Emergency Room Management Problems

Emergency Room @ Maggiore Hospital

We will now consider a couple of Emergency Room management problems

We will use a dataset for the "Maggiore" hospital in Bologna

We will consider two main use cases:

- Predicting future arrivals (a Machine Learning problem)
- Managing the ER center resources (a Combinatorial Optimization problem)

A Look at the Dataset

We will start as usual by having a look at the dataset

In [2]:
```
data = er.load_data(data_folder)
data
```

Out[2]:

	year	ID	Triage	TkCharge	Code	Outcome	Flow
0	2018	1	2018-01-01 00:17:33	2018-01-01 04:15:36	green	admitted	[triage,visit,RX,visit]
1	2018	2	2018-01-01 00:20:33	2018-01-01 03:14:19	green	admitted	[triage,visit,lab,visit]
2	2018	3	2018-01-01 00:47:59	2018-01-01 04:32:30	white	admitted	[triage,visit,otolaryngological visit,visit]
51238	2018	51239	2018-01-01 00:49:51	NaT	white	abandoned	[]
51240	2018	51241	2018-01-01 01:00:40	NaT	green	abandoned	[]
...	...	...	...	...	...	...	...
95665	2019	95666	2019-10-31 23:26:54	2019-10-31 23:41:13	yellow	admitted	[triage,visit,RX,visit]
95666	2019	95667	2019-10-31 23:46:43	2019-11-01 09:30:25	green	admitted	[triage,visit]
108622	2019	108623	2019-10-31 23:54:05	NaT	green	abandoned	[]
95667	2019	95668	2019-10-31 23:55:32	2019-11-01 00:18:46	yellow	admitted	[triage,visit]
108623	2019	108624	2019-10-31 23:59:21	NaT	green	abandoned	[]

108625 rows × 7 columns

A Look at the Dataset

In [4]:
```
data.iloc[:3]
```

Out[4]:

	year	ID	Triage	TkCharge	Code	Outcome	Flow
0	2018	1	2018-01-01 00:17:33	2018-01-01 04:15:36	green	admitted	[triage,visit,RX,visit]
1	2018	2	2018-01-01 00:20:33	2018-01-01 03:14:19	green	admitted	[triage,visit,lab,visit]
2	2018	3	2018-01-01 00:47:59	2018-01-01 04:32:30	white	admitted	[triage,visit,otolaryngological visit,visit]

- Each row refers to a single patient
- `Triage` is the arrival time of each patient
- `TKCharge` is the time when a patient starts the first visit
- `Code` refers to the estimated priority (white < green < yellow < red)
- `Outcome` discriminates some special conditios (people quitting, fast tracks)
- `Flow` is the sequence of treatments that actually took place

A Look at the Dataset

Let's also have a look at the data types

```
In [5]: data.dtypes
```

```
Out[5]: year                  int64
        ID                    int64
        Triage       datetime64[ns]
        TkCharge     datetime64[ns]
        Code               category
        Outcome            category
        Flow                 object
        dtype: object
```

- `Flow` is actually a string

We will initially focus for now on predicting arrivals

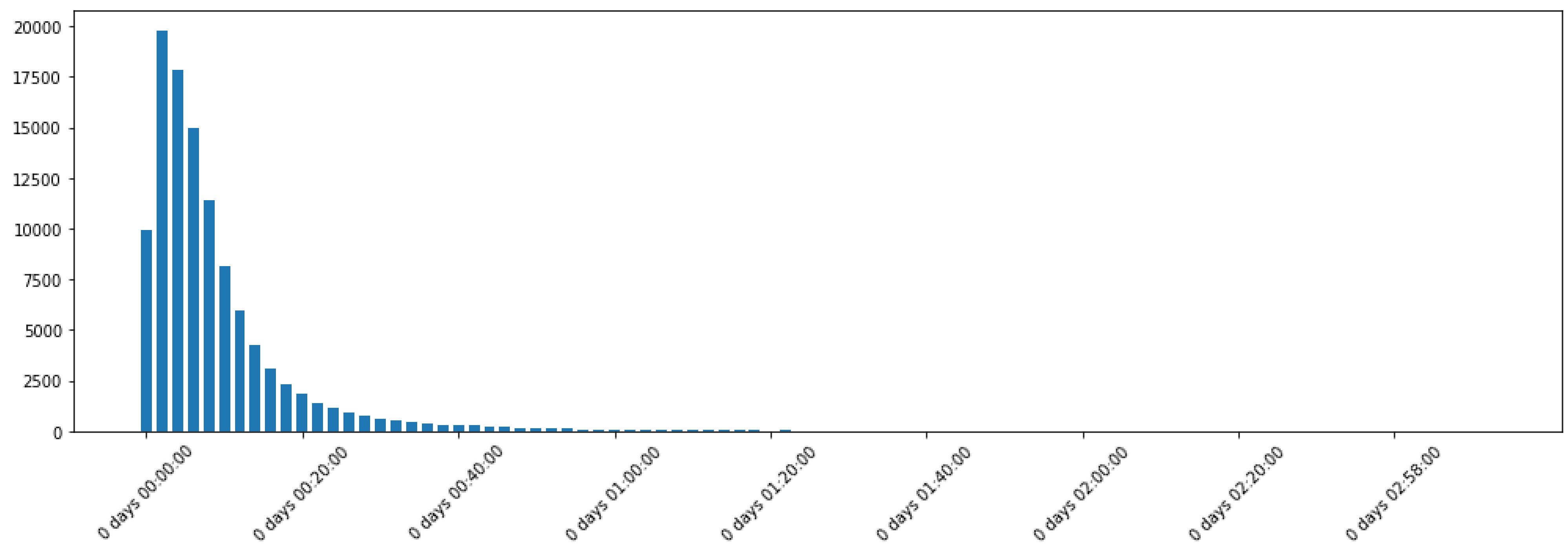
...Hence, it makes sense to sort rows by increasing triage time:

```
In [8]: data.sort_values(by='Triage', inplace=True)
```

