KyotoUx-009x_scratch (/github/ryo0921/KyotoUx-009x_scratch/tree/master)
/ 06 (/github/ryo0921/KyotoUx-009x_scratch/tree/master/06)

Stochastic Processes: Data Analysis and Computer Simulation

Stochastic processes in the real world

3. A Stochastic Dealer Model II

3.1. Preparation

In [1]:
```
% matplotlib inline
import numpy as np  # import numpy library as np
import math         # use mathematical functions defined by the C standa
import matplotlib.pyplot as plt # import pyplot library as plt
import pandas as pd # import pandas library as pd
from datetime import datetime
from pandas_datareader import data as pdr
from pandas_datareader import wb   as pwb
plt.style.use('ggplot') # use "ggplot" style for graphs
pltparams = {'legend.fontsize':16,'axes.labelsize':20,'axes.titlesize':2
             'xtick.labelsize':12,'ytick.labelsize':12,'figure.figsize':
plt.rcParams.update(pltparams)
```

In [2]:
```
# Logarithmic return of price time series
def logreturn(St,tau=1):
    return np.log(St[tau:])-np.log(St[0:-tau]) # Eq.(J2) : G_tau(t) = lc
# normalize data to have unit variance (<(x - <x>)^2> = 1)
def normalized(data):
    return ((data)/np.sqrt(np.var(data)))
# compute normalized probability distribution function
def pdf(data,bins=50):
    hist,edges=np.histogram(data[~np.isnan(data)],bins=bins,density=True
    edges   = (edges[:-1] + edges[1:])/2.0 # get bar center
    nonzero = hist > 0.0                   # non-zero points
    return edges[nonzero], hist[nonzero]
# add logarithmic return data to pandas DataFrame data using the 'Adjust
def computeReturn(data, name, tau):
    data[name]=pd.Series(normalized(logreturn(data['Adj Close'].values,
```

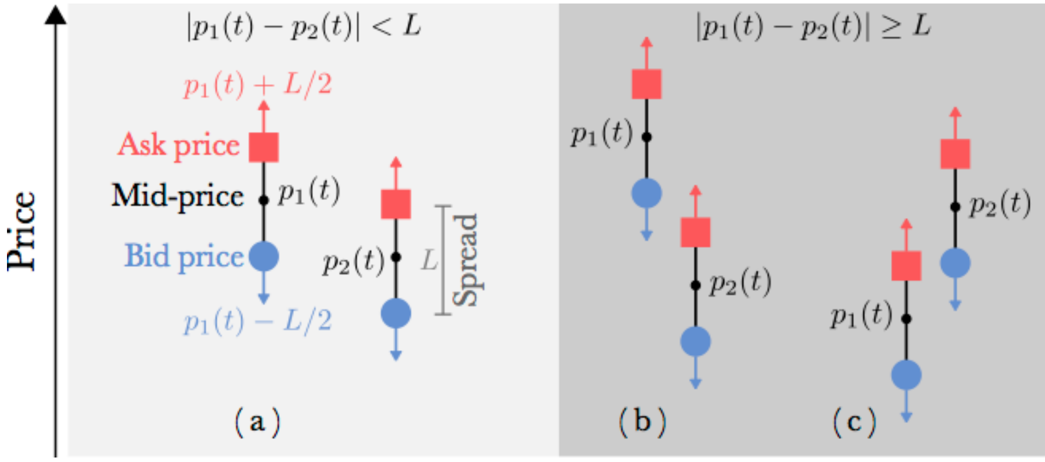
In [ ]:
```
end_time   = datetime.now()
start_time = datetime(end_time.year - 20, end_time.month, end_time.day)
toyota     = pdr.DataReader('7203','yahoo',start_time,end_time)  # impor
computeReturn(toyota, 'Return d1', 1)
```

In [3]:
```
# ONLY execute this cell if the PREVIOUS cell returns an error
def read_yahoo_data(fname):
    return pd.read_csv(fname, index_col=0, na_values="null").dropna()

toyota     = read_yahoo_data('./yahoo_finance/TM.csv')
computeReturn(toyota, 'Return d1', 1)
```

3.2. The Dealer Model

- K. Yamada, H. Takayasu, T. Ito and M. Takayasu, *Physical Revew E* **79**, 051120 (2009).



