Clipboard Health Shifts Analysis

April 25, 2025

1 Shift Offers Analysis

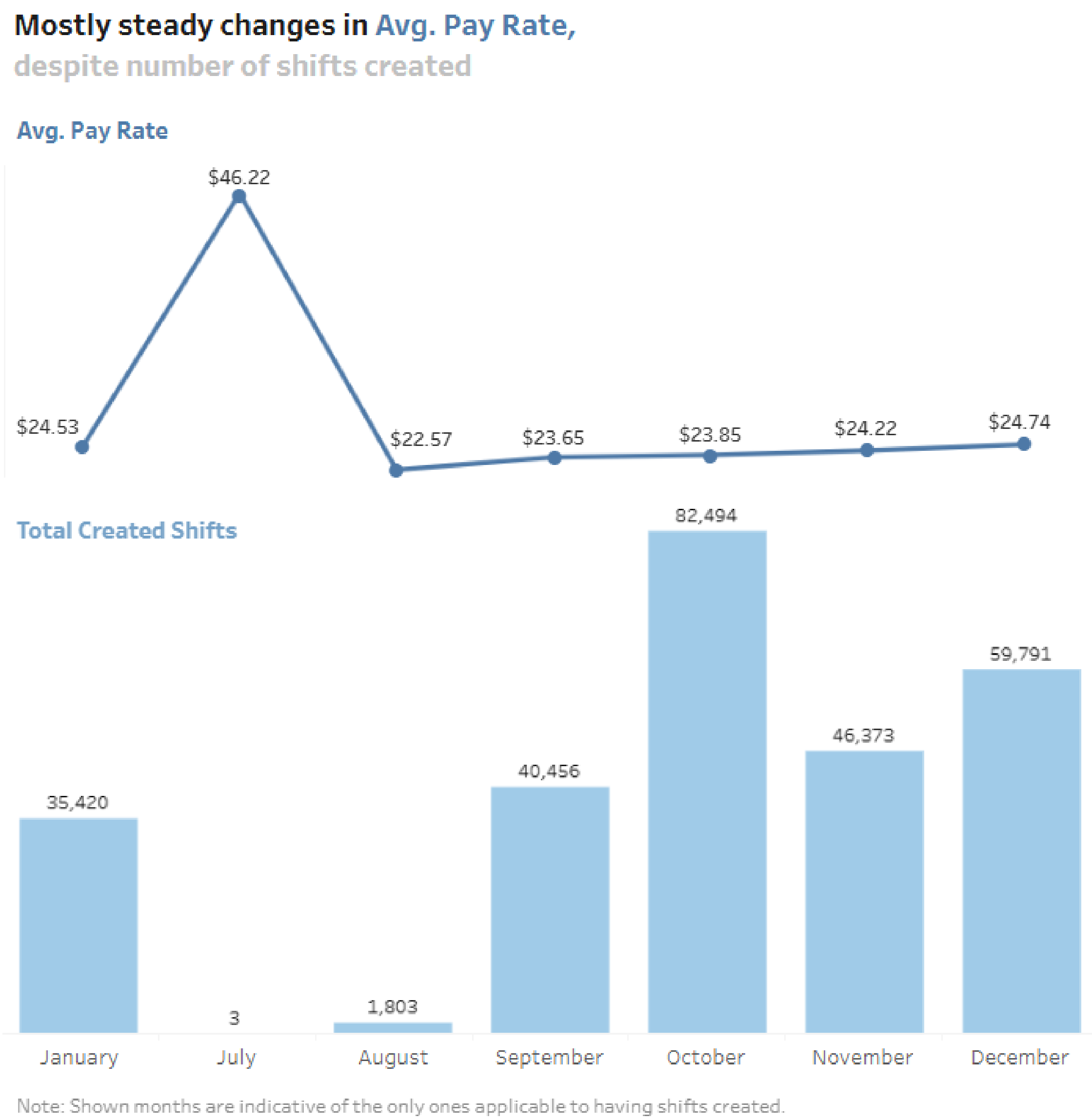
1.1 Project Overview

The purpose of this analysis was to identify signals in the data which are reflective upon a two-sided marketplace with strong network effects, where workers transact with workplaces to book per diem shifts in the future. The intent being to provide stakeholders with initial insights, recommending directions for further inquiry, with a particular analytical focus on worker and workplace behavior within the product. Conducting an analysis on 266k+ records for 07/2024 – 01/2025, the insights found and detailed can be found in the following summary.

1.2 Summary of Insights

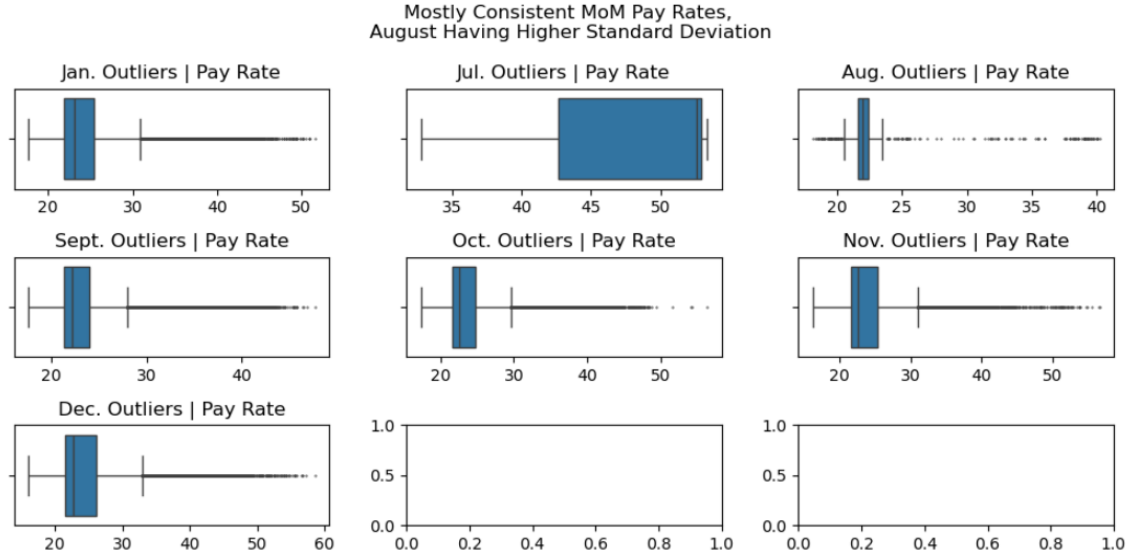
1.2.1 1) Created Shifts & Pay Rate

- **Shifts are only created within January, and from July – December,** with a pause in creation from February – June. This could be due to missing data, impacting the insights found - it's highly advised to confirm with Data Engineering or applicable stakeholders that there is no unexpected missing data, and what has been collected is accurate.
- **October observes the largest proportion of shifts created,** having ~31% of total shifts created during this time. Historically, July observes a small amount of shifts created (.0011%) with a large spike following from August – October, before sharply declining in November and having a small rebound into December. This could be due to workplaces accounting for expected increases in patients, due to the proliferation of illness in colder months. Shift deletions and claims follow the same aforementioned pattern.
- **Average MoM pay rate remains relatively steady** as the number of total created shifts fluctuates throughout the year. A sharp increase in creations occur from January – July due to the apparent pause in created shifts from February – June. The overall average pay rate is ~$24.17; July observes the highest average rate, due to the small proportion of shifts posted, at ~$46.22. This subsequently drops to ~$24.21 throughout August – December; however, the pay rate increases on avg. ~$0.54 throughout this time, with September's increase in shift creations seemingly inducing a ~$1.08 jump from August.



1.2.2 2) Consistency in MoM Pay Ranges

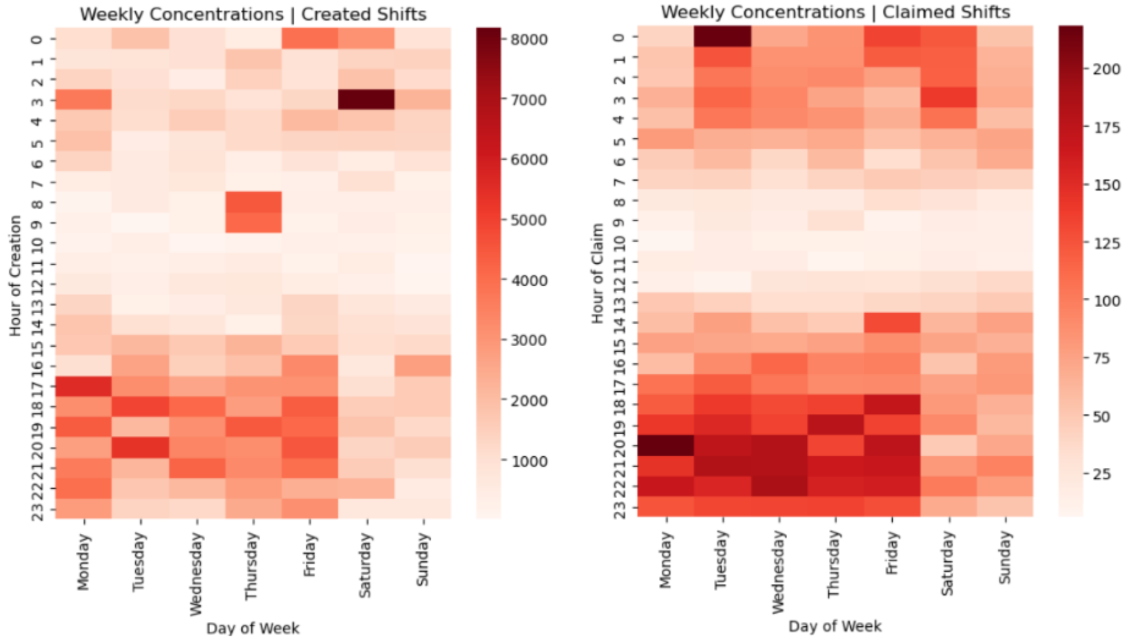
- **The spread of pay rates is fairly consistent** throughout the year, ranging from $21-$26. Notably, although July observes little activity in workplaces creating shifts, the range of pay rates that are posted for this month are about double the usual range. Furthermore, while August comes in second for lowest total shifts created, it experiences a higher standard deviation than other months - meaning pay rates can fall far from its average.



1.2.3 3) Weekly Concentrations - Shift Creations & Claims

- **Monday – Friday between the hours of 4pm-11pm observe consistently large concentrations of shift creations & claims.** While there are high concentrations found from the hours of 12am-5am, these are all likely due to workers being more active on the platform before, leading up to, and after, a typical workday, likely in preparation for upcoming shifts throughout the current/future weeks.
  - *Within created shifts:* **Notably, the highest concentration of created shifts occur on Saturdays at 3am.** Mondays at 5pm, Tuesdays at 6pm and 8pm, comprise the top three most common times for creations during the 4pm-11pm timeblock. There is an instance on Thursdays from 8am-10am, where workplaces have high activity. As this is observed to be a typical downtime, understanding if this activity is contributed by a specific workplace, or subset, will help aid in knowing the likely reason(s) for such a deviation and if more attention to this case is warranted/needed.
  - *Within claimed shifts:* **Mondays at 8pm comprise the highest concentration for shift claims,** with other claims during the 4pm-11pm timeblock being relatively consistently high. This general pattern seems to track with the flow of the workplace-worker relation in the product, having high-concentrations of created shifts being followed by high concentrations of claimed shifts. Tuesdays at 12am comprise the 2nd highest concentration for claimed shifts, following the observed pattern of worker-activity outside of the typical workday hours. Similarly to the high amount of shifts typically created at 3am on Saturday, claims observe a high period of activity from 3-5am, albeit not its most observed for a specific timeblock.
- **Throughout the whole week, 6am-1pm has relatively low periods of shift creations & claims**.

High concentrations of Workplace-creation activity followed by high concentrations of Worker-claim activity



Note: Annotations have been intentionally omitted to focus audience's attention on color-depicted concentrations, rather than individual values.

1.2.4 4) Workplace Shift Deletions

- **No workplace deletes more shifts than they create.**
- **~21% of all shifts are deleted,** with ~.07% of these shifts having already been claimed by a worker. Depending on the deletion tolerance of stakeholders, understanding what contributes to a worker deleting a shift can provide direction on product adjustments that may lower the total percentage of shifts being deleted.
- **5% of workplaces nearly delete shifts as much as they create,** one workplace in particular deleting 99.7% of their created shifts, others deleting above 50%.

Workplaces That Nearly Delete Almost as Much as They Create

Workplace Id	Shifts Created	Shifts Deleted	Deletion:Creation Ratio	Deletion Rate
5f4d42e3d621a000165c5..	614	612	99.7%	49.9%
61b8fee2167e2201801e6..	17	14	82.4%	45.2%
65b953d241782d50f9d4..	17	13	76.5%	43.3%
602ed7d4c778ed00169bf..	127	85	66.9%	40.1%
61ddb491f2fac2018a267..	199	118	59.3%	37.2%
5f52a9138c405c0016d30..	821	445	54.2%	35.2%
6564d795a3497ddd40ab..	68	35	51.5%	34.0%

1.2.5 5) Recommendations

1. **Validate gap in data from Feb – Jun,** ensuring that data not found for these months within this dataset is expected. If not, acquiring and including missing data will ensure accuracy of insights found, and subsequent recommendations, for product teams.