Inter-Arrival Times

Let's check empirically the distribution of the inter-arrival times

In [6]:
```
f = '2min'
delta = data['Triage'].iloc[1:].round(f) - data['Triage'].iloc[:-1].round(f).values
er.plot_bars(delta.value_counts().sort_index(), tick_gap=10, figsize=figsize)
```

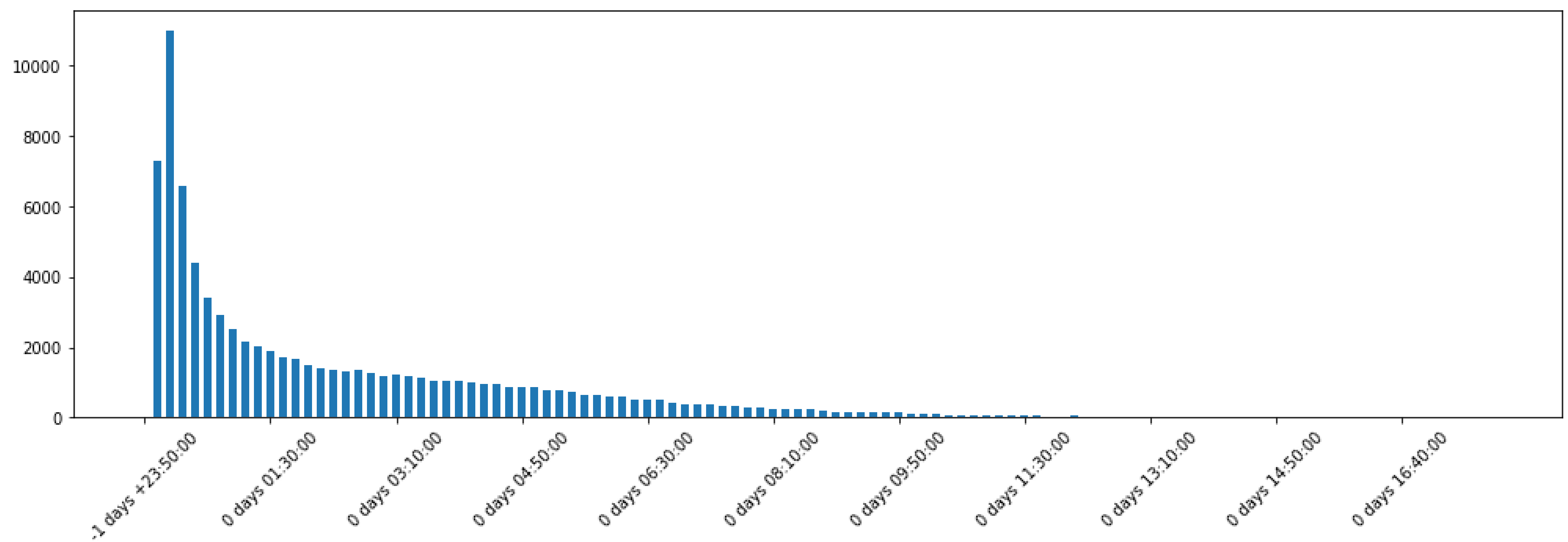


- There is a number of very low inter-arrival times
- It may be due to how triage is performed (bursts, rather than a steady flow)

Waiting Time

Here is the distribution of the waiting times

In [7]:
```
tmp = data[~data['TkCharge'].isnull()]
wait_time = tmp['TkCharge'].round('10min') - tmp['Triage'].round('10min')
er.plot_bars(wait_time.value_counts().sort_index(), tick_gap=10, figsize=figsize)
```