- Transaction criterion

$$|p_i(t) - p_j(t)| \geq L \tag{L1}$$

- Market price of transaction

$$P = \frac{1}{2}(p_1 + p_2) \tag{L2}$$

- Logarithmic price return

$$G_\tau(t) \equiv \log P(t+\tau) - \log P(t) \tag{L3}$$

3.3. The dealer model with memory (model 2)

- To improve the model, Yamada et al. (PRE 79, 051120, 2009) added the effect of "trend-following" predictions.
- Dynamics is captured by a random walk with a drift/memory term

$$p_i(t+\Delta t) = p_i(t) + d\langle\Delta P\rangle_M \Delta t + cf_i(t), \qquad i = 1,2 \tag{L4}$$

$$f_i(t) = \begin{cases} +\Delta p & \text{prob.}1/2 \\ -\Delta p & \text{prob.}1/2 \end{cases} \tag{L5}$$

- The constant d determines whether the dealer is a "trend-follower" ($d > 0$) or a "contrarian" ($d < 0$)
- The added term represents a moving average over the previous price changes

$$\langle\Delta P\rangle_M = \frac{2}{M(M+1)}\sum_{k=0}^{M-1}(M-k)\Delta P(n-k) \tag{L6}$$

$$\Delta P(n) = P(n) - P(n-1) : \text{Market price change at the n-th tick}$$

- $\langle\Delta P\rangle_M$ is constant during the Random-Walk process, it is only updated at the transaction events

3.3. Dealer model as a 2D random walk

- The dealer model can again be understood as a standard 2D Random walk with absorbing boundaries.
- Introduce the price difference $D(t)$ and average $A(t)$

$$D(t) = p_1(t) - p_2(t) \tag{L7}$$

$$A(t) = \frac{1}{2}\left(p_1(t) + p_2(t)\right) \tag{L8}$$

- Dynamics of D and A describe a 2D random walk

$$D(t+\Delta t) = D(t) + \begin{cases} +2c\Delta p & \text{probability } 1/4 \\ 0 & \text{probability } 1/2 \\ -2c\Delta p & \text{probability } 1/4 \end{cases} \tag{L9}$$

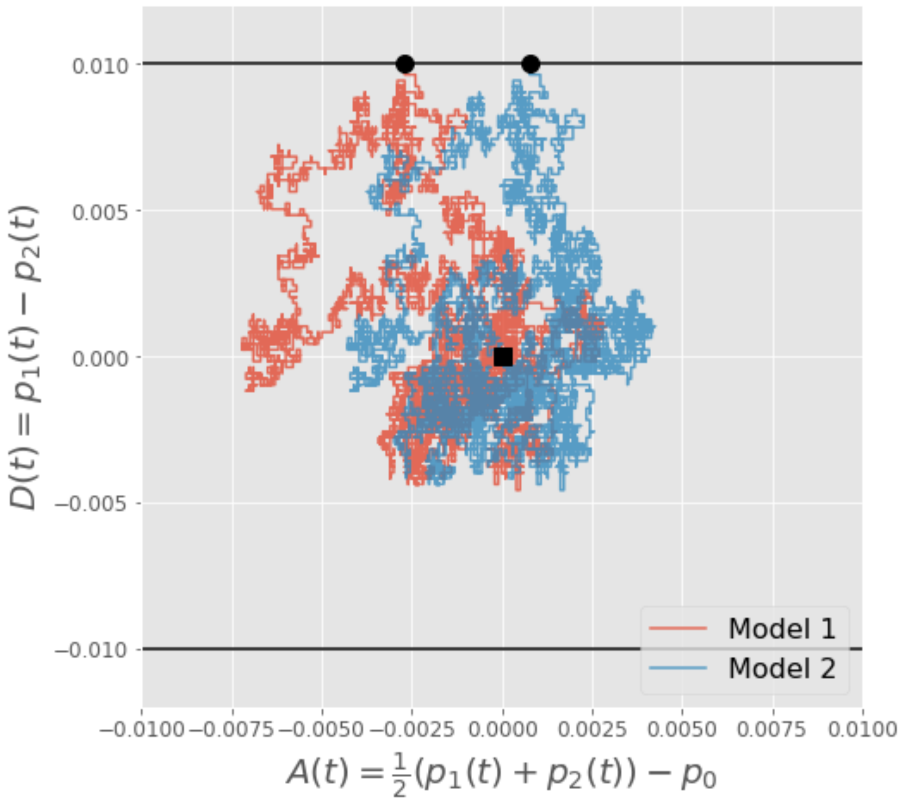
$$A(t+\Delta t) = A(t) + d\langle \Delta P\rangle_M \Delta t + \begin{cases} +c\Delta p & \text{probability } 1/4 \\ 0 & \text{probability } 1/2 \\ -c\Delta p & \text{probability } 1/4 \end{cases} \tag{L10}$$