2. **Investigate the large spike of shift creations during the winter months, October in particular.**
   - This may be due to the expectation of a rise in illness during the colder months of the year, as is typically observed of society. Workplaces may be attempting to account for an influx of patients during peak periods.
   - Further corroborating theory on the large spike can potentially provide new avenues for accommodating any flexibility needed in the platform for workplaces, when trying to balance predictions of peak periods and their resulting realities.
3. **Further investigate concentrations of shift creations.**
   - Understanding if specific concentrations are attributed to a select number of workplaces will aid in knowing which workplaces may be highly influential in the data being shown. This is especially true for any concentrations observed which do not follow general patterns - e.g., Thursdays from 8-10am, and Saturdays at 3am for shift creations.
   - Further context will aid in understanding of the contributing factors to a shift being created during certain hours, and can possibly aid in a paired-supplementation of understanding the deletions of shifts observed.
4. **Understand what contributes to ostensible anomalies in July & August.**
   - With July having such little shifts created and no deletions, but with higher pay rates, it'd prove useful to know what's contributing to this deviation - is it a specific workplace; are there factors about the shifts that contribute to higher rates; do these factors not occur often and is why there is a low amount of these high rate shifts being created? This understanding can be paired with further contextual data on why workplaces decide to post a shift with a certain rate, creating a potential avenue for product improvement by accommodating for the needs of these "unique" shifts.
   - With August following July in the lowest number of shifts created, understanding why it has a higher standard deviation than months with greater number of shifts created can provide a more detailed insight into factors that contribute to pay rate decisions. This would aid in workplace relations by creating a better understanding of shift use-cases/scenarios and continue further informing potential product improvement opportunities.
5. **Collate qualitative data to understand what factors contribute to a workplace deleting a shift.**
   - While workplaces may be overestimating their workforce needs for peak periods, causing shifts to be subsequently deleted once posted, there may also be mistakes made when a shift is posted which aren't able to be corrected without deleting the shift.
   - Understanding why workplaces delete shifts can potentially provide insight(s) that allows for platform adjustments to be made, decreasing the overall percentage of shifts deleted, and increasing the opportunities available for workers.

For a detailed technical understanding of the EDA undergone, please see below:

2 Initial EDA

[111]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[112]:
```
# importing data from Google-hosted table
url='https://docs.google.com/spreadsheets/d/' +␣
 ↪'1sGa4oxX3wC2gbGBkUF_G5p_kBzHlKU_p84W9roV7620' + '/export?
 ↪gid=1708261856&format=csv'
raw_df = pd.read_csv(url,
                 # setting index to not use first column
                 index_col = False,
                # parse column values to datetime
                 parse_dates=['SHIFT_START_AT', 'SHIFT_CREATED_AT',␣
 ↪'CLAIMED_AT', 'CANCELED_AT', 'DELETED_AT']
                )
```

[113]:
```
# validating import
print(raw_df.shape)
raw_df.head(5)
```

```
(266340, 15)
```

[113]:
```
                   SHIFT_ID                 WORKER_ID  \
0  6757580b1e2d97752fd69167  65b01f2e46c0645699081cbe
1  675d37d8a1ca6192a74d23f4  65298a18cc967a5cebbd40b6
2  67550bddd79613f860549322  6696d1c1d0200bf317ee5d3c
3  66f5d05de01fd3697b18c206  66b285d5d0200bf317738e59
4  66ee3848e62bb5f43e3baee5  620c6429e2ceb601ad203920

               WORKPLACE_ID      SHIFT_START_AT    SHIFT_CREATED_AT  \
0  5e7e45243bfbb200165914ae 2024-12-09 23:00:00 2024-12-09 20:50:19
1  5e1ce78827ff480016e9133e 2024-12-14 22:30:00 2024-12-14 07:46:32
2  626b0b89596c0601c2c39642 2024-12-08 15:00:00 2024-12-08 03:00:46
3  5cb9f07135163900163f532c 2024-09-27 14:00:00 2024-09-26 21:21:34
4  611af67795f4c501662edb31 2024-10-08 21:30:00 2024-09-21 03:06:48

       OFFER_VIEWED_AT  DURATION SLOT CLAIMED_AT          DELETED_AT  \
0  2024-12-09 21:18:42         8   pm        NaT                 NaT
1  2024-12-14 13:19:30         9   pm        NaT 2024-12-14 19:23:43
2   2024-12-08 4:04:14         6   am        NaT                 NaT
3   2024-09-27 4:19:45         8   am        NaT                 NaT
4   2024-10-06 0:46:37         8   pm        NaT                 NaT

   IS_VERIFIED CANCELED_AT  IS_NCNS  PAY_RATE  CHARGE_RATE
0        False         NaT    False     21.29           29
```

```
1        False          NaT    False     23.23            30
2        False          NaT    False     21.97            30
3        False          NaT    False     19.05            28
4        False          NaT    False     22.13            24
```

[114]:
```python
# validating data types
raw_df.dtypes
```

[114]:
```
SHIFT_ID                      object
WORKER_ID                     object
WORKPLACE_ID                  object
SHIFT_START_AT        datetime64[ns]
SHIFT_CREATED_AT      datetime64[ns]
OFFER_VIEWED_AT               object
DURATION                       int64
SLOT                          object
CLAIMED_AT            datetime64[ns]
DELETED_AT            datetime64[ns]
IS_VERIFIED                     bool
CANCELED_AT           datetime64[ns]
IS_NCNS                         bool
PAY_RATE                     float64
CHARGE_RATE                    int64
dtype: object
```

[115]:
```python
# reviewing basic info
raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 266340 entries, 0 to 266339
Data columns (total 15 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   SHIFT_ID          266340 non-null  object
 1   WORKER_ID         266340 non-null  object
 2   WORKPLACE_ID      266340 non-null  object
 3   SHIFT_START_AT    266340 non-null  datetime64[ns]
 4   SHIFT_CREATED_AT  266340 non-null  datetime64[ns]
 5   OFFER_VIEWED_AT   266340 non-null  object
 6   DURATION          266340 non-null  int64
 7   SLOT              266340 non-null  object
 8   CLAIMED_AT        13064 non-null   datetime64[ns]
 9   DELETED_AT        55644 non-null   datetime64[ns]
 10  IS_VERIFIED       266340 non-null  bool
 11  CANCELED_AT       321 non-null     datetime64[ns]
 12  IS_NCNS           266340 non-null  bool
 13  PAY_RATE          266340 non-null  float64
 14  CHARGE_RATE       266340 non-null  int64
```

```
dtypes: bool(2), datetime64[ns](5), float64(1), int64(2), object(5)
memory usage: 26.9+ MB
```

[116]:
```
# copy of data frame for augmentive use
df = raw_df.copy()
```

[117]:
```
# converting columns to lowercase
df.columns = df.columns.str.lower()
```

[118]:
```
# validating
df.head()
```

[118]:
```
                   shift_id                 worker_id  \
0  6757580b1e2d97752fd69167  65b01f2e46c0645699081cbe
1  675d37d8a1ca6192a74d23f4  65298a18cc967a5cebbd40b6
2  67550bddd79613f860549322  6696d1c1d0200bf317ee5d3c
3  66f5d05de01fd3697b18c206  66b285d5d0200bf317738e59
4  66ee3848e62bb5f43e3baee5  620c6429e2ceb601ad203920

               workplace_id      shift_start_at    shift_created_at  \
0  5e7e45243bfbb200165914ae 2024-12-09 23:00:00 2024-12-09 20:50:19
1  5e1ce78827ff480016e9133e 2024-12-14 22:30:00 2024-12-14 07:46:32
2  626b0b89596c0601c2c39642 2024-12-08 15:00:00 2024-12-08 03:00:46
3  5cb9f07135163900163f532c 2024-09-27 14:00:00 2024-09-26 21:21:34
4  611af67795f4c501662edb31 2024-10-08 21:30:00 2024-09-21 03:06:48

       offer_viewed_at  duration slot claimed_at          deleted_at  \
0  2024-12-09 21:18:42         8   pm        NaT                 NaT
1  2024-12-14 13:19:30         9   pm        NaT 2024-12-14 19:23:43
2   2024-12-08 4:04:14         6   am        NaT                 NaT
3   2024-09-27 4:19:45         8   am        NaT                 NaT
4   2024-10-06 0:46:37         8   pm        NaT                 NaT

   is_verified canceled_at  is_ncns  pay_rate  charge_rate
0        False         NaT    False     21.29           29
1        False         NaT    False     23.23           30
2        False         NaT    False     21.97           30
3        False         NaT    False     19.05           28
4        False         NaT    False     22.13           24
```

[119]:
```
# summary stats
df.describe()
```

[119]:
```
                      shift_start_at                shift_created_at  \
count                         266340                          266340
mean   2024-11-19 03:22:32.691420672  2024-11-12 17:51:37.541537280
min              2024-09-22 00:00:00             2024-07-29 17:36:11
25%              2024-10-16 22:00:00             2024-10-09 23:48:08
```

```
50%              2024-11-15 22:30:00            2024-11-05 16:49:28
75%              2024-12-24 14:30:00            2024-12-17 20:21:18
max              2025-01-20 23:30:00            2025-01-21 23:45:56
std                              NaN                            NaN

            duration                    claimed_at  \
count  266340.000000                         13064
mean        8.342164    2024-11-15 02:20:09.969152
min         0.000000           2024-07-29 21:41:01
25%         8.000000           2024-10-13 22:03:01
50%         8.000000    2024-11-13 20:08:32.500000
75%         9.000000  2024-12-17 03:58:59.750000128
max        18.000000           2025-01-21 23:46:08
std         1.155281                           NaN

                           deleted_at                     canceled_at  \
count                           55644                             321
mean   2024-11-14 03:44:18.094655488  2024-11-19 04:40:11.542056448
min              2024-08-26 06:02:46            2024-08-26 05:48:12
25%              2024-10-13 23:40:02            2024-10-15 07:49:44
50%              2024-11-06 08:49:20            2024-11-20 18:25:44
75%              2024-12-17 18:51:53            2024-12-24 05:35:45
max              2025-01-20 21:00:04            2025-01-19 16:50:09
std                              NaN                            NaN

            pay_rate    charge_rate
count  266340.000000  266340.000000
mean       24.164936      31.511906
min        16.140000      24.000000
25%        21.580000      27.000000
50%        22.520000      31.000000
75%        25.100000      36.000000
max        58.570000      64.000000
std         4.651970       5.414566
```

Reviewing NaTs

[120]:
```python
# reviewing NaTs noted from raw_df
print(f'claimed_at NaTs: {df.claimed_at.isna().sum()}')
print(f'deleted_at NaTs: {df.deleted_at.isna().sum()}')
print(f'canceled_at NaTs: {df.canceled_at.isna().sum()}')
```

```
claimed_at NaTs: 253276
deleted_at NaTs: 210696
canceled_at NaTs: 266019
```

Reveiewing Dupes

[121]:
```
# validating duplicates in shift_id
print(f'num shift_id dupes: {df.shift_id.duplicated().sum()}') #19,900 unique

# validating duplicates in worker_id
print(f'num worker_id dupes: {df.worker_id.duplicated().sum()}') #10,291 unique

# validating duplicates in workplace_id
print(f'num workplace_id dupes: {df.workplace_id.duplicated().sum()}') #132␣
↪unique
```

```
num shift_id dupes: 246440
num worker_id dupes: 256049
num workplace_id dupes: 266208
```

Time-Series Inclusion of Months & Years

[122]:
```
# adding created-month column w/ numeric representation
df['created_month'] = df.shift_created_at.dt.month

# adding created-year column w/ numeric representation
df['created_year'] = df.shift_created_at.dt.year

# adding column for day (named) of shift creation
df['created_day_name'] = df.shift_created_at.dt.day_name()

# adding column for hour of shift creation
df['created_hour'] = df.shift_created_at.dt.hour

# adding deleted-month column w/ numeric representation
df['deleted_month'] = df.deleted_at.dt.month.astype('Int64')

# adding deleted-year column w/ numeric representation
df['deleted_year'] = df.deleted_at.dt.year.astype('Int64')

# adding deleted-month column w/ numeric representation
df['claimed_month'] = df.claimed_at.dt.month.astype('Int64')

# adding deleted-year column w/ numeric representation
df['claimed_year'] = df.claimed_at.dt.year.astype('Int64')

# adding column for day (named) of shift claim
df['claimed_day_name'] = df.claimed_at.dt.day_name()

# adding column for hour of shift claim
df['claimed_hour'] = df.claimed_at.dt.hour
```

