# Imports

In [2]:

```
import numpy as np
import scipy as sp
import scipy.optimize
import matplotlib.pyplot as plt
```

# Import data

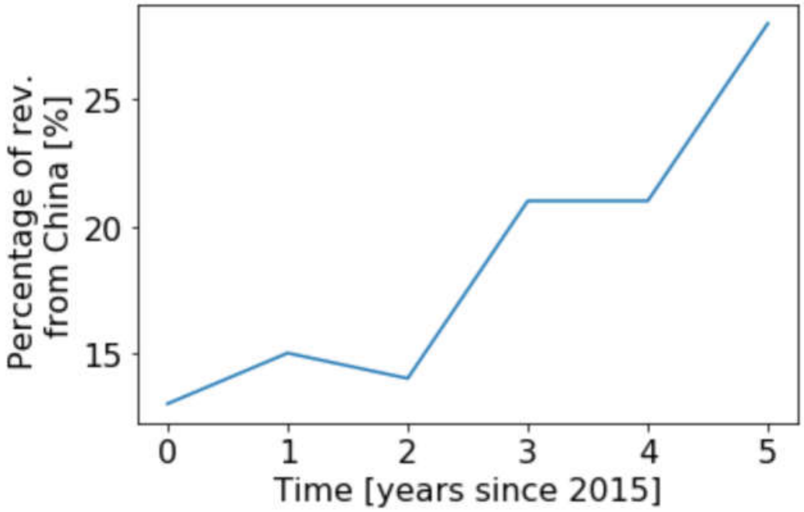
https://www.cset-foretell.com/questions/100-what-percentage-of-the-collective-revenue-of-the-leading-semiconductor-manufacturing-equipment-producers-will-come-from-china-between-july-1-2020-and-june-30-2021-inclusive (https://www.cset-foretell.com/questions/100-what-percentage-of-the-collective-revenue-of-the-leading-semiconductor-manufacturing-equipment-producers-will-come-from-china-between-july-1-2020-and-june-30-2021-inclusive)

In [14]:

```
# Data from the graph on the above webpage
data = {"date": np.array([2015, 2016, 2017, 2018, 2019, 2020]) - 2015,
       "quant": np.array([13,   15,   14,   21,   21,   28])}

xlabel = 'Time [years since 2015]'
ylabel = 'Percentage of rev. \nfrom China [%]'
```

In [15]:

```python
plt.rcParams.update({'font.size': 16})
fig, ax = plt.subplots(1,1)

ax.plot(data['date'], data['quant'])
ax.set_xlabel(xlabel)
ax.set_ylabel(ylabel)

plt.tight_layout()
```



# Generate trend-fit values, linear

In [16]:

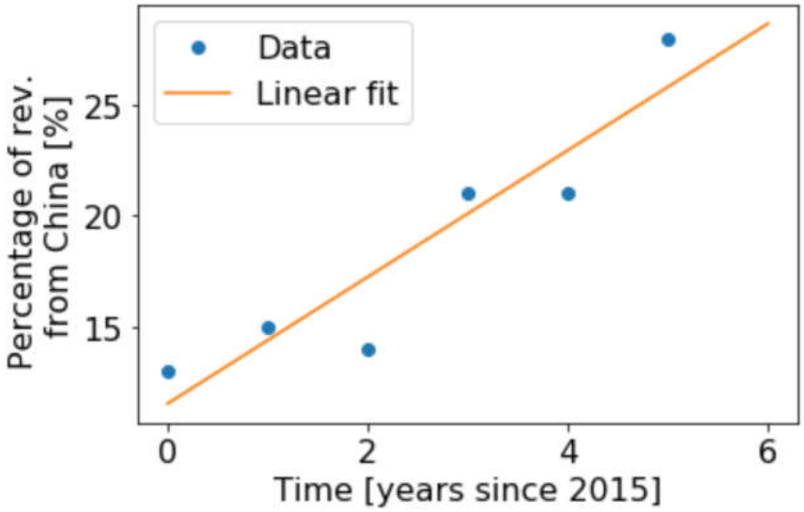
```python
def outside_func(t, m, b):
    return m*t + b
```

In [17]:

```python
slope_guess = 2 # 2 percentage points / year
offs_guess = 13
popt, pcov = sp.optimize.curve_fit(outside_func, data['date'], data['quant'], p0=[slope_guess, offs_guess])
perr = np.sqrt(np.diag(pcov)) # The standard deviations of the parameters
```

In [25]:

```
fig, ax = plt.subplots(1,1)

t_final = 6
fit_label = 'Linear fit'
ax.plot(data['date'], data['quant'], 'o', label='Data')
t_plot = np.linspace(0, t_final, 100)
ax.plot(t_plot, outside_func(t_plot, *popt), label=fit_label)
ax.set_xlabel(xlabel)
ax.set_ylabel(ylabel)

ax.legend()

plt.tight_layout()
```