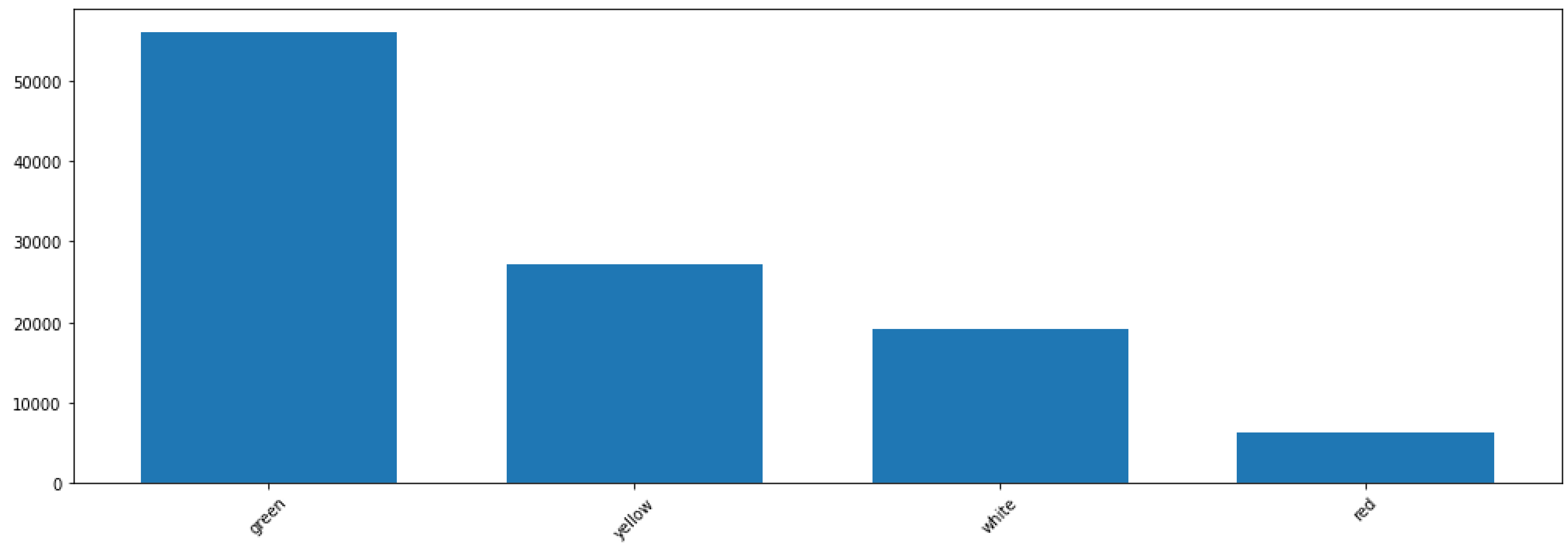


- The distritbution is heavy-tailed
- I.e. the probability of very long waiting times is non-negligible

Code Distribution

The distribution of the priority codes

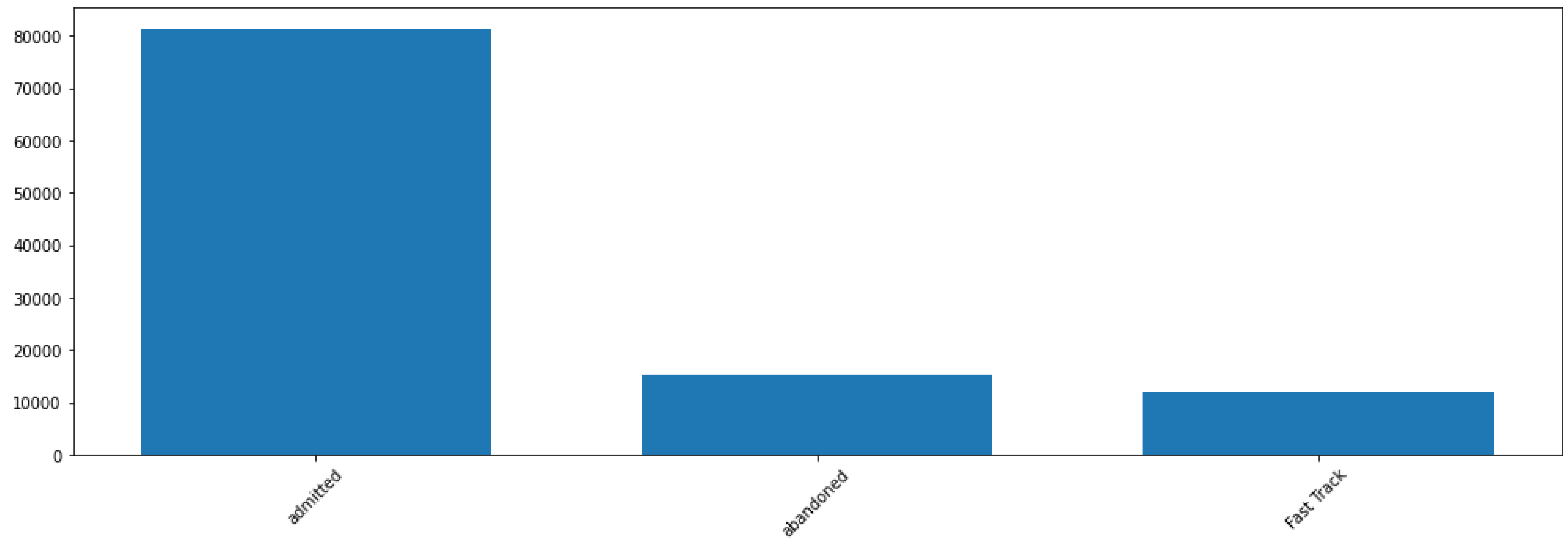
In [8]:
```
er.plot_bars(data['Code'].value_counts(), figsize=figsize)
```



- Green code (low severity) form the majority of arrivals
- Yello and red codes (mid and high severity) are in smaller numbers
- White codes (lowest priority) are also not very frequent