[123]:
```
# validating column additions
df.head(2)
```

[123]:
```
                       shift_id                 worker_id  \
0  6757580b1e2d97752fd69167  65b01f2e46c0645699081cbe
1  675d37d8a1ca6192a74d23f4  65298a18cc967a5cebbd40b6

               workplace_id      shift_start_at    shift_created_at  \
0  5e7e45243bfbb200165914ae 2024-12-09 23:00:00 2024-12-09 20:50:19
1  5e1ce78827ff480016e9133e 2024-12-14 22:30:00 2024-12-14 07:46:32

       offer_viewed_at  duration slot claimed_at          deleted_at  …  \
0  2024-12-09 21:18:42         8   pm        NaT                 NaT  …
1  2024-12-14 13:19:30         9   pm        NaT 2024-12-14 19:23:43  …

   created_month created_year  created_day_name  created_hour  deleted_month  \
0             12         2024            Monday            20           <NA>
1             12         2024          Saturday             7             12

   deleted_year  claimed_month claimed_year  claimed_day_name  claimed_hour
0          <NA>           <NA>         <NA>               NaN           NaN
1          2024           <NA>         <NA>               NaN           NaN

[2 rows x 25 columns]
```

[124]:
```python
# validating data types for new columns
df.dtypes
```

[124]:
```
shift_id                    object
worker_id                   object
workplace_id                object
shift_start_at      datetime64[ns]
shift_created_at    datetime64[ns]
offer_viewed_at             object
duration                     int64
slot                        object
claimed_at          datetime64[ns]
deleted_at          datetime64[ns]
is_verified                   bool
canceled_at         datetime64[ns]
is_ncns                       bool
pay_rate                   float64
charge_rate                  int64
created_month                int32
created_year                 int32
created_day_name            object
created_hour                 int32
deleted_month                Int64
deleted_year                 Int64
claimed_month                Int64
```

```
claimed_year                  Int64
claimed_day_name             object
claimed_hour                float64
dtype: object
```

Initial EDA Tracking Doc

1. NaTs in following columns:
   - claimed_at : 253276
   - deleted_at : 210696
   - canceled_at : 266019
2. No NaNs to consider
3. Duplicates in `shift_id`, `worker_id`, `workplace_id` makes sense, as multiple workers can apply for multiple shifts; multiple workplaces can post shifts.
4. Consideration needed for any outliers.
5. Max `shift_created_at` is 01/21/2025 - may want to consider any limitations/normalization of dt columns
6. Likely more interesting to look at any time-series from month perspective, as yearly data is only from 2024-2025 (*could compare using bar graph to start foundational magnitude trends for future data collection*)
7. Can graph pairplot or correlation matrix for investigative direction (will need to handle NAs).
8. `charge_rate` is flat rate (integer).

Initial Investigative Questions 1. How many workers are verified *(worker worked shift)* for a shift? - How does this number compare to shifts that have been deleted by a workplace? 2. Any extreme outliers to take notice of? - Consider initiating focus on scales of `pay_rate` & `charge_rate` - *Any significant magnitudes to take note of?* 3. Frequencies in `deleted_at` : time-series 4. Frequencies in `canceled_at` : time-series - e.g. during major holidays; *or perhaps there is an uptick*? 5. Why are min. dates incongruous? - `shift_created_at` 07/29/2024 -> `claimed_at` 07/29/2024 -> `shift_start_at` 09/22/2024 - Why is there a 2 month gap from when a shift was first recorded as being claimed, to the first shift starting? Does this have anything to do with `canceled_at` & `deleted_at` being 08/26/2024? Is this related to the same shift posted; if so, is/are shift(s) related to a specific workplace; how many shifts were created in the 07/2024-08/2024 time-frame? 7. Ranges of `pay_rate` that may hint at user preference(s)? - i.e., which ranges show the **most verified** shifts? which ranges show the **most claimed** shifts?

3 Overall Frequencies | Pay Rate & Shifts

- Investigating the seasonality of pay_rate and noting any coinciding patterns with **overall** trends in shifts

[125]:
```
df.head(2)
```

[125]:
```
                   shift_id                 worker_id  \
0  6757580b1e2d97752fd69167  65b01f2e46c0645699081cbe
1  675d37d8a1ca6192a74d23f4  65298a18cc967a5cebbd40b6

               workplace_id      shift_start_at    shift_created_at  \
```

```
0  5e7e45243bfbb200165914ae 2024-12-09 23:00:00 2024-12-09 20:50:19
1  5e1ce78827ff480016e9133e 2024-12-14 22:30:00 2024-12-14 07:46:32

       offer_viewed_at  duration slot claimed_at          deleted_at  …  \
0  2024-12-09 21:18:42         8   pm        NaT                 NaT  …
1  2024-12-14 13:19:30         9   pm        NaT 2024-12-14 19:23:43  …

   created_month created_year  created_day_name  created_hour  deleted_month  \
0             12         2024            Monday            20           <NA>
1             12         2024          Saturday             7             12

   deleted_year  claimed_month claimed_year  claimed_day_name  claimed_hour
0          <NA>           <NA>         <NA>               NaN           NaN
1          2024           <NA>         <NA>               NaN           NaN

[2 rows x 25 columns]
```

Overall observations by Month

[126]:
```
# creating dataframe for counts of creations, deletions, claims, avg. pay_rate,␣
↪by month
by_month_df = df.groupby(['created_month']).agg(
    {'shift_created_at': 'count',
     'deleted_at': 'count',
     'claimed_at' : 'count',
     'pay_rate' : 'mean'
    }
).reset_index().rename(columns={'created_month' : 'month' ,'shift_created_at' :␣
↪'num_creations', 'deleted_at' : 'num_deletions', \
                    'claimed_at' : 'num_claims', 'pay_rate' : 'avg_pay_rate'})
```

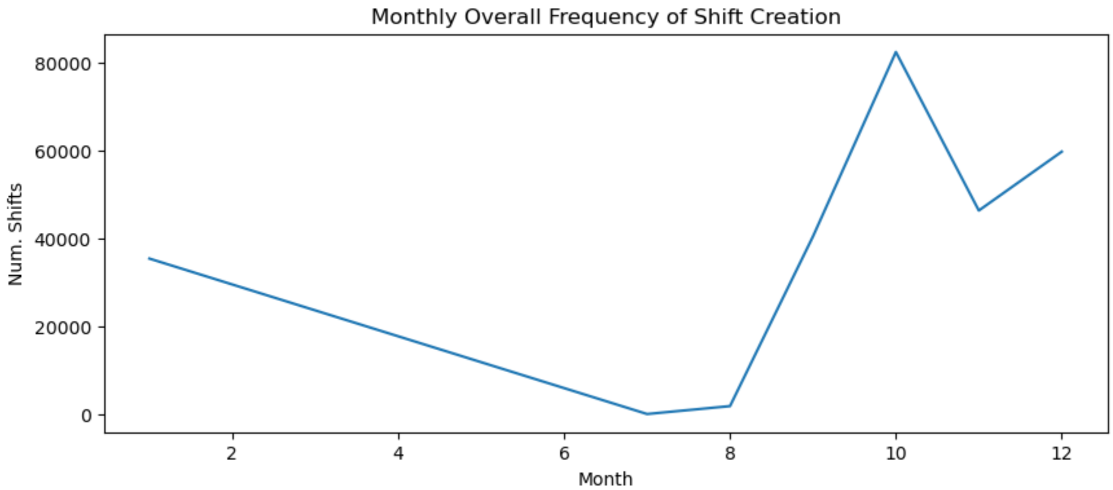
[127]:
```
by_month_df.head()
```

[127]:

	month	num_creations	num_deletions	num_claims	avg_pay_rate
0	1	35420	5063	1421	24.527619
1	7	3	0	3	46.220000
2	8	1803	689	105	22.574842
3	9	40456	11761	1676	23.649063
4	10	82494	18626	3825	23.847578

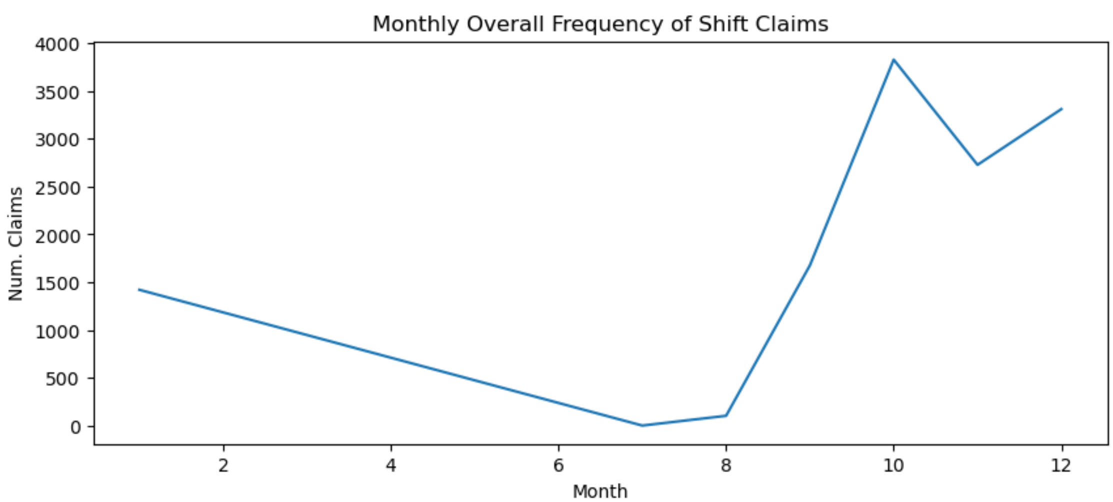
[128]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(by_month_df, x='month', y='num_creations')

plt.xlabel('Month')
plt.ylabel('Num. Shifts')
plt.title('Monthly Overall Frequency of Shift Creation')
```

[128]:
```
Text(0.5, 1.0, 'Monthly Overall Frequency of Shift Creation')
```



[129]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(by_month_df, x='month', y='num_claims')

plt.xlabel('Month')
plt.ylabel('Num. Claims')
plt.title('Monthly Overall Frequency of Shift Claims')
```

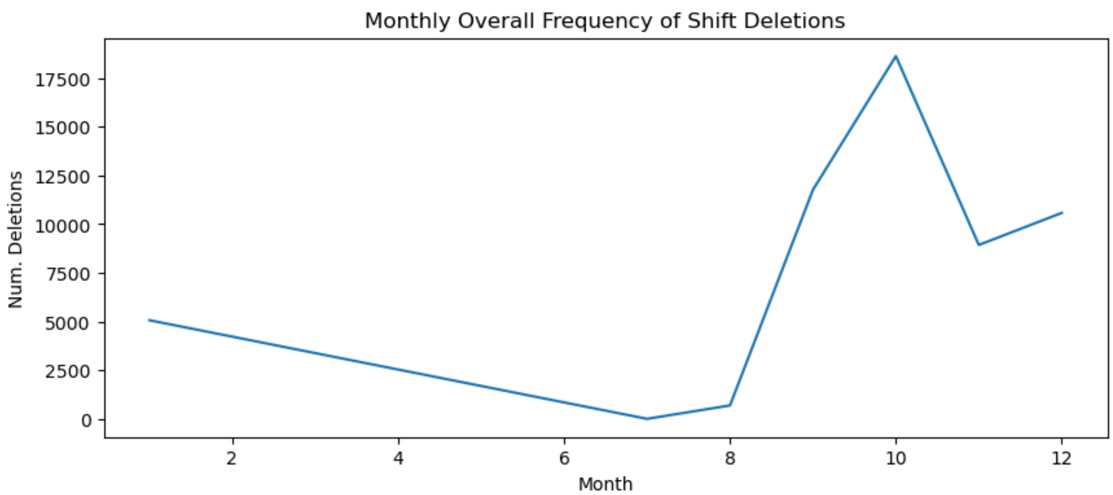
[129]: Text(0.5, 1.0, 'Monthly Overall Frequency of Shift Claims')



[130]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(by_month_df, x='month', y='num_deletions')
```

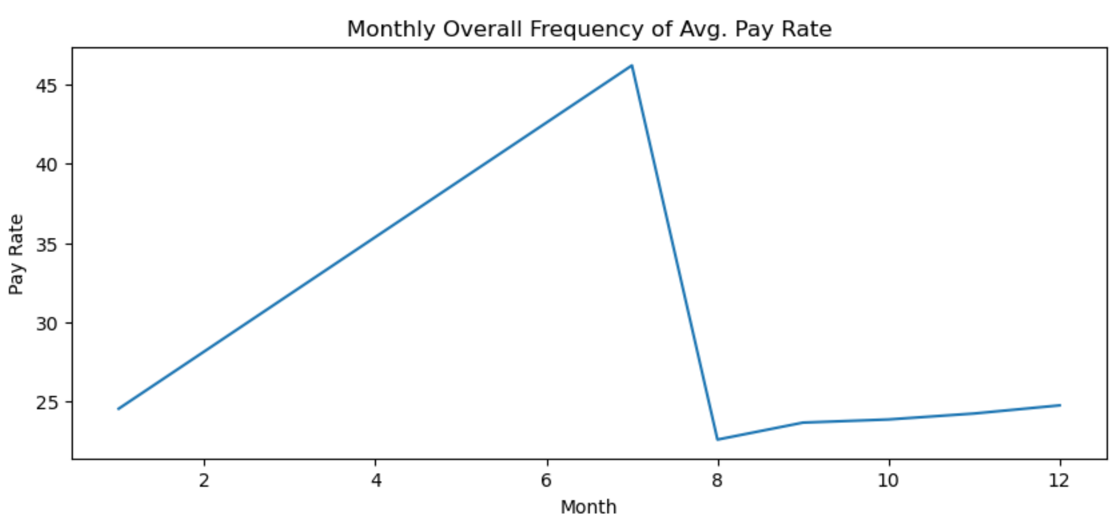
```
plt.xlabel('Month')
plt.ylabel('Num. Deletions')
plt.title('Monthly Overall Frequency of Shift Deletions')
```

[130]: Text(0.5, 1.0, 'Monthly Overall Frequency of Shift Deletions')



[131]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(by_month_df, x='month', y='avg_pay_rate')

plt.xlabel('Month')
plt.ylabel('Pay Rate')
plt.title('Monthly Overall Frequency of Avg. Pay Rate')
```