In [26]:

```
outside_func(t_final, *popt)
```

Out[26]:

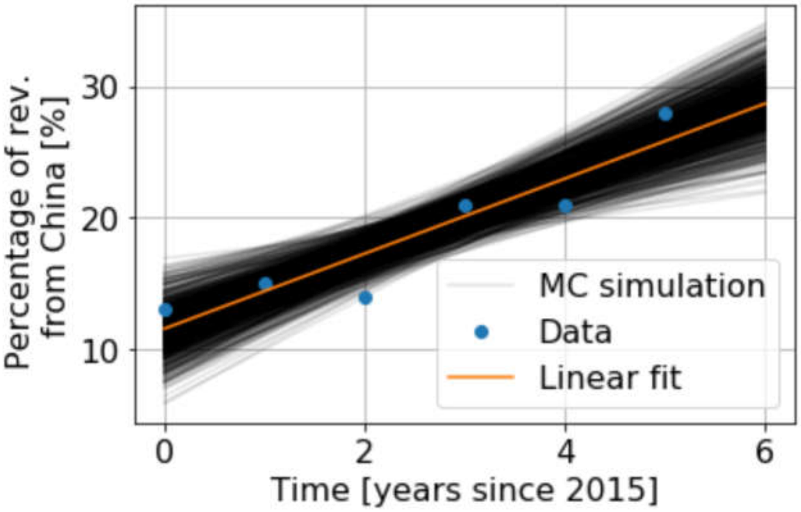
```
28.6666667521394
```

## Monte Carlo of trends

I think with the fit we could probably just build up the probability density function P(y) = Pr(f(x) = y) for the ranges of y we care about, just given our fit parameters and covariance matrix. However, I think an equivalent way to do this is to just run a monte carlo simulation were we randomly sample from our fit parameters, drawing the fit parameters form the multivariate gaussian distribution defined by popt and pcov. Then bin the value of f(x) that we get from the simulation.

In [27]:

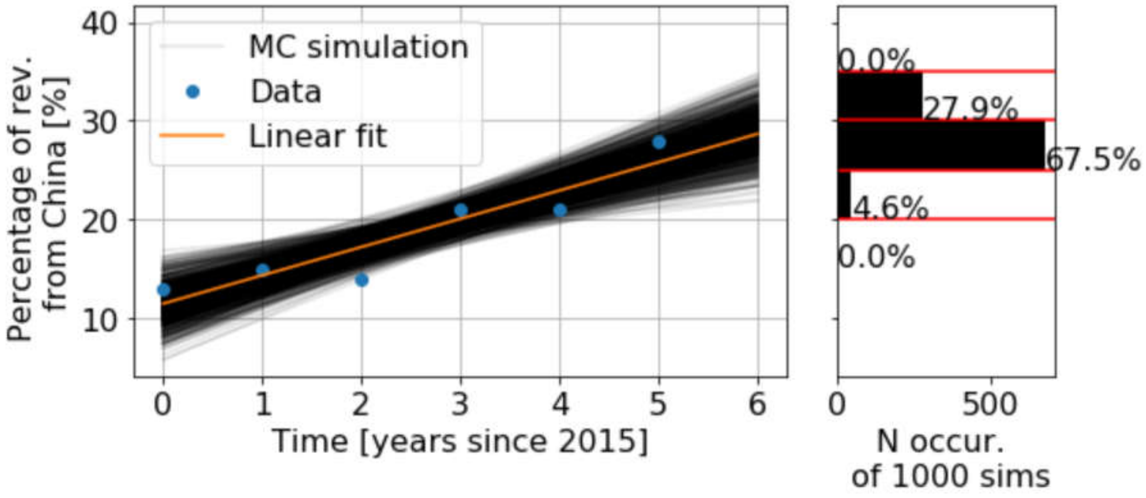
```
# Generate fits

n_fits = 1000
fit_params_gen = np.random.multivariate_normal(popt, pcov, n_fits)


fit_params = fit_params_gen
# Comment out the line above and uncomment the below lines to clean to fit based on some criteria.
# Be very careful throwing only a lot of data though!!
# fit_params = []
# n_removed = 0
# for fit_list in fit_params_gen:
#     if fit_list[0] < 0:
#         n_removed += 1
#         n_fits -= 1
#     else:
#         fit_params.append(fit_list)
# print('Generated %i plots, discarded %i' %(n_fits + n_removed, n_removed))


# Plot MC simualtions and build MC data
fig, ax_mc = plt.subplots(1,1)

final_vals = []
for i, popt_mc in enumerate(fit_params):
    label = 'MC simulation' if i == 0 else None
    t_plot = np.linspace(0, t_final, 100)
    ax_mc.plot(t_plot, outside_func(t_plot, *popt_mc), 'k', alpha=0.1, label=label)

    final_vals.append(outside_func(np.array([t_final]), *popt_mc)[0])

# Plot original data and fit
ax_mc.plot(data['date'], data['quant'], 'o', label='Data')
t_plot = np.linspace(0, t_final, 100)
ax_mc.plot(t_plot, outside_func(t_plot, *popt), label=fit_label)

ax_mc.set_xlabel(xlabel)
ax_mc.set_ylabel(ylabel)

ax_mc.grid()
ax_mc.legend()

plt.tight_layout()
```