- When $D(t) = \pm L$ a transaction occurs and the random walk ends, the "particle" is absorbed by the boundary.

In [4]:
```
params={'L':0.01,'c':0.01,'dp':0.01,'dt':0.01**2, 'd':1.25, 'M':1} # def
def model2RW(params,p0,deltapm):        # simulate Random-Walk for 1 tra
    price = np.array([p0[0], p0[1]])    # initialize mid-prices for deal
    cdp   = params['c']*params['dp']    # define random step size
    ddt   = params['d']*params['dt']    # define trend drift term
    Dt    = [price[0]-price[1]]         # initialize price difference as
    At    = [np.average(price)]         # initialize avg price as empy l
    while np.abs(price[0]-price[1]) < params['L']:
        price=price+np.random.choice([-cdp,cdp],size=2) # random walk st
        price=price+ddt*deltapm         # Model 2 : add trend-following 
        Dt.append(price[0]-price[1])
        At.append(np.average(price))
    return np.array(Dt),np.array(At)-At[0] # return difference array anc
```

In [5]:
```
fig,ax=plt.subplots(figsize=(7.5,7.5),subplot_kw={'xlabel':r'$A(t) = \fr
p0 = [100.25, 100.25]
params={'L':0.01,'c':0.01,'dp':0.01,'dt':0.01**2, 'd':1.25, 'M':1} # def
for deltapm,lbl in zip([0, 0.003], ['Model 1', 'Model 2']):
    np.random.seed(123456)
    Dt,At = model2RW(params, p0, deltapm)
    ax.plot(At,Dt,alpha=0.8,label=lbl) #plot random walk trajectory
    ax.plot(At[-1],Dt[-1],marker='o',color='k', markersize=10) #last poi
    print(lbl+' : number of steps = ',len(At),', price change = ', At[-1
ax.plot(0, 0, marker='s', color='k', markersize=10) # starting position
ax.plot([-0.01,0.03],[params['L'],params['L']],color='k') #top absorbing
ax.plot([-0.01,0.03],[-params['L'],-params['L']],color='k') #bottom absc
ax.set_ylim([-0.012, 0.012])
ax.set_xlim([-0.01, 0.01])
ax.legend(loc=4,framealpha=0.8)
plt.show()
```

```
Model 1 : number of steps =  9248 , price change =  -0.00270000000009
Model 2 : number of steps =  9248 , price change =  0.000767624991155
```