[131]: Text(0.5, 1.0, 'Monthly Overall Frequency of Avg. Pay Rate')



[132]:
```
# count of created shifts by month
df.created_month.value_counts(normalize=True)
```

[132]:
```
created_month
10    0.309732
12    0.224491
11    0.174112
9     0.151896
1     0.132988
8     0.006770
7     0.000011
Name: proportion, dtype: float64
```

[133]:
```
# overall avg. pay_rate
df.pay_rate.mean()
```

[133]:
```
24.164935984080497
```

[134]:
```
# overall avg. pay_rate by month
df.groupby(['created_month'])[['pay_rate']].mean().sort_values(by='pay_rate')
```

[134]:

created_month	pay_rate
8	22.574842
9	23.649063
10	23.847578
11	24.223727
1	24.527619
12	24.738242
7	46.220000

Observations

- Avg. Pay rate looks to be reciprocal to pattern seen in creations, claims, deletions: There is an increase in pay_rate from Jan - Jul, before a sharp decrease heading into August, where the pay begins to slightly increase again. This is interesting given that the pattern for creations, claims, deletions show an overall decline from Jan - July, with July experiencing a small increase heading into August, and a sharp increase occurring from Aug - October, before things decline again (a small increase occurring from Nov-Dec)
- When there are less shifts being created and claimed, the pay rate observes increases; however, as soon as shifts begin to increase in creations, claims, and deletions, the pay rate significantly decreases and then increases in relatively small increments.
- **Shifts are observed to only be created in January, and then from Jul - Dec. No shifts are created from Feb. - Jun.**
  - From this, the avg. MoM pay_rate jumps to high-levels in July when shifts are posted

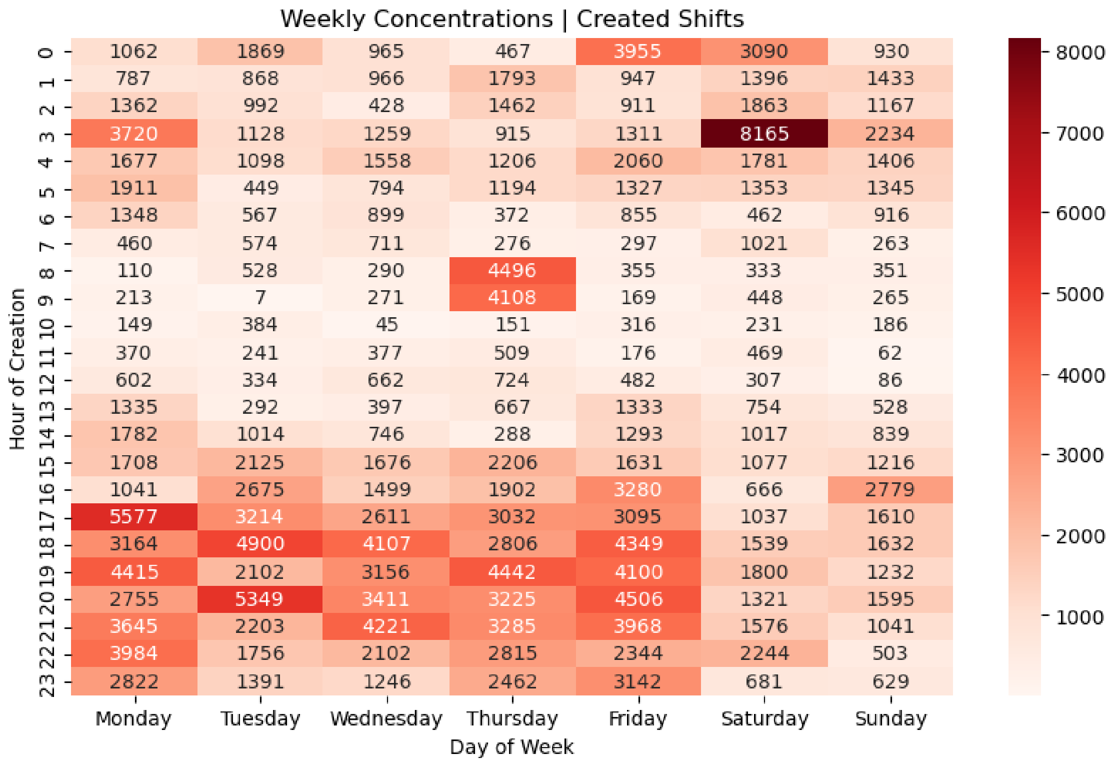
again, before quickly falling to seemingly "normal" levels during the winter months. Avg. pay in July is \$46.22 compared to Jan. (\$24.53) and Aug - Dec (\$24.12) - likely reflecting only 3 shifts being created in July before jumping to the thousands in August. (Overall pay avg. is \$24.17)

4 Concentrations of Created & Claimed Shifts

4.0.1 Created Shifts

[135]:
```
# dataframe based on num. of shifts created in specific times of day
created_tod_df = df.
↪groupby(['created_hour','created_day_name'])[['shift_created_at']].count().
↪reset_index()

# pivoting for heatmap plotting
created_tod_df = created_tod_df.pivot(index='created_hour',␣
↪columns='created_day_name', values='shift_created_at')

# reordering for expected days-of-week order
created_tod_df = created_tod_df[['Monday', 'Tuesday', 'Wednesday', 'Thursday',␣
↪'Friday', 'Saturday', 'Sunday']]
```

[136]:
```
# fig, ax = plt.subplots(figsize=(6,6)) # sizing for screenshot
fig, ax = plt.subplots(figsize=(10,6))

# sns.heatmap(created_tod_df, cmap='Reds') # w/o annotations for screenshot
sns.heatmap(created_tod_df, cmap='Reds', annot=True, fmt='g')

plt.title('Weekly Concentrations | Created Shifts')
plt.xlabel('Day of Week')
plt.ylabel('Hour of Creation')
plt.show()
```

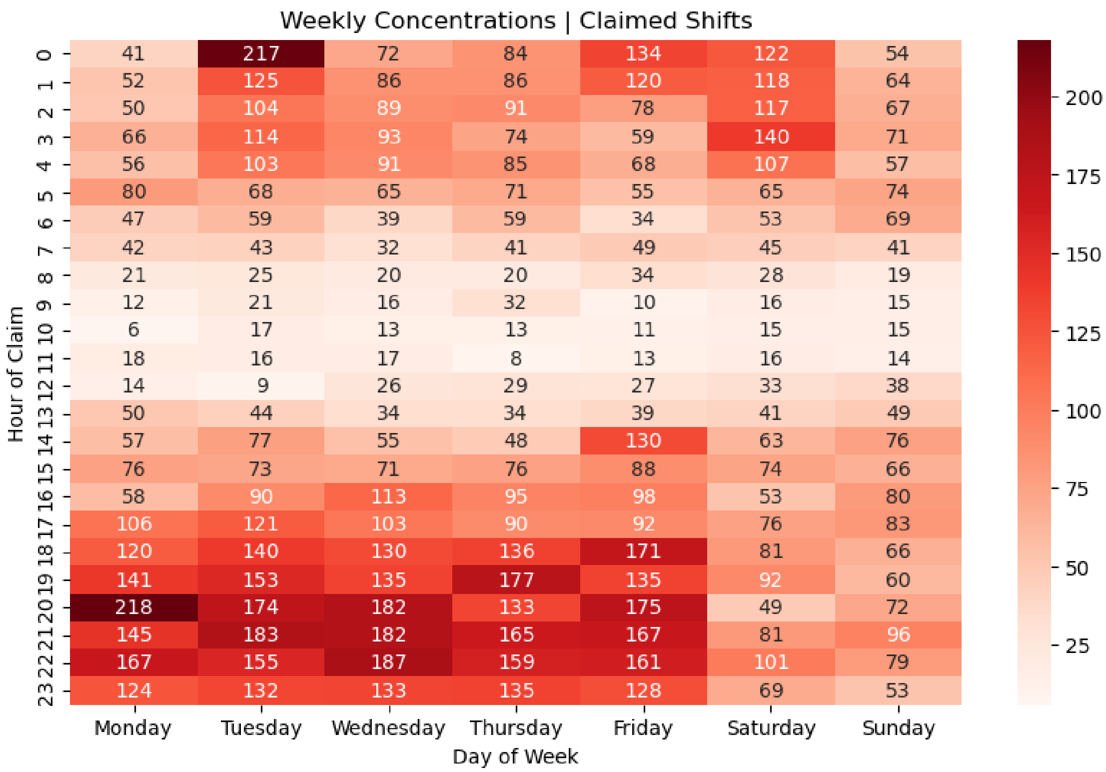


4.0.2 Claimed Shifts

[137]:
```python
# dataframe based on num. of shifts claimed in specific times of day
claimed_tod_df = df.groupby(['claimed_hour','claimed_day_name'])[['claimed_at']].count().reset_index()

# pivoting for heatmap plotting
claimed_tod_df = claimed_tod_df.pivot(index='claimed_hour', columns='claimed_day_name', values='claimed_at')

# reordering for expected days-of-week order
claimed_tod_df = claimed_tod_df[['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']]

# changing hours from float to index
claimed_tod_df.index = claimed_tod_df.index.astype('int')
```

[138]:
```python
# fig, ax = plt.subplots(figsize=(6,6)) # sizing for screenshot
fig, ax = plt.subplots(figsize=(10,6))

# sns.heatmap(claimed_tod_df, cmap='Reds') # w/o annotations for screenshot
```

```
sns.heatmap(claimed_tod_df, cmap='Reds', annot=True, fmt='g')

plt.title('Weekly Concentrations | Claimed Shifts')
plt.xlabel('Day of Week')
plt.ylabel('Hour of Claim')
plt.show()
```

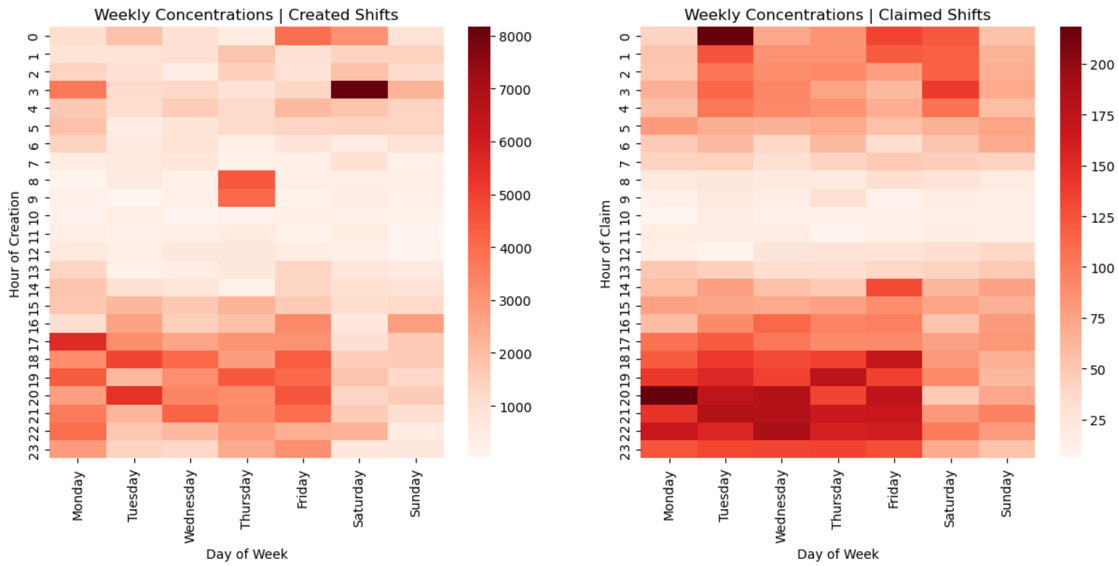


4.0.3 Overall Plot

[139]:
```
fig, axs = plt.subplots(1,2,figsize=(15,6))

# created
sns.heatmap(created_tod_df, cmap='Reds', ax= axs[0])

axs[0].set_title('Weekly Concentrations | Created Shifts')
axs[0].set_xlabel('Day of Week')
axs[0].set_ylabel('Hour of Creation')


# claimed
sns.heatmap(claimed_tod_df, cmap='Reds', ax=axs[1])
```

```
axs[1].set_title('Weekly Concentrations | Claimed Shifts')
axs[1].set_xlabel('Day of Week')
axs[1].set_ylabel('Hour of Claim')
```