Outcome Distribution

In [9]:
```
er.plot_bars(data['Outcome'].value_counts(), figsize=figsize)
```

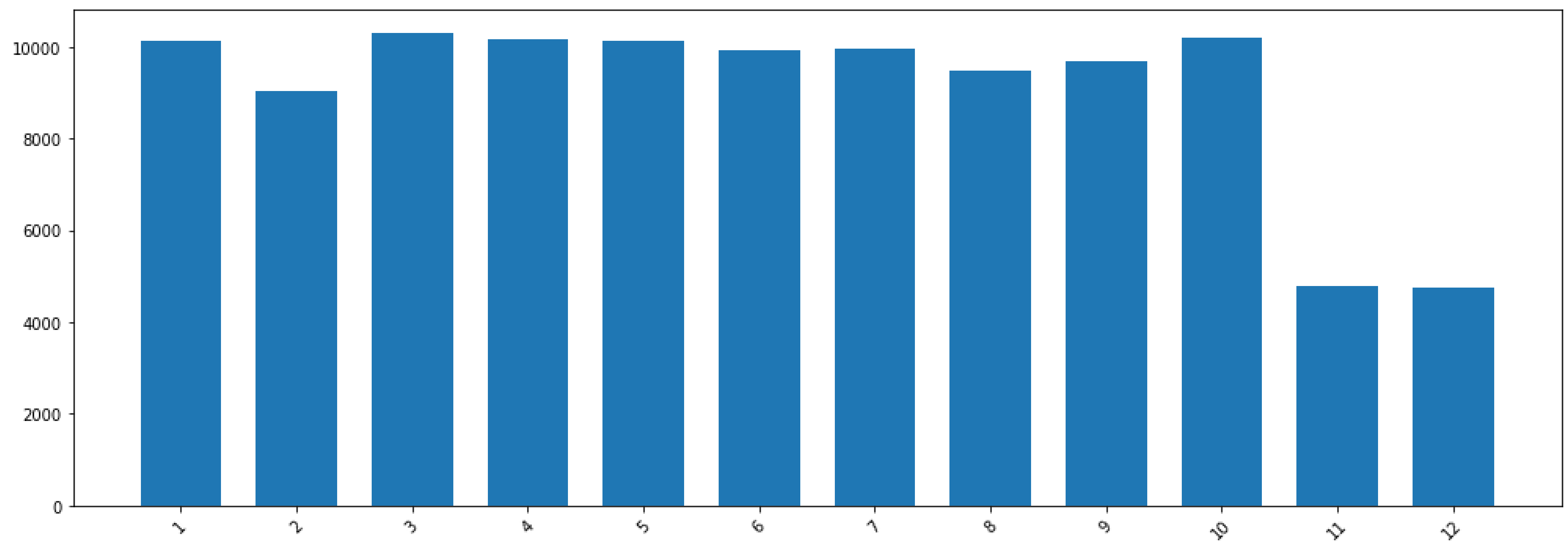


- Abandons are infrequent, as are "fast track" patients

Arrival Distribution over Months

Let's look at the arrival distribution over months

In [10]:
```
months = data['Triage'].dt.month
er.plot_bars(months.value_counts().sort_index(), figsize=figsize)
```

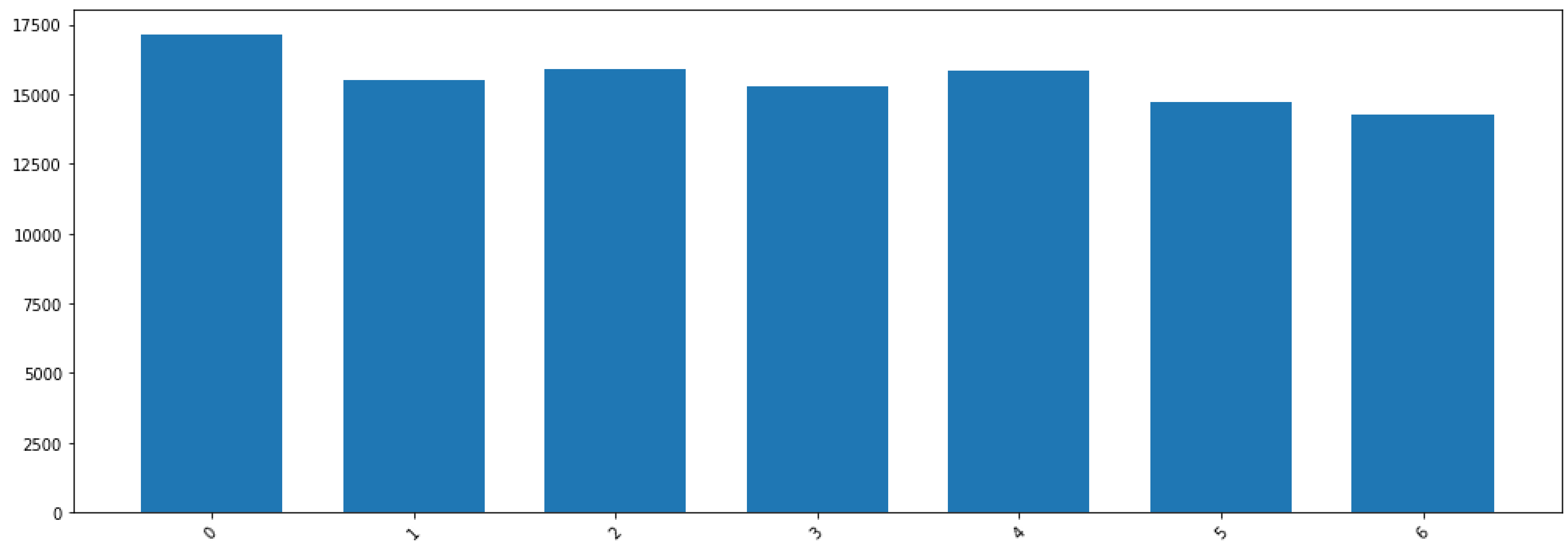


- The low values for Nov. and Dec. are due to the 2019 series ending in October
- The distribution seems stable (but we are not plotting standard deviations!)