3.4. Perform simulations

In [6]:
```
params={'L':0.01,'c':0.01,'dp':0.01,'dt':0.01**2, 'd':1.25, 'M':1} # def
def model2(params,p0,numt):
    def avgprice(dpn): # compute running average Eq.(L6)
        M = len(dpn)    #
        weights  = np.array(range(1,M+1))*2.0/(M*(M+1))
        return weights.dot(dpn)

    mktprice = np.zeros(numt)   # initialize market price P(n)
    dmktprice= np.zeros(numt)   # initialize change in price dP(n) neede
    ticktime = np.zeros(numt,dtype=np.int) #initialize array for tick ti
    price    = np.array([p0[0], p0[1]])    #initialize dealer's mid-pric
    time,tick= 0,0 # real time(t) and time time (n)
    deltapm  = 0.0 # trend term d <dP>_m dt for current random walk
    cdp      = params['c']*params['dp'] # define random step size
    ddt      = params['d']*params['dt'] # define amplitude of trend term
    while tick < numt: # loop over ticks
        while np.abs(price[0]-price[1]) < params['L']: # transaction cri
            price = price + deltapm + np.random.choice([-cdp,cdp], size=
            time += 1 #update ral time
        price[:]       = np.average(price) #set mid-prices to new market
        mktprice[tick] = price[0]  # save market price
        dmktprice[tick]= mktprice[tick] - mktprice[np.max([0,tick-1])] #
        ticktime[tick] = time # save transaction time
        tick += 1 #update ticks
        tick0 = np.max([0, tick - params['M']]) #compute tick start for
        deltapm = avgprice(dmktprice[tick0:tick])*ddt #compute updated t
    return ticktime,mktprice
```

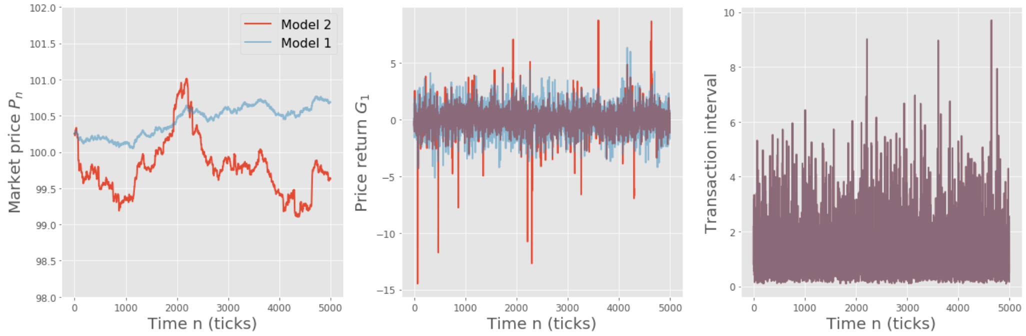
- A simulation is performed if you run the cell below, but depending on your computer power it may take quite long time until it finishes with properly creating the simulation data "model2.txt".
- You may skip this cell and use pre-calculated simulation data "model2.txt" which can be downloaded from our website to continue further data analyses.

In [ ]:
```
np.random.seed(0)
ticktime2,mktprice2 = model2(params, [100.25, 100.25], 5000)
np.savetxt('model2.txt',np.transpose([ticktime2, mktprice2]))
```