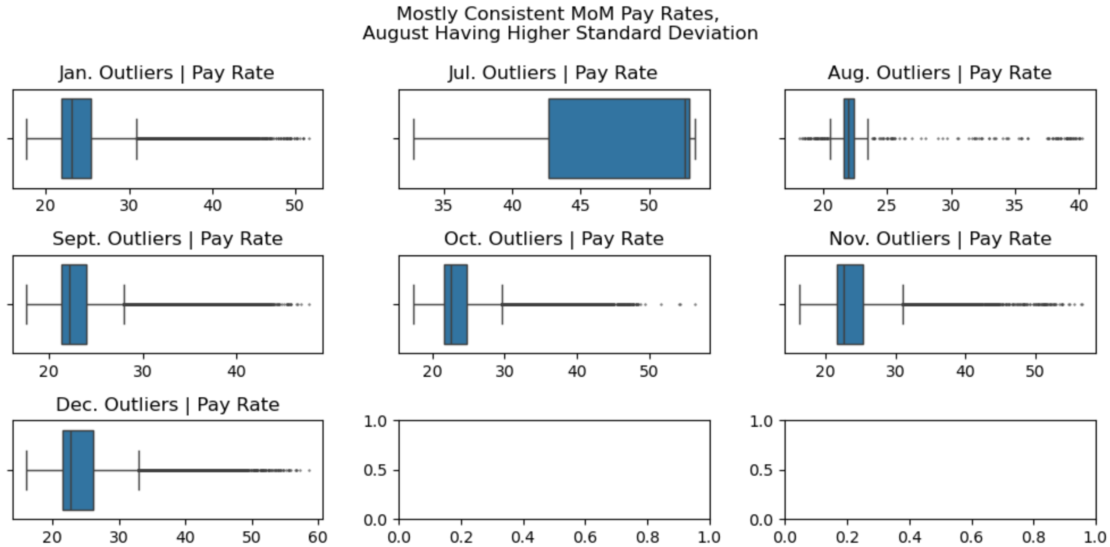
[139]: Text(792.3131313131312, 0.5, 'Hour of Claim')



5 Outliers | MoM Pay Rate

[140]:
```
fig, axs = plt.subplots(3,3,figsize=(10,5))
# january
sns.boxplot(ax=axs[0,0], data=df[(df.created_month == 1)], x='pay_rate',␣
↪fliersize=.5)
axs[0,0].set_title("Jan. Outliers | Pay Rate")
axs[0,0].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual)

# july
sns.boxplot(ax=axs[0,1], data=df[(df.created_month == 7)], x='pay_rate',␣
↪fliersize =.5)
axs[0,1].set_title("Jul. Outliers | Pay Rate")
axs[0,1].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

# august
sns.boxplot(ax=axs[0,2], data=df[(df.created_month == 8)], x='pay_rate',␣
↪fliersize =.5)
axs[0,2].set_title("Aug. Outliers | Pay Rate")
```

```
axs[0,2].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

# september
sns.boxplot(ax=axs[1,0], data=df[(df.created_month == 9)], x='pay_rate',␣
↪fliersize =.5)
axs[1,0].set_title("Sept. Outliers | Pay Rate")
axs[1,0].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

# october
sns.boxplot(ax=axs[1,1], data=df[(df.created_month == 10)], x='pay_rate',␣
↪fliersize =.5)
axs[1,1].set_title("Oct. Outliers | Pay Rate")
axs[1,1].set_xlabel("")  # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

# november
sns.boxplot(ax=axs[1,2], data=df[(df.created_month == 11)], x='pay_rate',␣
↪fliersize =.5)
axs[1,2].set_title("Nov. Outliers | Pay Rate")
axs[1,2].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

# december
sns.boxplot(ax=axs[2,0], data=df[(df.created_month == 12)], x='pay_rate',␣
↪fliersize =.5)
axs[2,0].set_title("Dec. Outliers | Pay Rate")
axs[2,0].set_xlabel("") # for removing unneeded labeling (inclusion in title &␣
↪creates cleaner visual

plt.suptitle('Mostly Consistent MoM Pay Rates,\n August Having Higher Standard␣
↪Deviation')
plt.tight_layout()
```



- Median looks consistent among 6/7 plots - July being incongruous.
- Aside from July (posited its plot being due to only 3 created shifts), most other monthly outliers follow the same pattern of an IQR ~22-~25. *Why does August:*
  - outlier IQR fall between 20-25?
  - have outliers past the lower limit?
  - due to specific workplaces? if so, what is their behavior in other months?

[141]:
```
# creating dataframe for august, specifically
aug_df = df[(df.created_month == 8)]
aug_df.shape
```

[141]: (1803, 25)

[142]:
```
# split into 25th and 75th percentiles
aug_percentile_75 = aug_df.pay_rate.quantile(0.75)
aug_percentile_25 = aug_df.pay_rate.quantile(0.25)

# calculate iqr
aug_pay_iqr = aug_percentile_75 - aug_percentile_25

# determine upper limit
aug_upper_limit_pay = aug_percentile_75 + 1.5 * aug_pay_iqr

# determine lower limit
aug_lower_limit_pay = aug_percentile_25 - 1.5 * aug_pay_iqr

# storing outliers & printing total number present
aug_outliers_pay_rate = aug_df[(aug_df.pay_rate > aug_upper_limit_pay) |
 ↪(aug_df.pay_rate < aug_lower_limit_pay)]
```

```python
print(f'Num. of outliers: {len(aug_outliers_pay_rate)}')

print(f'25th %: {aug_percentile_25}')
print(f'75th %: {aug_percentile_75}')
print(f'Upper Limit: {aug_upper_limit_pay}')
print(f'Lower Limit: {aug_lower_limit_pay}')
```

```
Num. of outliers: 163
25th %: 21.65
75th %: 22.4
Upper Limit: 23.525
Lower Limit: 20.525
```

[143]:
```python
# aug_lower
aug_lower = aug_df[(aug_df.pay_rate < aug_lower_limit_pay)]

# upper limit
aug_upper = aug_df[(aug_df.pay_rate > aug_upper_limit_pay)]
```

any patterns amongst workplaces within categorical below/upper groupings? :

[144]:
```python
# avg. pay rate (below lower limit) by workplace
aug_lower.groupby('workplace_id')[['pay_rate']].mean().
↪sort_values(by=['pay_rate'], ascending=False).reset_index()
```

[144]:

	workplace_id	pay_rate
0	5ebf1743a253570017a27d99	20.430000
1	6203e9b58fa46801a9ed5f21	19.902000
2	5e7266e3759cf60016d86c98	19.897500
3	5ebf16f8fe8b200017aebe0f	19.870000
4	637e71fd4a702e01b5e6261b	19.271351

[145]:
```python
# avg. pay rate (above upper limit) by workplace
aug_upper.groupby('workplace_id')[['pay_rate']].mean().
↪sort_values(by=['pay_rate'], ascending=False).reset_index()
```

[145]:

	workplace_id	pay_rate
0	637e71fd4a702e01b5e6261b	37.809333
1	6203e9b58fa46801a9ed5f21	35.322727
2	611af67795f4c501662edb31	34.029000
3	61c4d2a870dd500187dc98b1	32.590000
4	5ff4f626909f7a00160d06fd	31.930000
5	617195fe61cfc6016a47a1de	31.515556
6	628439ec1df59901b9c4f568	30.540000
7	5ebf1743a253570017a27d99	26.821429
8	6564d795a3497ddd40ab079f	25.914286
9	5e7266e3759cf60016d86c98	24.710000
10	5ebf16f8fe8b200017aebe0f	24.565000

MoM Outlier Considerations

- all workplaces that provided below lower limit pay, appear in those that provided pay above the upper limit.
- `6203e9b58fa46801a9ed5f21` comes 2nd in both below avg. pay rate & above avg. pay rate
- `637e71fd4a702e01b5e6261b` comes 5th (last) in below avg. pay rate but 1st in above avg. pay rate

1) Jan Limits:
   - Lower: 21.81 | Upper: 25.46
2) Jul Limits:
   - Lower: 42.66 | Upper: 52.945
3) Aug Limits:
   - Lower: 21.65 | Upper: 22.40
4) Sept Limits:
   - Lower: 21.38 | Upper: 24.01
5) Oct Limits:
   - Lower: 21.62 | Upper: 24.80
6) Nov Limits:
   - Lower: 21.55 | Upper: 25.36
7) Dec Limits:
   - Lower: 21.56 | Upper: 26.15

6 Workplace-Grouped Create, Claim, Delete Frequencies, Deletion Rate

- **Are there workplaces that delete shifts most often? (related to anchor question 3). More insightful correlation is likely created:deleted by workplace**

Note: Monthly reflections are aggregations of 2024-2025 years contained within dataset

[148]:
```python
# creating new df for workplace counts of shift creations & deletions
workplace_shiftcounts_df = df.groupby(['workplace_id'])[['shift_created_at', 'deleted_at']].count().sort_values(by=['deleted_at'], ascending=False).reset_index()
```

[149]:
```python
# num. of unique workplace IDs to use for validating grouping
df.workplace_id.nunique()
```

[149]:
```
132
```

[150]:
```python
# validating workplace_shiftcounts_df
print(workplace_shiftcounts_df.shape[0])
workplace_shiftcounts_df.head()
```

```
132
```

[150]:
```
               workplace_id  shift_created_at  deleted_at
0  611af67795f4c501662edb31             29671        9858
```

```
1  5bdb65eb27415b0004330ace         14843        4909
2  5c06fe1f61d521000488a0f2         17247        4523
3  5ebf09a7fe8b200017aeb9eb         19930        3477
4  5ebf16f8fe8b200017aebe0f         10326        2836
```

[151]:
```
# renaming columns for more accurate representations
workplace_shiftcounts_df = workplace_shiftcounts_df.
  ↪rename(columns={'shift_created_at' : 'created_count', 'deleted_at' :␣
  ↪'deleted_count'})
```

[152]:
```
# reviewing where deletions are greater than creations
workplace_shiftcounts_df[(workplace_shiftcounts_df.deleted_count >␣
  ↪workplace_shiftcounts_df.created_count)]
```

[152]:
```
Empty DataFrame
Columns: [workplace_id, created_count, deleted_count]
Index: []
```

[153]:
```
# reviewing % makeup of workplace shifts posted
df.workplace_id.value_counts(normalize=True)
```

[153]:
```
workplace_id
611af67795f4c501662edb31    0.111403
5ebf09a7fe8b200017aeb9eb    0.074829
5c06fe1f61d521000488a0f2    0.064756
5bdb65eb27415b0004330ace    0.055730
5e95d5f5cf5e8d001653314e    0.039754
                              …
64c2a4011aaeed08092a7bf6    0.000008
66f6fc534f4d6ca9b9c3254b    0.000008
6463e90ced386e01bbed93ce    0.000004
618eed8692efe30185e5b6c2    0.000004
6256fbc0913ce401ab50f0cf    0.000004
Name: proportion, Length: 132, dtype: float64
```

Frequency Reviewal - Creation

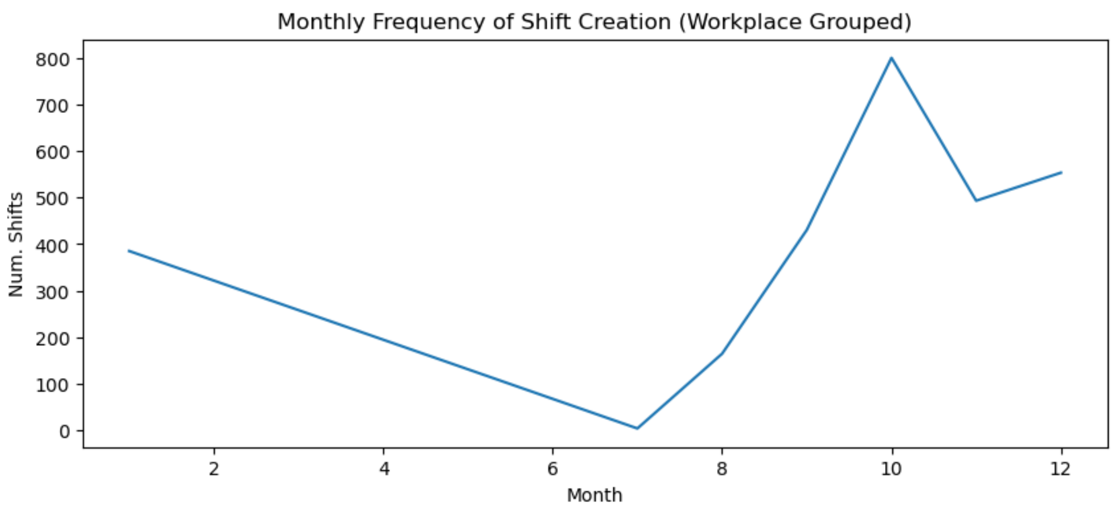
[154]:
```
# df for created shifts, grouped by workplace
created_df = df.groupby(['workplace_id', 'created_month',␣
  ↪'created_year'])[['shift_id']].count()\
            .rename(columns={'shift_id' : 'num_created_shifts'}).
  ↪sort_values(by=['num_created_shifts'], ascending=False).reset_index()

created_df.head()
```

[154]:
```
                workplace_id  created_month  created_year  num_created_shifts
0  611af67795f4c501662edb31             10          2024               10651
1  611af67795f4c501662edb31              9          2024                9320
```