## Including histogram

In [28]:

```
# Plot MC simualtions and build MC data
cset_boundaries = [20, 25, 30, 35]

fig, [ax_mc, ax_hist] = plt.subplots(1, 2, figsize=(8, 4), gridspec_kw={'width_ratios': [3, 1]}, sharey=True)

for i, popt_mc in enumerate(fit_params):
    label = 'MC simulation' if i == 0 else None
    t_plot = np.linspace(0, t_final, 100)
    ax_mc.plot(t_plot, outside_func(t_plot, *popt_mc), 'k', alpha=0.1, label=label)

# Plot original data and fit
ax_mc.plot(data['date'], data['quant'], 'o', label='Data')
t_plot = np.linspace(0, t_final, 100)
ax_mc.plot(t_plot, outside_func(t_plot, *popt), label=fit_label)

# for boundary in cset_boundaries:
#     ax_mc.axhline(boundary, color='r', linewidth=0.3)

ax_mc.set_xlabel(xlabel)
ax_mc.set_ylabel(ylabel)
# ax_mc.set_yscale('log')

ax_mc.grid()
ax_mc.legend()




# Plot histogram
bin_min = min(final_vals) if min(final_vals) < min(cset_boundaries) else min(cset_boundaries) - np.diff(cset_boundaries)[0]
bin_max = max(final_vals) if max(final_vals) > max(cset_boundaries) else max(cset_boundaries) + np.diff(cset_boundaries)[-1]

bins = np.concatenate([[bin_min], cset_boundaries, [bin_max]])

n, bins, patches = ax_hist.hist(np.array(final_vals), bins, color='k', orientation='horizontal')
# ax_hist.set_ylim(ax_mc.get_ylim())

ax_hist.set_xlabel('N occur. \n of {} sims'.format(n_fits))

for boundary in cset_boundaries:
    ax_hist.axhline(boundary, color='r')

text_offset = (max(bins) - min(bins)) / 100
percentages = [n_val / n_fits * 100 for n_val in n]
for n_val, bin_min, percent in zip(n, bins[:-1], percentages):
    ax_hist.text(n_val, bin_min + text_offset, '%.1f%%' %(percent))


plt.tight_layout()
```



# Generate final forcast

Before I saw any data, I would have put equal confidence in each of the 5 bins, so my prior was {0.2, 0.2, 0.2, 0.2, 0.2}.

I then tried to incorporate information about historical trends alone by doing a linear fit on the data, and estimating the distribution for 2021 given the uncertainty in this linear fit. From this curve fitting, my best estimate of the probabilities of the trend reaching the values {<20%, 20%-25%, 25%-30%, 30%-35%, >35%} is {0%, 4.6%, 67.5%, 27.9%, 0%} respectively (For how I arrived at these, see https://github.com/cphenicie/forecasts/tree/main/Foretell (https://github.com/cphenicie/forecasts/tree/main/Foretell) in the file 20201204_percent-of-revenue-from-china).

I arbitrarily assigned 50% confidence to my prior values and 50% confidence to these trend-fits values. I then arrived at updated values by taking the mean of the prior with the trend-fit value (0.5 *[prior]* + *(1-0.5)* [trend-fit value]), and then normalizing the resulting distribution

In the future, I will try to update these priors as I learn more about the specifics of this case

In [32]:

```
prior = [0.2, 0.2, 0.2, 0.2, 0.2]
fit = [p/100 for p in percentages]
c_fit = 0.5
mean_vals = [(1-c_fit) * p + c_fit * f for p, f in zip(prior, fit)]
final_dist = mean_vals / np.sum(mean_vals)
print('Prior = ', prior)
print('Fit values = ', fit)
print('Final distribution = ', final_dist)
```

```
Prior =  [0.2, 0.2, 0.2, 0.2, 0.2]
Fit values =  [0.0, 0.046, 0.675, 0.279, 0.0]
Final distribution =  [0.1    0.123  0.4375 0.2395 0.1   ]
```

In [ ]: