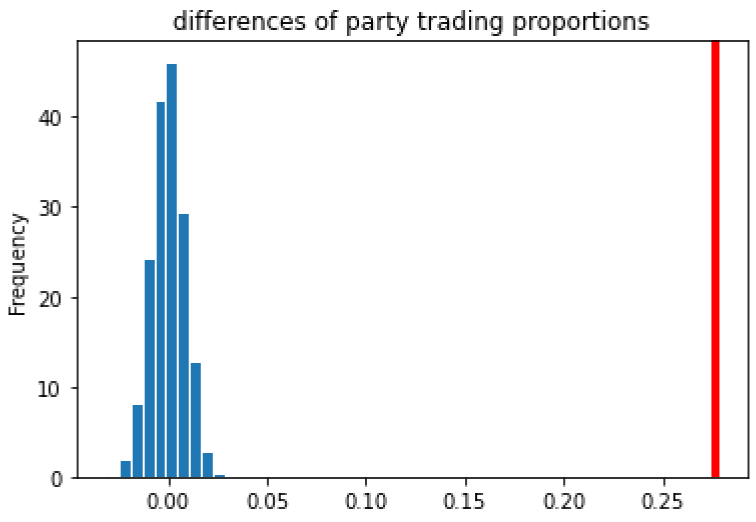
```
I think this test might be too easy but I have other homework and I
think it answers an honest question so we'll go ahead
```

In [345]:
```
N = 10000

# 10000 times, we want to 'flip a coin' the size of original data se
results = []
for _ in range(N):
    simulation = np.random.choice([0, 1], p=[0.5, 0.5], size=merged.
    party_prop_diff = (simulation == 0).mean() - (simulation == 1).m
    results.append(party_prop_diff)
```

In [346]:
```
results
```

Out[346]:
```
[-0.013310914950259267,
 -0.001961608518985525,
 -0.005884825556956741,
 0.0,
 -0.004763906403250695,
 -0.012189995796553221,
 0.015973097940311043,
 0.003502872355331421,
 0.0025220680958386033,
 -0.003502872355331421,
 -0.005464480874316946,
 -0.008547008547008517,
 0.01429171920975203,
 0.015973097940311043,
 0.004483676614824183б,
 -0.008126663864368833,
 -0.008547008547008517,
 0.0009808042594927624,
 0.0030825276726915707,
```

In [347]:
```
pd.Series(results).plot(kind='hist',
                        density=True,
                        ec='w',
                        title='differences of party trading proporti
plt.axvline(x=observed, color='red', linewidth=4);
```



In [348]:
```
p_val = (results >= observed).mean()
p_val
```

Out[348]:
```
0.0
```

It was pretty obvious from the graph but this difference in proportions is definitely not a feasible occurance under the null hypothesis even with an extreme significance level of 0.01. Based on the p value of zero we will reject the null hypothesis that the interest of trading is evenly divided among republicans and democrats in favor of the alternative that democrats are more interested in trading than republicans.

trading than republicans?