2	5c06fe1f61d521000488a0f2	10	2024	7843
3	5ebf09a7fe8b200017aeb9eb	12	2024	5941
4	611af67795f4c501662edb31	12	2024	5319

[155]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(created_df, x='created_month', y='num_created_shifts' ,␣
↪errorbar=None)

plt.xlabel('Month')
plt.ylabel('Num. Shifts')
plt.title('Monthly Frequency of Shift Creation (Workplace Grouped)')
```

[155]:
```
Text(0.5, 1.0, 'Monthly Frequency of Shift Creation (Workplace Grouped)')
```



[156]:
```
# percentage makeup of shift creations, by month
df.created_month.value_counts(normalize=True)
```

[156]:
```
created_month
10    0.309732
12    0.224491
11    0.174112
9     0.151896
1     0.132988
8     0.006770
7     0.000011
Name: proportion, dtype: float64
```

Frequency Reviewal - Claim

- Inquiring into patterns that may or may not align with shift creations/deletions

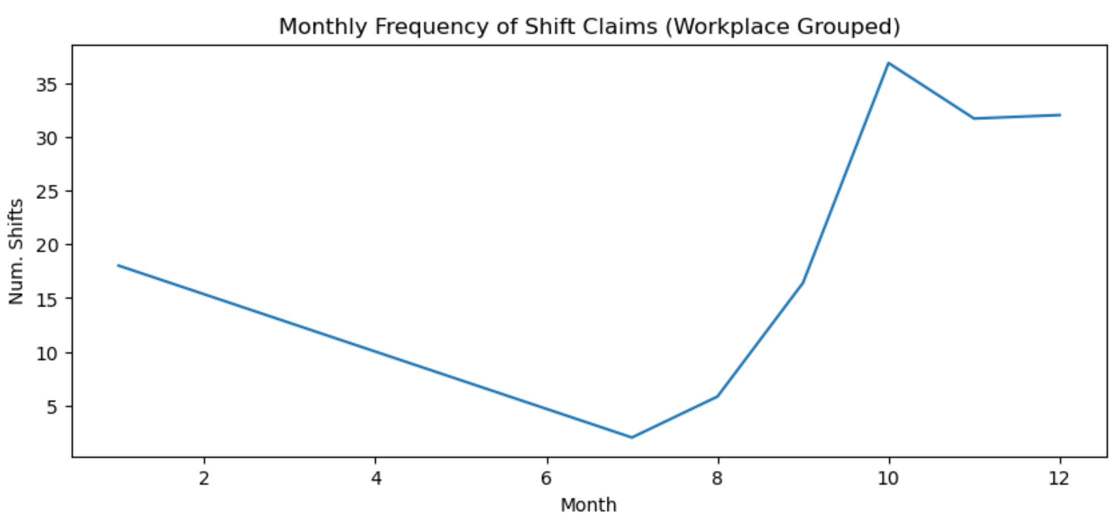
[157]:
```
# df for claimed shifts, grouped by workplace
claimed_df = df.groupby(['workplace_id', 'claimed_month',␣
↪'claimed_year'])[['shift_id']].count()\
            .rename(columns={'shift_id' : 'num_claimed_shifts'}).
↪sort_values(by=['num_claimed_shifts'], ascending=False).reset_index()

claimed_df.head()
```

[157]:

	workplace_id	claimed_month	claimed_year	num_claimed_shifts
0	611af67795f4c501662edb31	12	2024	361
1	610c3e4bb0d8850166b2bd41	10	2024	333
2	5bdb65eb27415b0004330ace	11	2024	223
3	5bdb65eb27415b0004330ace	12	2024	213
4	5ebf09a7fe8b200017aeb9eb	12	2024	210

[158]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(claimed_df, x='claimed_month', y='num_claimed_shifts' ,␣
↪errorbar=None)

plt.xlabel('Month')
plt.ylabel('Num. Shifts')
plt.title('Monthly Frequency of Shift Claims (Workplace Grouped)')
```

[158]:
```
Text(0.5, 1.0, 'Monthly Frequency of Shift Claims (Workplace Grouped)')
```



Frequency Reviewal - Deletion

[159]:
```
# df for deleted shifts, grouped by workplace
deleted_df = df.groupby(['workplace_id', 'deleted_month',␣
↪'deleted_year'])[['shift_id']].count()\
```

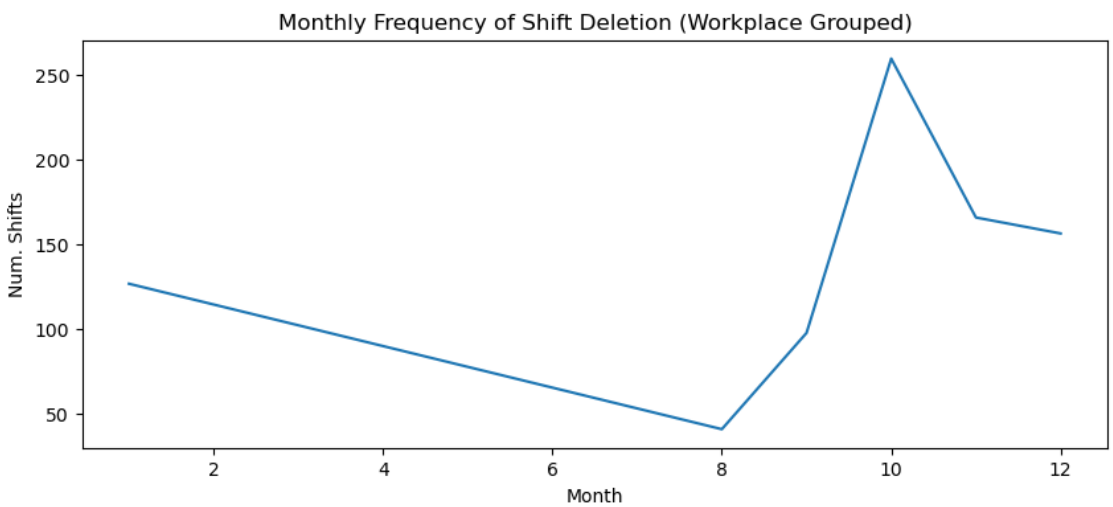
```
            .rename(columns={'shift_id' : 'num_deleted_shifts'}).
 ↪sort_values(by=['num_deleted_shifts'], ascending=False).reset_index()

deleted_df.head()
```

[159]:

	workplace_id	deleted_month	deleted_year	num_deleted_shifts
0	611af67795f4c501662edb31	10	2024	4650
1	611af67795f4c501662edb31	11	2024	2217
2	5bdb65eb27415b0004330ace	10	2024	2038
3	5c06fe1f61d521000488a0f2	12	2024	1486
4	5c06fe1f61d521000488a0f2	11	2024	1445

[160]:
```
fig, ax = plt.subplots(figsize=(10,4))
sns.lineplot(deleted_df, x='deleted_month', y='num_deleted_shifts' ,␣
 ↪errorbar=None)

plt.xlabel('Month')
plt.ylabel('Num. Shifts')
plt.title('Monthly Frequency of Shift Deletion (Workplace Grouped)')
```

[160]: Text(0.5, 1.0, 'Monthly Frequency of Shift Deletion (Workplace Grouped)')



[161]:
```
# rows where shift created in July, and deleted in August
df[(df.created_month == 7) & (df.deleted_month == 8)]
```

[161]: Empty DataFrame
Columns: [shift_id, worker_id, workplace_id, shift_start_at, shift_created_at,
offer_viewed_at, duration, slot, claimed_at, deleted_at, is_verified,
canceled_at, is_ncns, pay_rate, charge_rate, created_month, created_year,
created_day_name, created_hour, deleted_month, deleted_year, claimed_month,

```
claimed_year, claimed_day_name, claimed_hour]
Index: []

[0 rows x 25 columns]
```

[162]:
```
# rows of deleted shifts that have not been claimed
df[(df.claimed_at.isna()) & ~(df.deleted_month.isna())].shape[0]
```

[162]:
```
55447
```

[163]:
```
# rows of deleted shifts that have been claimed
df[~(df.claimed_at.isna()) & ~(df.deleted_month.isna())].shape[0]
```

[163]:
```
197
```

Deletion Rate

[165]:
```
# creating df to house rate
rate_df = df.groupby('workplace_id')[['shift_created_at', 'deleted_at']].
↪count().copy()
```

[166]:
```
# column for proportion of projects deleted
rate_df['deletion_rate'] = rate_df.deleted_at / (rate_df.shift_created_at +␣
↪rate_df.deleted_at)

# column for deletion rate
rate_df['delete_create_ratio'] = rate_df.deleted_at / rate_df.shift_created_at

# renaming columns
rate_map = {'shift_created_at' : 'num_created',
            'deleted_at' : 'num_deleted'
           }
rate_df = rate_df.rename(columns=rate_map)

# sorting dataframe by deletion rate
rate_df = rate_df.sort_values(by='deletion_rate', ascending=False).reset_index()
```

[202]:
```
rate_df.head(15)
```

[202]:
```
                 workplace_id  num_created  num_deleted  deletion_rate  \
31   5f4d42e3d621a000165c5cfd          614          612       0.499184
69   61b8fee2167e2201801e6b16           17           14       0.451613
121  65b953d241782d50f9d43d54           17           13       0.433333
46   602ed7d4c778ed00169bf292          127           85       0.400943
75   61ddb491f2fac2018a26712a          199          118       0.372240
32   5f52a9138c405c0016d30feb          821          445       0.351501
120  6564d795a3497ddd40ab079f           68           35       0.339806
98   638f685562e61b01b6719d8f          337          156       0.316430
```

47	6081f3fc667fa6016195942c	1118	517	0.316208
42	5ff4f626909f7a00160d06fd	1011	455	0.310368
81	624756a8f9a7c801aaf46df7	145	60	0.292683
51	60dba05c86c2470166fb1296	946	382	0.287651
61	615b663fbd4bd10188739177	1009	383	0.275144
108	644ad704e30bb601b9ec5b76	2242	824	0.268754
30	5f3411cd934b8c001618bc0a	579	208	0.264295

	delete_create_ratio
31	0.996743
69	0.823529
121	0.764706
46	0.669291
75	0.592965
32	0.542022
120	0.514706
98	0.462908
47	0.462433
42	0.450049
81	0.413793
51	0.403805
61	0.379584
108	0.367529
30	0.359240

Workplace Deletions | Tracking Considerations

- No workplaces with more shift deletions than creations
- Top 3 workplaces that account for shifts posted:
  1. `611af67795f4c501662edb31` : 0.111403
  2. `5ebf09a7fe8b200017aeb9eb` : 0.074829
  3. `5c06fe1f61d521000488a0f2` : 0.064756
- Top 7 delete:create ratios for workplaces are above 50% - these workplaces are deleting nearly as much as they create, especially the top workplace at very nearly 100%. This only makes up ~.69% of the total dataset, depending on the company's definition of a high deletion:creation, or deletion rate, the reflected total-makeup may shift.
  - Gathering insights into what makes a company delete a shift may ensure that workplaces deleting almost as much as they create doesn't proliferate into the wider user base.

Time-Series - July-October timeframe observes sharp increase in created shifts - **Should investigate if there are any coinciding frequencies of deletions/claims within the same timeframe** - August-October timeframe observers sharp increase in deleted shift - There is a coinciding decrease with creation & deletion from Jan.-July; with deletions low likely due to the low shift creations. **Is there anything unique about July which doesn't observe the increase in deletions - perhaps due to this being when shifts are first posted and deletions are reflected in August?** *Can review creations in July, with corresponding deletions in August for quantitative check.* {Reviewed and found no records reflecting such an occurrence} - No records in dataset where shift created in July and subsequently deleted in August - Increase in shift claims coincide with increase in shift creations. There is a less severe increase from July-Aug. for claims, when compared to the same timeframe of shift creation, but an increase nonetheless. - Deletions also coincide with pattern of shift creations.

Tracking Recs.

1. Investigate cause of incremental increase in shift deletions during Aug.-Oct. timeframe. E.g., are workplaces overestimating their workforce needs, causing shifts to be subsequently deleted once posted; are there mistakes in posting an issue that aren't able to be corrected without deleting the shift; social reasonings, or any others, for increasing deletions?
2. Increase in shift creations could be correlated with general pattern of sickness increasing as the weather becomes colder - in the same months as the increase is obsrerved - with workplaces needing more workforce to account for any expected increase in patients. An underestimation in the increase of patient population by a workplace may also be attributed to why deletions increase in the same pattern as creation.

7 Supplemental Inquiry

7.1 Investigative Question Set | Verified Shifts

1. How many workers are verified *(worker worked shift)* for a shift?
   - How does this number compare to shifts that have been deleted by a workplace?

Verified Shifts

[168]:
```
# creating separate DF for verified shifts
verified_df = df[df.is_verified == True]

# printing for num. of verified shifts
verified_df.shape[0]
```

[168]:
```
12649
```

[169]:
```
unique_shifts_df = df.drop_duplicates(subset=['shift_id'])
```

[170]:
```
unique_shifts_df.head()
```

[170]:
```
                   shift_id                 worker_id  \
0  6757580b1e2d97752fd69167  65b01f2e46c0645699081cbe
1  675d37d8a1ca6192a74d23f4  65298a18cc967a5cebbd40b6
2  67550bddd79613f860549322  6696d1c1d0200bf317ee5d3c
3  66f5d05de01fd3697b18c206  66b285d5d0200bf317738e59
4  66ee3848e62bb5f43e3baee5  620c6429e2ceb601ad203920

               workplace_id       shift_start_at     shift_created_at  \
0  5e7e45243bfbb200165914ae 2024-12-09 23:00:00 2024-12-09 20:50:19
1  5e1ce78827ff480016e9133e 2024-12-14 22:30:00 2024-12-14 07:46:32
2  626b0b89596c0601c2c39642 2024-12-08 15:00:00 2024-12-08 03:00:46
3  5cb9f07135163900163f532c 2024-09-27 14:00:00 2024-09-26 21:21:34
```

```
4  611af67795f4c501662edb31 2024-10-08 21:30:00 2024-09-21 03:06:48

       offer_viewed_at  duration slot claimed_at          deleted_at  …  \
0  2024-12-09 21:18:42         8   pm        NaT                 NaT  …
1  2024-12-14 13:19:30         9   pm        NaT 2024-12-14 19:23:43  …
2   2024-12-08 4:04:14         6   am        NaT                 NaT  …
3   2024-09-27 4:19:45         8   am        NaT                 NaT  …
4   2024-10-06 0:46:37         8   pm        NaT                 NaT  …

   created_month created_year  created_day_name  created_hour  deleted_month  \
0             12         2024            Monday            20           <NA>
1             12         2024          Saturday             7             12
2             12         2024            Sunday             3           <NA>
3              9         2024          Thursday            21           <NA>
4              9         2024          Saturday             3           <NA>

   deleted_year  claimed_month claimed_year  claimed_day_name  claimed_hour
0          <NA>           <NA>         <NA>               NaN           NaN
1          2024           <NA>         <NA>               NaN           NaN
2          <NA>           <NA>         <NA>               NaN           NaN
3          <NA>           <NA>         <NA>               NaN           NaN
4          <NA>           <NA>         <NA>               NaN           NaN

[5 rows x 25 columns]
```

[171]:
```python
# of unique shifts that have been deleted by workplace
unique_shifts_df[~(unique_shifts_df.deleted_at.isna())].shape[0]
```

[171]:
```
3671
```

Deletion & Unverified Inquiry

[172]:
```python
# records that are both verified and have been deleted by worplace
verified_df[~(verified_df.deleted_at.isna())]
```

[172]:
```
                        shift_id                 worker_id  \
95162  67101f8674cbb3ffc03b2835  6001df03fc4eb6001662c503

                    workplace_id shift_start_at    shift_created_at  \
95162  65428c5eb9ae7bfe06a31fec     2024-10-20 2024-10-16 20:18:14

           offer_viewed_at  duration slot          claimed_at  \
95162  2024-10-16 20:18:14        12   pm 2024-10-16 20:18:14

               deleted_at  …  created_month created_year  created_day_name  \
95162 2024-10-21 17:21:04  …             10         2024         Wednesday

       created_hour  deleted_month  deleted_year  claimed_month claimed_year  \
```

```
95162          20          10       2024          10       2024

       claimed_day_name  claimed_hour
95162         Wednesday          20.0

[1 rows x 25 columns]
```

[173]:
```python
# num. of unverified shifts
df[df.is_verified == False].shape[0]
```

[173]:
```
253691
```

Why are there 253,691 unverified shifts? - Check records where `canceled_at` is also true - Check records where `is_ncns` is also true

Unverified Shifts

[174]:
```python
# creating separate DF for unverified shifts
notverified_df = df[df.is_verified == False]

# validating num. of unverified shifts
notverified_df.shape[0]
```

[174]:
```
253691
```

[175]:
```python
# prints num of records for canceled shifts
print(f'Num. Canceled: {notverified_df[~(notverified_df.canceled_at.isna())].
 ↪shape[0]}')

# prints num. records where workers are ncns
print(f'Num. NCNS: {notverified_df[(notverified_df.is_ncns == True)].shape[0]}')

# prints num. of records that were deleted by workplace
print(f'Num. Workplace Deleted: {notverified_df[~(notverified_df.deleted_at.
 ↪isna())].shape[0]}')
```

```
Num. Canceled: 165
Num. NCNS: 20
Num. Workplace Deleted: 55643
```

[176]:
```python
# storing where canceled_at is false
canceled_false = (notverified_df.canceled_at.isna())

# storing where is_ncns is false
ncns_false = (notverified_df.is_ncns != True)

# storing where deleted_at is false
deleted_false = (notverified_df.deleted_at.isna())
```

[177]:
```
# num. of records where cancellation, ncns, and deletion-by-workplace aren't␣
↪factors
notverified_df[(canceled_false) & (ncns_false) & (deleted_false)].shape[0]
```

[177]: 197901

Verified Shifts | Tracking Considerations

- Shifts Verified: 12,649 (4.749% of dataset)
- Shifts Unverified: 253,691 (95.251% of dataset) | (particular worker hasn't worked that shift)
  - 185 records have either been canceled or ncns | .073% of notverified dataset
  - 55,643 records have been deleted by workplace | 21.933% of notverified dataset
  - **What about 197,863 remaining?**
    - 197,901 records where shift wasn't cancelled, no NCNS, and wasn't deleted by workplace. 38 rogue records. *Assumption in cause of discrepancy is due to something with duplicate records, as multiple shifts can correspond with multiple worker_id records. Likely something to confirm with an Engineering team about, and/or perform further investigation but not necessary for current analysis.*
- One verified record where the shift was deleted after the timestamp for shift_start. shift_id: 67101f8674cbb3ffc03b2835
  - Cadence doesn't occur often, as there is only one verified record where this occurred
- Need to consider accounting for duplicates when performing any statistical analyses
- Correlation matrix to help guide initial inquiries?

Noted Insight

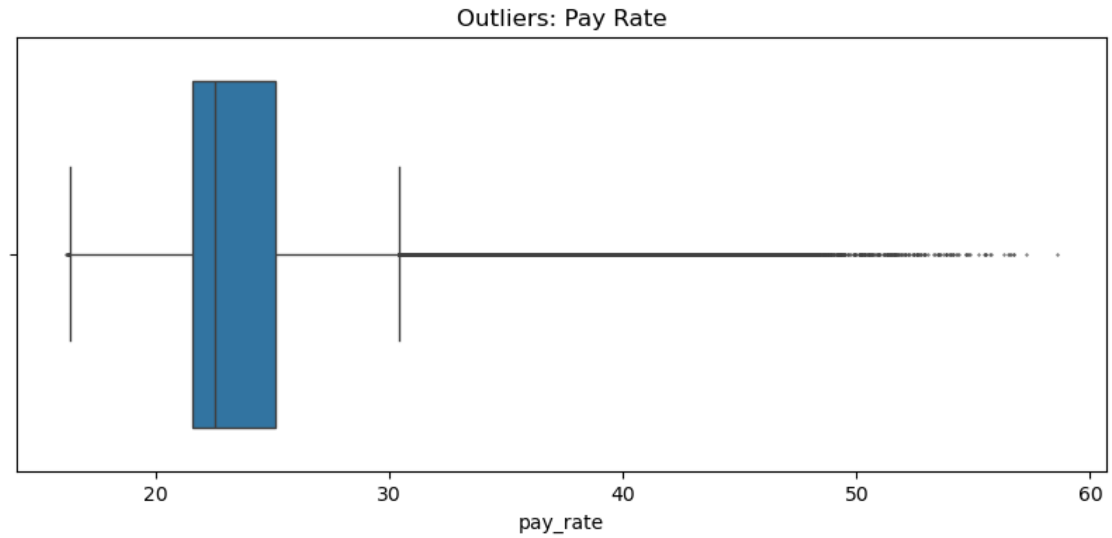
- 12,649 verified shifts : 3671 deletions by workplace
  - **Are there workplaces that delete shifts most often? (related to anchor question 3). More insightful correlation is likely created:deleted by workplace**

7.2 Investigative Questions Set | Pay & Charge Rate Overall Outliers

2. Any extreme outliers to take notice of?
   - Consider initiating focus on scales of `pay_rate` & `charge_rate`
     - *Any significant magnitudes to take note of?*

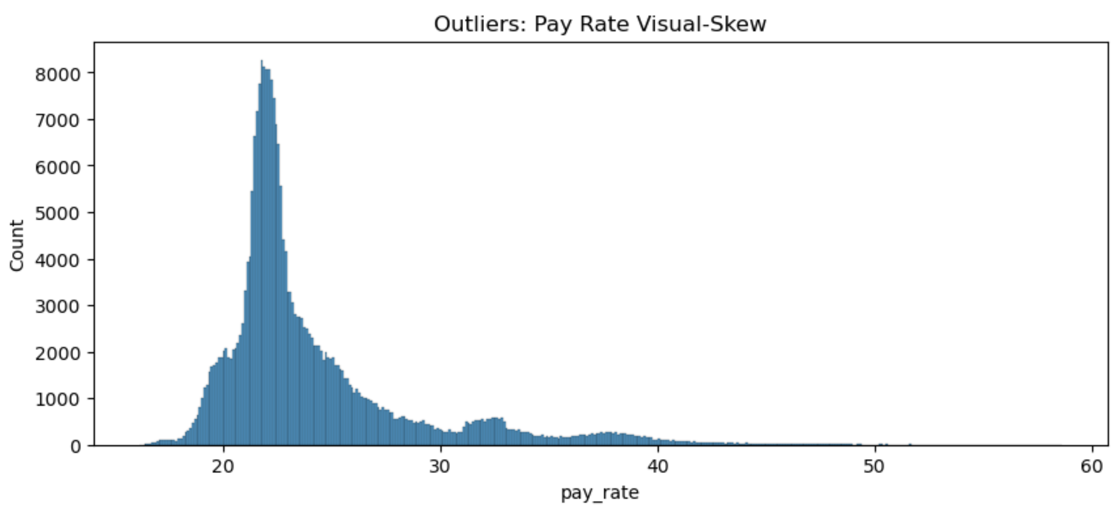
[178]:
```
# plotting `pay_rate` boxplot
fig, ax = plt.subplots(figsize=(10,4))
sns.boxplot(df, x='pay_rate', fliersize = .5)
plt.title('Outliers: Pay Rate')
```

[178]: Text(0.5, 1.0, 'Outliers: Pay Rate')



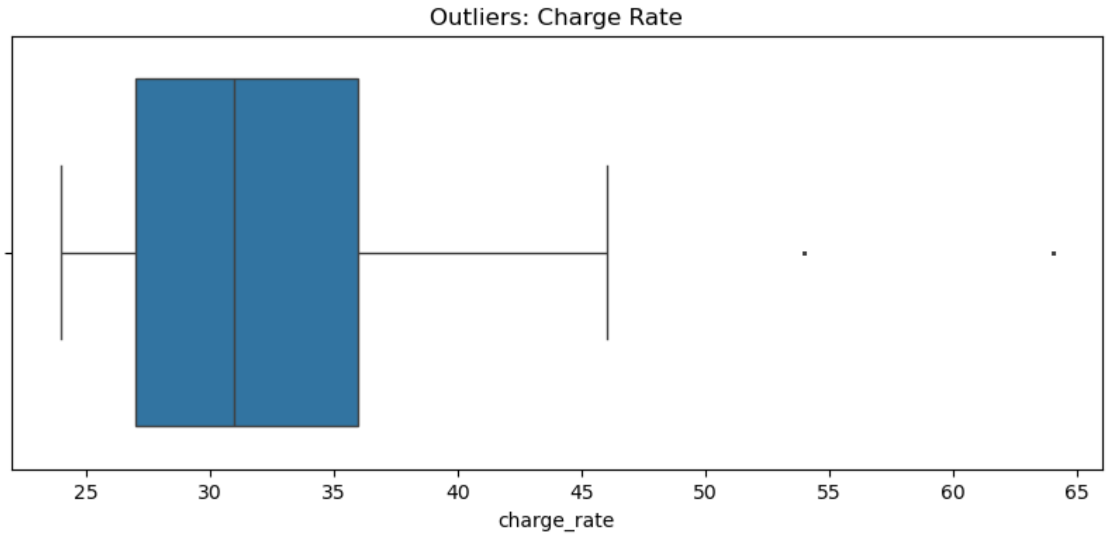
[179]:
```
# plotting `pay_rate` histogram for distribution
fig, ax = plt.subplots(figsize=(10,4))
sns.histplot(df, x='pay_rate')
plt.title('Outliers: Pay Rate Visual-Skew')
```

[179]: Text(0.5, 1.0, 'Outliers: Pay Rate Visual-Skew')



[180]:
```
# plotting `charge_rate` boxplot
fig, ax = plt.subplots(figsize=(10,4))
sns.boxplot(df, x='charge_rate', fliersize = 1)
plt.title('Outliers: Charge Rate')
```

[180]: Text(0.5, 1.0, 'Outliers: Charge Rate')



Extreme Outliers Tracking Considerations Pay Rate: - Outliers both below and above quartiles, especially above. - **Why are there so many above upper extreme outliers?** - *Gather/Investigate records where rate is an outlier.* - Further inquiry into how pay rates are determined would likely help with contextual understanding.