Arrival Distribution over Weekdays

Let's look at the distribution over weekdays

```
In [11]: weekdays = data['Triage'].dt.weekday
         er.plot_bars(weekdays.value_counts().sort_index(), figsize=figsize)
```

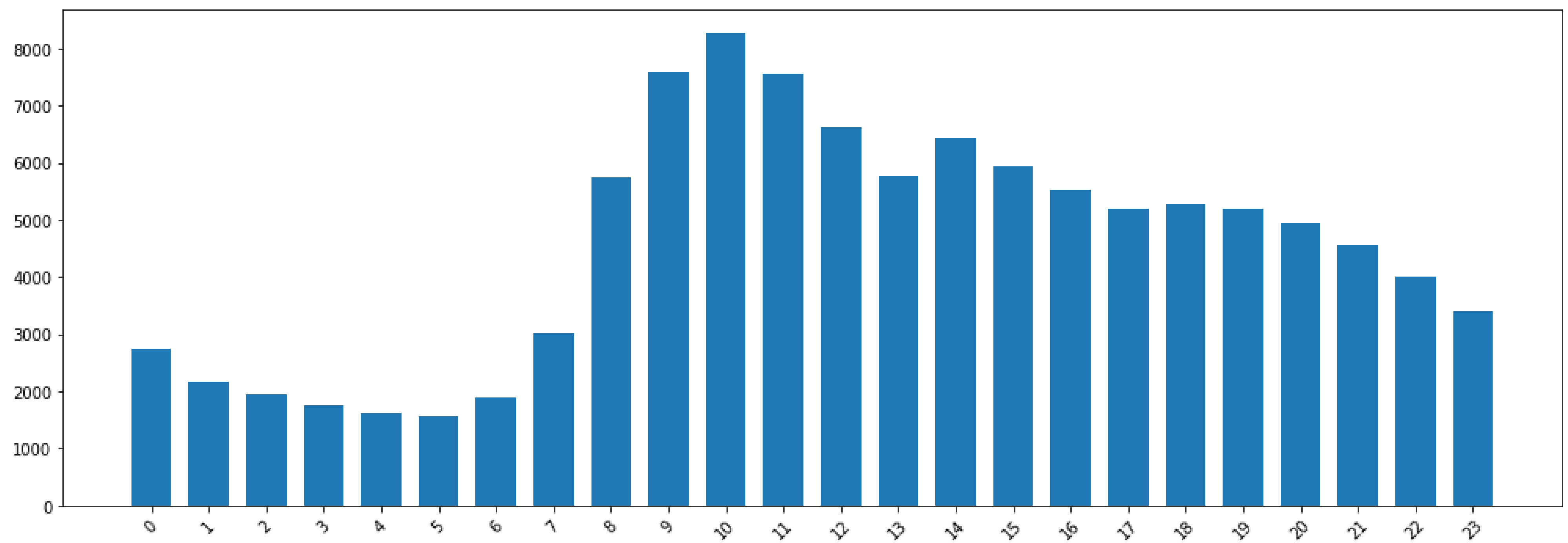


- Similarly to months, weekdays are likelly to have little predictive power
- ...But it's better not to rush conclusions (we still are not plotting the stddev!)

Arrival Distribution over Hours

Let's see now the arrival distribution over the hours of the day

In [12]:
```
hours = data['Triage'].dt.hour
er.plot_bars(hours.value_counts().sort_index(), figsize=figsize)
```



- There is a clear pattern: the hour of the day will have strong predictive power
- Again, analyzing the standard deviation may provide better insights

Data Preparation

Binning

In our two considered problems:

- We are not going to revise our decisions continuosly
- We are not interested in predicting the next arrival

Rather:

- We will take decisions at fixed intervals
- We care about the expected arrivals in a given horizon

Overall, we need to choose a meaningful time unit

In other words, we need to perform some kind of binning

- We used binning to downsample high-frequency data
- ...We will use binning to aggregate events with a variable frequency

Code-Based Counts

We will prepare the data to track counts for all priority codes

In [13]:
```
codes = pd.get_dummies(data['Code'])
codes.set_index(data['Triage'], inplace=True)
codes.columns = codes.columns.to_list()
print(f'Number of examples: {len(codes)}')
codes.head()
```

```
Number of examples: 108625
```

Out[13]:

	green	red	white	yellow
Triage				
2018-01-01 00:17:33	1	0	0	0
2018-01-01 00:20:33	1	0	0	0
2018-01-01 00:47:59	0	0	1	0
2018-01-01 00:49:51	0	0	1	0
2018-01-01 01:00:40	1	0	0	0

- The `get_dummies` function applies a one-hot encoding to categorical value
- The method generates a categorial column index (then converted to list)

Resampling

Then, we need to aggregate data with a specified frequency

In [16]:
```
codes_b = codes.resample('H').sum()
print(f'Number of examples: {len(codes_b)}')
codes_b.head()
```

```
Number of examples: 16056
```

Out[16]:

	green	red	white	yellow
Triage				
2018-01-01 00:00:00	2	0	2	0
2018-01-01 01:00:00	7	1	1	1
2018-01-01 02:00:00	4	1	4	3
2018-01-01 03:00:00	7	0	1	1
2018-01-01 04:00:00	3	0	2	0