3.5. Analyses

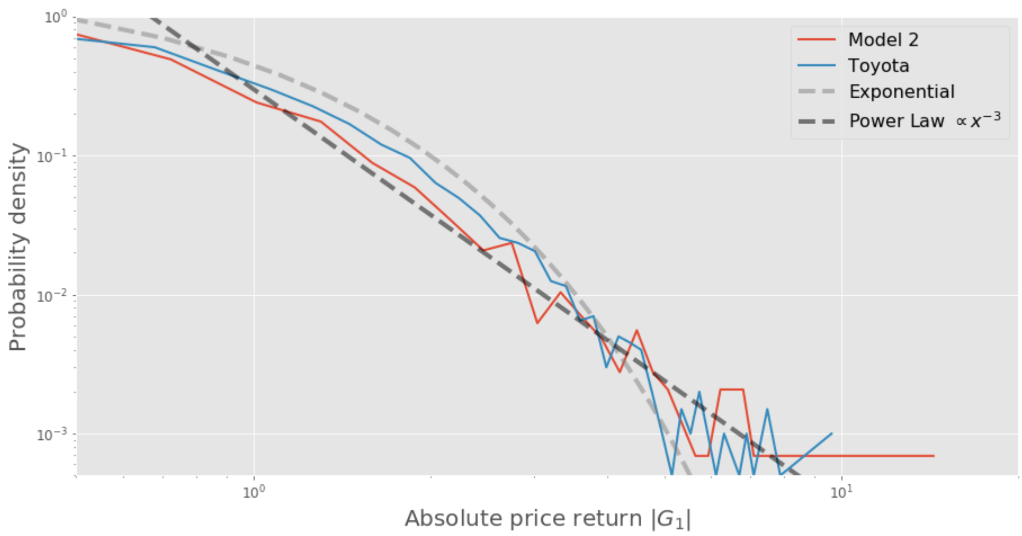
In [7]:

```
ticktime,mktprice=np.loadtxt('model1.txt',unpack=True) # read saved data
ticktime2,mktprice2=np.loadtxt('model2.txt', unpack=True)
timeinterval=normalized((ticktime[1:]-ticktime[0:-1])*params['dt']) # cc
timeinterval2=normalized((ticktime2[1:]-ticktime2[0:-1])*params['dt'])
dprice=normalized(logreturn(mktprice,1)) # compute logarithmic return of
dprice2=normalized(logreturn(mktprice2,1))
fig,[ax,bx,cx]=plt.subplots(figsize=(18,6),ncols=3,subplot_kw={'xlabel':
ax.plot(mktprice2, lw=2, label='Model 2')
ax.plot(mktprice, alpha=0.5, lw=2, label='Model 1')
ax.legend()
ax.set_ylim(98,102)
ax.set_ylabel(r'Market price $P_n$')
bx.plot(dprice2, lw=2)
bx.plot(dprice, alpha=0.5, lw=2)
bx.set_ylabel(r'Price return $G_1$')
cx.plot(timeinterval2,  lw=2)
cx.plot(timeinterval, alpha=0.5, lw=2)
cx.set_ylabel(r'Transaction interval')
fig.tight_layout() # get nice spacing between plots
plt.show()
```



In [8]:

```
fig,ax,=plt.subplots(figsize=(15,7.5),subplot_kw={'xlabel':r'Absolute pr
for data,lbl in zip([dprice2, toyota['Return d1']], ['Model 2', 'Toyota'
    edges, hist = pdf(np.abs(data), bins=50)
    ax.plot(edges, hist, label=lbl, lw=2)
x = np.linspace(0.1, 10)
ax.plot(x, 2*np.exp(-1.5*x),lw=4,color='gray',ls='--',alpha=0.5,label=r'
ax.plot(x, 0.3*x**(-3), lw=4, color='k', ls='--', alpha=0.5, label=r'Pow
ax.set_xlim(5e-1, 2e1)
ax.set_ylim(5e-4, 1)
ax.legend()
ax.semilogx()
ax.semilogy()
plt.show()
```