Charge Rate: - Two outliers located above upper quartile

Pay Rate Outliers

[181]:
```
# split into 25th and 75th percentiles
pay_percentile_75 = df.pay_rate.quantile(0.75)
pay_percentile_25 = df.pay_rate.quantile(0.25)

# calculate iqr
pay_iqr = pay_percentile_75 - pay_percentile_25

# determine upper limit
upper_limit_pay = pay_percentile_75 + 1.5 * pay_iqr

# determine lower limit
lower_limit_pay = pay_percentile_25 - 1.5 * pay_iqr

# storing outliers & printing total number present
outliers_pay_rate = df[(df.pay_rate > upper_limit_pay) | (df.pay_rate <
 ↪lower_limit_pay)]
print(f'Num. of outliers: {len(outliers_pay_rate)}')
```

```
Num. of outliers: 28382
```

[182]:
```python
# num above upper extreme
df[(df.pay_rate > upper_limit_pay)].shape[0]
```

[182]: 28373

[183]:
```python
# num below lower extreme
df[(df.pay_rate < lower_limit_pay)].shape[0]
```

[183]: 9

[184]:
```python
# reviewing df
outliers_pay_rate.head(1)
```

[184]:
```
                   shift_id                 worker_id  \
6  677b553df0e33d9606282ec6  632565c79603d78083c25520

               workplace_id      shift_start_at    shift_created_at  \
6  6081f3fc667fa6016195942c 2025-01-06 06:00:00 2025-01-06 03:59:58

      offer_viewed_at  duration slot claimed_at deleted_at  …  \
6  2025-01-06 4:13:02         8  noc        NaT        NaT  …

   created_month created_year  created_day_name  created_hour  deleted_month  \
6              1         2025            Monday             3           <NA>

   deleted_year  claimed_month claimed_year  claimed_day_name  claimed_hour
6          <NA>           <NA>         <NA>               NaN           NaN

[1 rows x 25 columns]
```

[185]:
```python
avg_pay = outliers_pay_rate.pay_rate.mean()
median_pay = outliers_pay_rate.pay_rate.median()
mode_pay = outliers_pay_rate.pay_rate.mode()

print(f'Mean: {avg_pay}')
print(f'Median: {median_pay}')
print(f'Mode: {mode_pay}')
```

```
Mean: 35.38984567683744
Median: 34.11
Mode: 0    31.93
Name: pay_rate, dtype: float64
```

Pay Rate Outliers % Makeup

- Total 28382 (10.656% of records)
  - above upper extreme: 28373
  - below lower extreme: 9

Charge Rate Outliers

[186]:
```
# split into 25th and 75th percentiles
charge_percentile_75 = df.charge_rate.quantile(0.75)
charge_percentile_25 = df.charge_rate.quantile(0.25)

# calculate iqr
charge_iqr = charge_percentile_75 - charge_percentile_25

# determine upper limit
upper_limit_charge = charge_percentile_75 + 1.5 * charge_iqr

# determine lower limit
lower_limit_charge = charge_percentile_25 - 1.5 * charge_iqr

# storing outliers & printing total number present
outliers_charge_rate = df[(df.charge_rate > upper_limit_charge) | (df.
 ↪charge_rate < lower_limit_charge)]
print(f'Num. of outliers: {len(outliers_charge_rate)}')
```

```
Num. of outliers: 32
```

[187]:
```
avg_charge = outliers_charge_rate.charge_rate.mean()
median_charge = outliers_charge_rate.charge_rate.median()
mode_charge = outliers_charge_rate.charge_rate.mode()

print(f'Mean: {avg_charge}')
print(f'Median: {median_charge}')
print(f'Mode: {mode_charge}')
```

```
Mean: 60.25
Median: 64.0
Mode: 0    64
Name: charge_rate, dtype: int64
```

Charge Rate Outliers % Makeup - Total 32 (.012% of records)

// To focus on Pay Rate (`pay_rate`), as there is such a small percentage of charge_rate outliers and while it may be capable to ideate on directions for investigating correlating patterns, more attention would reasonably be made in regard to pay_rate; current dataset is correlated more with shifts and users, rather than workplace-focused.

Next Steps

- Investigate pay_rate ranges that coincide with creation of shifts (*reminder:* claiming of shifts will follow same pattern)
  - Can look at users' patterns of claims with shift pay_rates
  - Jul. - Oct.
  - Nov. - Dec. (smaller increase); will focus on Jul. - Oct. for purposes of this initial analysis so as not to include observed decrease from Oct. - Nov. and have Jul. - Oct. suffice as representative sample.

7.2.1 Zooming-In to Increase in Shift Creation timing

Note: This increase was observed in the aggregation by workplace_id

Observed Increase (July - Oct) DF of Shift Creations

[188]:
```
# storing observed Jul. - Oct. observed increases in df
range_increase_df = df[(df.created_month > 6) & (df.created_month <= 10)].copy()
```

[189]:
```
range_increase_df.shape[0]
```

[189]:
```
124756
```

[190]:
```
range_increase_df.head(2)
```

[190]:
```
                   shift_id                 worker_id  \
3  66f5d05de01fd3697b18c206  66b285d5d0200bf317738e59
4  66ee3848e62bb5f43e3baee5  620c6429e2ceb601ad203920

               workplace_id      shift_start_at    shift_created_at  \
3  5cb9f07135163900163f532c 2024-09-27 14:00:00 2024-09-26 21:21:34
4  611af67795f4c501662edb31 2024-10-08 21:30:00 2024-09-21 03:06:48

     offer_viewed_at  duration slot claimed_at deleted_at  …  \
3  2024-09-27 4:19:45         8   am        NaT        NaT  …
4  2024-10-06 0:46:37         8   pm        NaT        NaT  …

   created_month created_year  created_day_name  created_hour  deleted_month  \
3              9         2024          Thursday            21           <NA>
4              9         2024          Saturday             3           <NA>

   deleted_year  claimed_month claimed_year  claimed_day_name  claimed_hour
3          <NA>           <NA>         <NA>               NaN           NaN
4          <NA>           <NA>         <NA>               NaN           NaN

[2 rows x 25 columns]
```

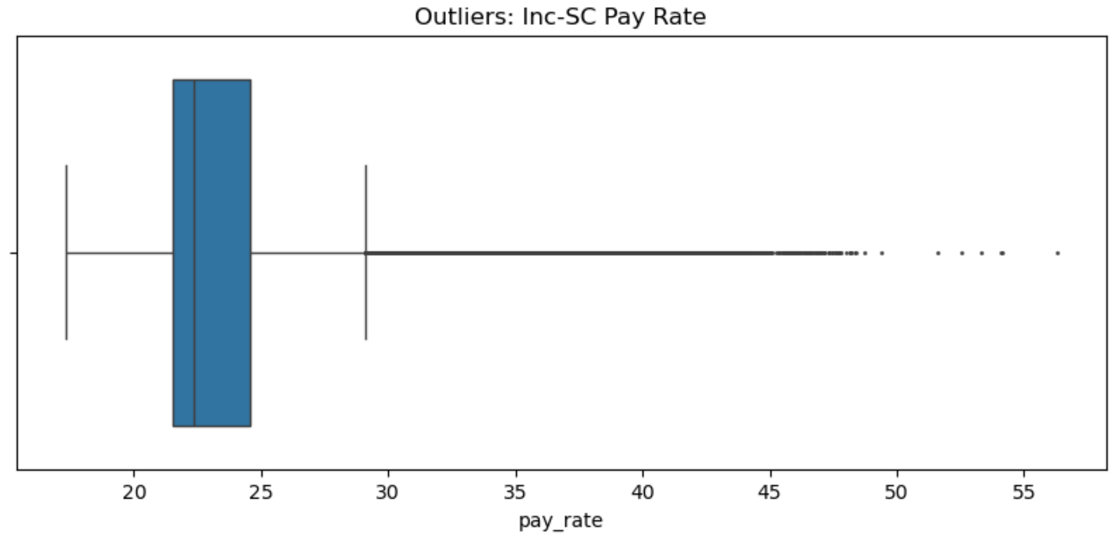
[191]:
```
avg_pay_inc = range_increase_df.pay_rate.mean()
median_pay_inc = range_increase_df.pay_rate.median()
mode_pay_inc = range_increase_df.pay_rate.mode()

print(f'Mean: {avg_pay_inc}')
print(f'Median: {median_pay_inc}')
print(f'Mode: {mode_pay_inc}')
```

```
Mean: 23.765347317964668
Median: 22.37
Mode: 0    21.99
Name: pay_rate, dtype: float64
```

Increase Shift Creation (Inc-SC) Pay Rate Outliers

[192]:
```python
# plotting `charge_rate` boxplot
fig, ax = plt.subplots(figsize=(10,4))
sns.boxplot(range_increase_df, x='pay_rate', fliersize = 1)
plt.title('Outliers: Inc-SC Pay Rate')
```

[192]:
```
Text(0.5, 1.0, 'Outliers: Inc-SC Pay Rate')
```



[193]:
```python
# split into 25th and 75th percentiles
inc_percentile_75 = range_increase_df.pay_rate.quantile(0.75)
inc_percentile_25 = range_increase_df.pay_rate.quantile(0.25)

# calculate iqr
inc_iqr = inc_percentile_75 - inc_percentile_25

# determine upper limit
upper_limit_inc = inc_percentile_75 + 1.5 * inc_iqr

# determine lower limit
lower_limit_inc = inc_percentile_25 - 1.5 * inc_iqr

# storing outliers & printing total number present
outliers_inc_pay_rate = range_increase_df[(range_increase_df.pay_rate >
 ↪upper_limit_inc) | (range_increase_df.pay_rate < lower_limit_inc)]
print(f'Num. of outliers: {len(outliers_inc_pay_rate)}')
print(f'Upper Limit: {upper_limit_inc}')
print(f'Lower Limit: {lower_limit_inc}')
```

```
Num. of outliers: 12790
```

```
Upper Limit: 29.08
Lower Limit: 17.0
```

Observed (Shift Creation) Increase Tracking

- 124,756 total records in Jul. - Oct. timeframe
  - 12,790 *outlier* `pay_rate` records (10.252%) - all above upper extreme of pay rate

Possible Story (Deprecated) *This choice of using this ideation is specific to the circumstance of this case study being done. In "regular circumstance" a question from a stakeholder would be crux of investigation and story told based on findings; this is similar, however with the wide breadth of control given over investigation, a need for clear direction of a possible final story (with flexible paths of investigation) became necessary:*

- There is an increase in creation of shifts during this time -> Most claimed shifts are within this pay range (and possibly claimed faster than shifts in other ranges) -> (possible deletions found are within this pay range for the same timeframe; which (possibly coincide with the shifts that are being claimed most) -> recommendations on pay rate & notices of creations and/or deletions by workplaces.

1. Look at timeframe of increase in creation of shifts (Jul. - Oct.) ->
2. Determine ranges of pay: **Next Step: How to parse/label these into groups?**
   - Not to use mean as a divider, so as to avoid misrepresenting true typical values in the dataset via impact from outliers.
   - Manually categorizing around median, or using pd.qcut() to split into 3 equal quantiles?
   - *Reach out to Data community for thoughts*
3. Observe avg. times of post-to-claim for each grouping
4. Observe num of claims for each grouping
   - *Note: Outliers will likely influence ranges of grouping*
5. Plot claims:pay-groupings ->
6. Look at deletions within:
   - Same pay ranges as above
   - Aug. - Oct. timeframe, as July is still in its prior pattern of decrease for deletions. *Ensure anecotal note if depciting*
   - Plot/observe num. of deletions in each pay range
     - Note any connections to claim:pay-groupings previously observed ->
7. Recs.

[194]:
```
# assigning quartiles to pay ranges for categorizing
range_increase_df['quartiles_pay_rate'] = pd.qcut(range_increase_df.pay_rate,␣
↪4, ['1stQ', '2ndQ', '3rdQ', '4thQ'])
```

[195]:
```
range_increase_df.head(2)
```

[195]:
```
                   shift_id                 worker_id  \
3  66f5d05de01fd3697b18c206  66b285d5d0200bf317738e59
4  66ee3848e62bb5f43e3baee5  620c6429e2ceb601ad203920

               workplace_id      shift_start_at    shift_created_at  \
```

```
3  5cb9f07135163900163f532c 2024-09-27 14:00:00 2024-09-26 21:21:34
4  611af67795f4c501662edb31 2024-10-08 21:30:00 2024-09-21 03:06:48

      offer_viewed_at  duration slot claimed_at deleted_at  …  created_year  \
3  2024-09-27 4:19:45         8   am        NaT        NaT  …          2024
4  2024-10-06 0:46:37         8   pm        NaT        NaT  …          2024

  created_day_name  created_hour  deleted_month  deleted_year  claimed_month  \
3         Thursday            21           <NA>          <NA>           <NA>
4         Saturday             3           <NA>          <NA>           <NA>

   claimed_year claimed_day_name  claimed_hour  quartiles_pay_rate
3          <NA>              NaN           NaN                1stQ
4          <NA>              NaN           NaN                2ndQ

[2 rows x 26 columns]
```