- We used the `resample` iterator
- `resample` generater a dataframe with a dense index
- We chose 1 hours are our time unit

Computing Totals

We also compute the total number of arrivals for each interval

In [18]:
```
cols = ['white', 'green', 'yellow', 'red']
codes_b['total'] = codes_b[cols].sum(axis=1)
codes_b.head()
```

Out[18]:

	green	red	white	yellow	total
Triage					
2018-01-01 00:00:00	2	0	2	0	4
2018-01-01 01:00:00	7	1	1	1	10
2018-01-01 02:00:00	4	1	4	3	12
2018-01-01 03:00:00	7	0	1	1	9
2018-01-01 04:00:00	3	0	2	0	5

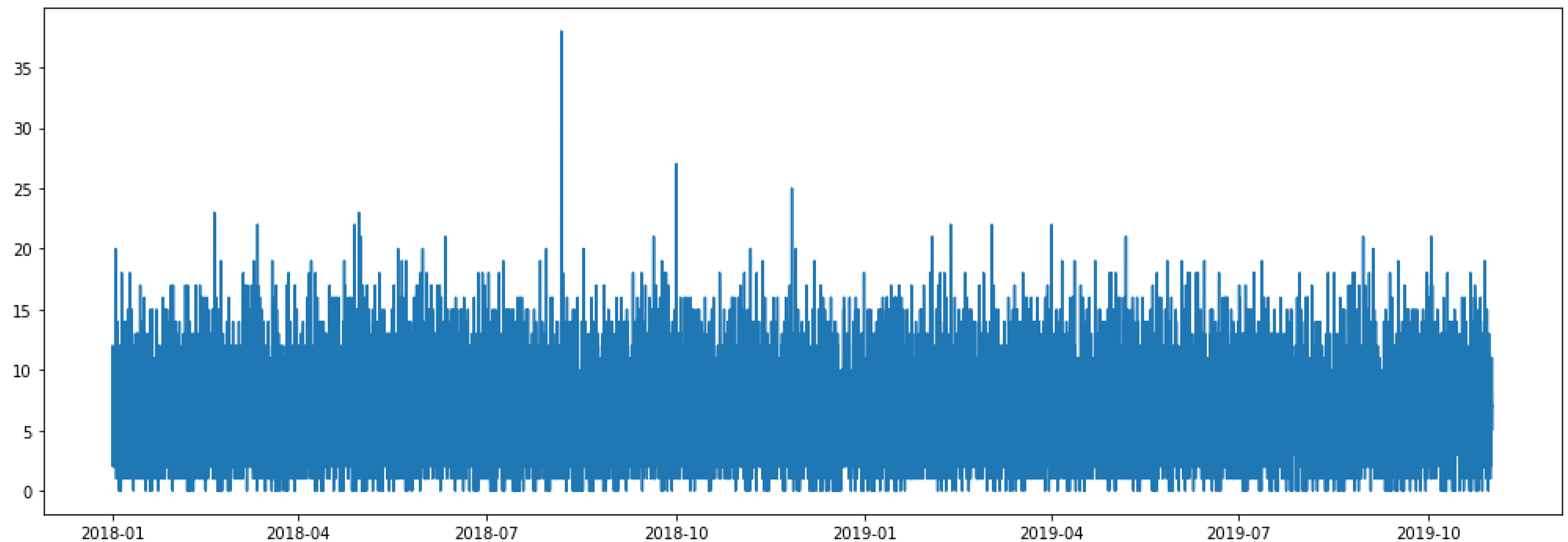
- We use a fixed column list to obtain the same result for multiple executions
- The total count will be less noisy, if the individual terms are independent

Counts over Time

Our resampled series can be plotted easily over time

Let's see the total counts as an example:

In [19]:
```
er.plot_series(codes_b['total'], figsize=figsize)
```

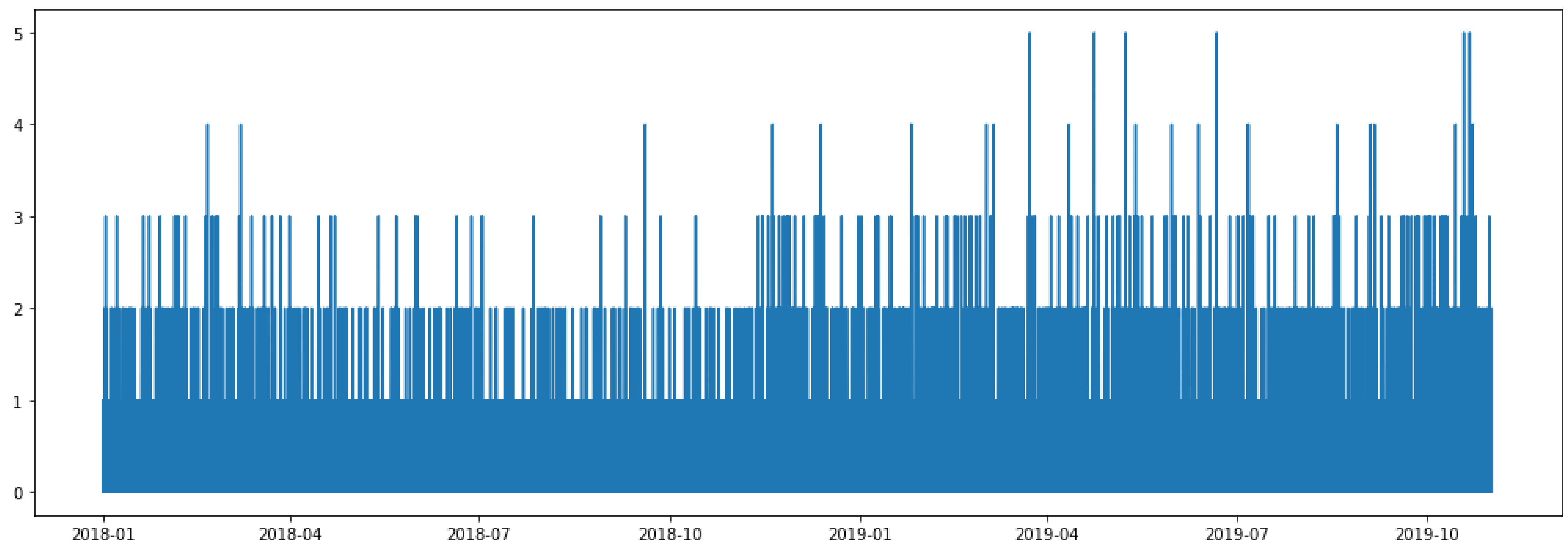


Counts over Time

Our resampled series can be plotted easily over time

The same plot, for the red codes (the counts are significanly lower):

```
In [20]: er.plot_series(codes_b['red'], figsize=figsize)
```



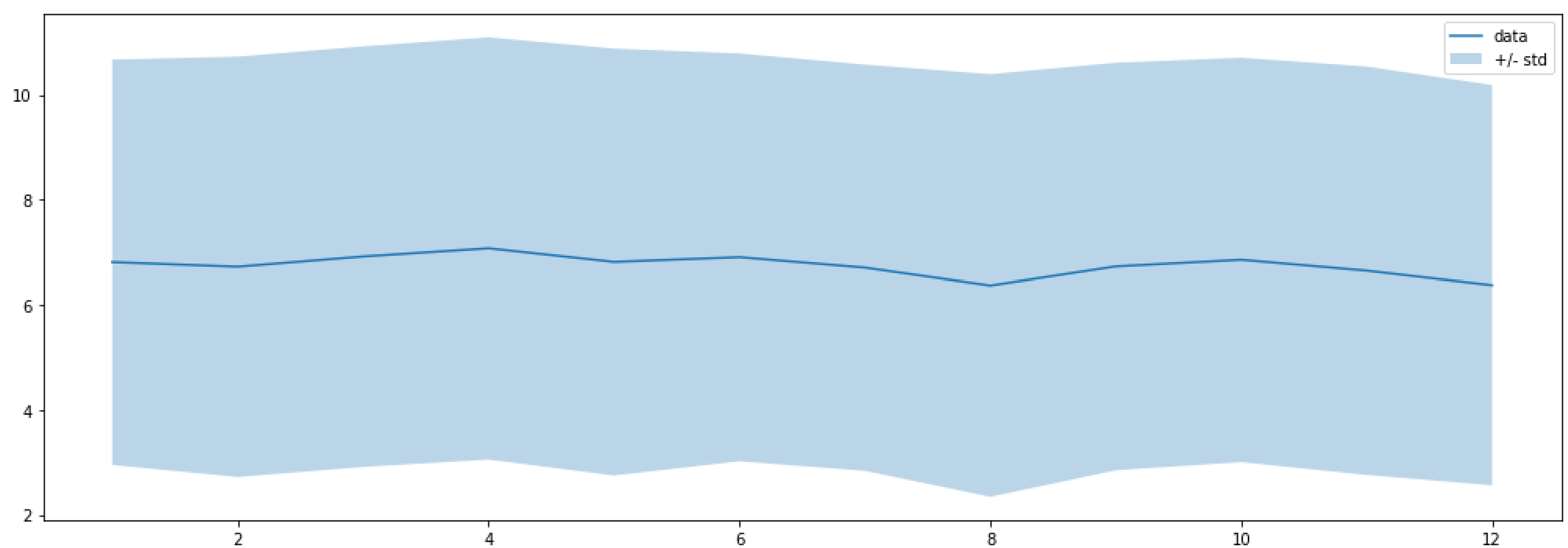
We are now ready to tackle the first of our ER management problems

Variability

With our binned series, we can compute standard deviations

Let's check it over different months:

In [21]:
```
means = codes_b.groupby(codes_b.index.month).mean()
stds = codes_b.groupby(codes_b.index.month).std()
er.plot_series(means['total'], std=stds['total'], figsize=figsize)
```

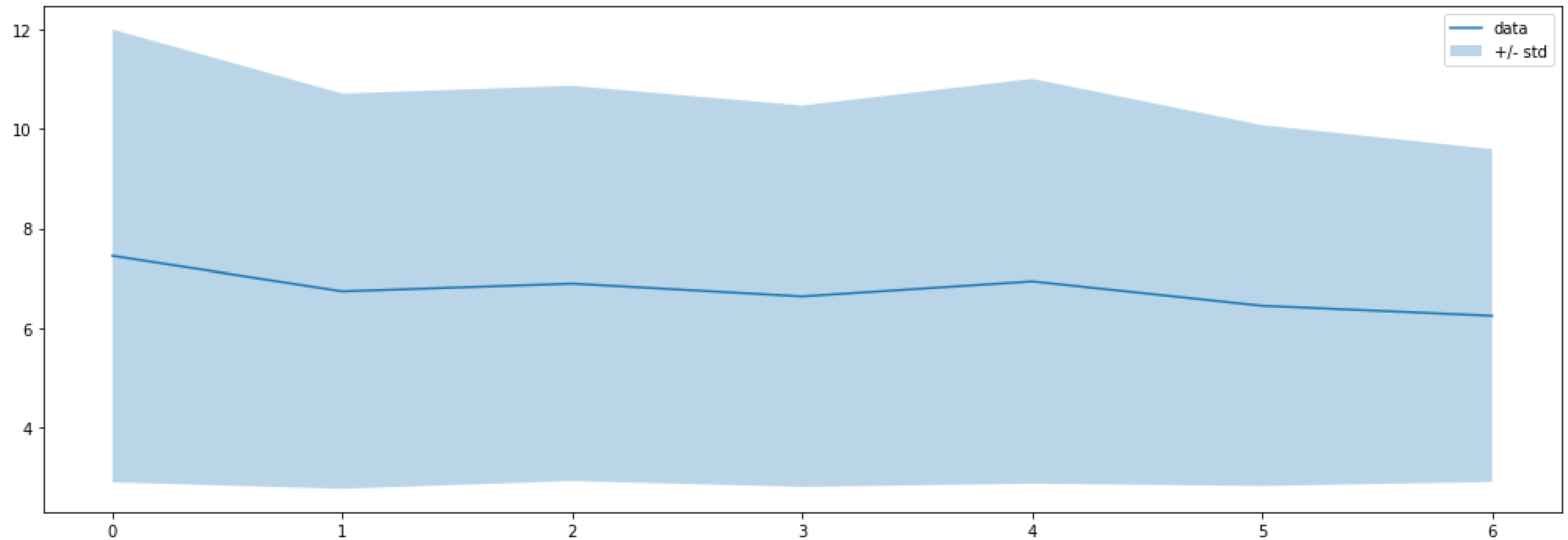


- The variability does not change much over different months

Variability

Here is the standard deviation over weekdays

In [22]:
```
means = codes_b.groupby(codes_b.index.weekday).mean()
stds = codes_b.groupby(codes_b.index.weekday).std()
er.plot_series(means['total'], std=stds['total'], figsize=figsize)
```

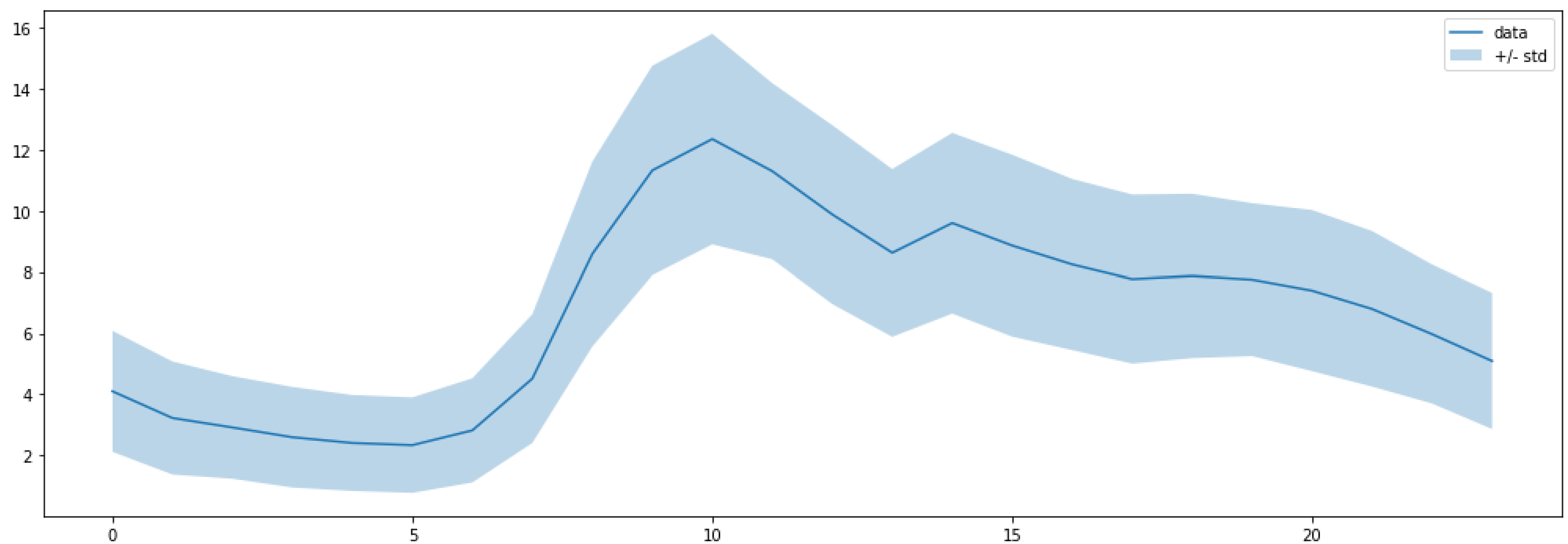


- A decreasing trend, but rather weak

Variability

...And finally over hours

In [25]:
```
means = codes_b.groupby(codes_b.index.hour).mean()
stds = codes_b.groupby(codes_b.index.hour).std()
er.plot_series(means['total'], std=stds['total'], figsize=figsize)
```



- Again, unlike the mean, the stdev is similar over the hours of a day