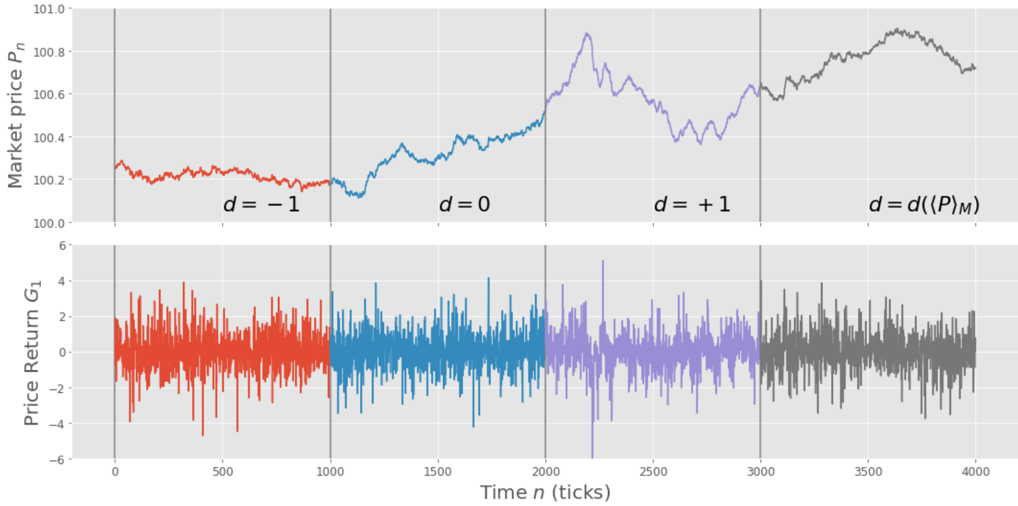
In [9]:
```
params={'L':0.01,'c':0.01,'dp':0.01,'dt':0.01**2, 'd':1.00, 'M':10} # de
def model2t(params,p0,numt):
    def avgprice(dpn): # compute running average Eq.(L6)
        M = len(dpn)    #
        weights  = np.array(range(1,M+1))*2.0/(M*(M+1))
        return weights.dot(dpn)
    def dtime(i, dpm): # return time varying d-coefficient
        if i <= 1000:  # contrarians
            return -params['d']
        elif i <= 2000:# random walkers: no memory
            return 0.0
        elif i <= 3000:# trend-followers
            return params['d']
        elif dpm >= 0.0: # trend-followers if running average increasing
            return params['d']
        else: # contrarians if running average decreasing
            return -params['d']
    mktprice = np.zeros(numt)   # initialize market price P(n)
    dmktprice= np.zeros(numt)   # initialize change in price dP(n) neede
    ticktime = np.zeros(numt,dtype=np.int) #initialize array for tick ti
    price    = np.array([p0[0], p0[1]])    #initialize dealer's mid-pric
    time,tick= 0,0 # real time(t) and time time (n)
    deltapm  = 0.0 # trend term d <dP>_m dt for current random walk
    cdp      = params['c']*params['dp'] # define random step size
    while tick < numt: # loop over ticks
        ddt      = dtime(tick, deltapm)*params['dt'] # define amplitude
        while np.abs(price[0]-price[1]) < params['L']: # transaction cri
            price = price + deltapm + np.random.choice([-cdp,cdp], size=
            time += 1 #update ral time
        price[:]       = np.average(price) #set mid-prices to new market
        mktprice[tick] = price[0]  # save market price
        dmktprice[tick]= mktprice[tick] - mktprice[np.max([0,tick-1])] #
        ticktime[tick] = time # save transaction time
        tick += 1 #update ticks
        tick0 = np.max([0, tick - params['M']]) #compute tick start for
        deltapm = avgprice(dmktprice[tick0:tick])*ddt #compute updated t
    return ticktime,mktprice
```

- A simulation is performed if you run the cell below, but depending on your computer power it may take quite long time until it finishes with properly creating the simulation data "model2t.txt".
- You may skip this cell and use pre-calculated simulation data "model2t.txt" which can be downloaded from our website to continue further data analyses.

In [ ]:
```
np.random.seed(0)
ticktime2t,mktprice2t = model2t(params, [100.25, 100.25], 4001)
np.savetxt('model2t.txt',np.transpose([ticktime2t, mktprice2t]))
```

In [10]:

```
ticktime2t,mktprice2t=np.loadtxt('model2t.txt',unpack=True) # read savec
fig,[ax,bx]=plt.subplots(figsize=(15,7.5),nrows=2, sharex=True)
for i,lbl in zip(range(4), [r'$d=-1$', r'$d=0$', r'$d=+1$', r'$d=d(\left
    n0,n1 = i*1000, (i+1)*1000
    dprice=normalized(logreturn(mktprice2t[n0:n1],1))
    ax.plot(range(n0,n1), mktprice2t[n0:n1])
    ax.plot([n0,n0],[100,102], color='gray')
    ax.text(n0+500, 100.05, lbl, fontsize=22)
    bx.plot([n0,n0],[-6,6],color='gray')
    bx.plot(range(n0+1,n1), dprice)
ax.set_ylim(100,101)
bx.set_ylim(-6,6)
ax.set_ylabel(r'Market price $P_n$')
bx.set_ylabel(r'Price Return $G_1$')
bx.set_xlabel(r'Time $n$ (ticks)')
fig.tight_layout()
plt.show()
```



In [ ]: