

# What if we (sort of) knew what the future brings?

Peter Bank



based on joint papers with  
Yan Dolinsky, Miklos Rasonyi

The 9th International Colloquium  
on BSDEs and Mean Field Systems

Annecy, June 27-July 1, 2022

# Problem formulation: Frontrunning with price impact

Bachelier stock price dynamics, zero interest rate:

$$S_t = s_0 + \mu t + \sigma W_t, \quad t \geq 0$$

Information flow: peek  $\Delta$  time units ahead  $\leadsto$  “frontrunning”

$$\mathcal{G}_t^\Delta = \mathcal{F}_{t+\Delta}^S, \quad t \geq 0.$$

Egregious arbitrage opportunities

# Problem formulation: Frontrunning with price impact

Bachelier stock price dynamics, zero interest rate:

$$S_t = s_0 + \mu t + \sigma W_t, \quad t \geq 0$$

Information flow: peek  $\Delta$  time units ahead  $\leadsto$  “frontrunning”

$$\mathcal{G}_t^\Delta = \mathcal{F}_{t+\Delta}^S, \quad t \geq 0.$$

Egregious arbitrage opportunities curtailed by price impact because execution price is

$$S_t^\phi = S_t + \frac{\Lambda}{2} \phi_t$$

where  $\phi_t = \frac{d}{dt} \Phi_t$  is the frontrunner's turnover rate  $\leadsto$  temporary price impact à la Almgren-Chriss

# Problem formulation: Frontrunning with price impact

**Profits and losses** from trading according to  $\Phi_t = \Phi_0 + \int_0^t \phi_s ds$ :

$$\begin{aligned} V_T^{\Phi_0, \phi} &= - \int_0^T S_t^\phi d\Phi_t + \Phi_T S_T - \Phi_0 S_0 \\ &= \Phi_0 (S_T - S_0) + \int_0^T \phi_t (S_T - S_t) dt - \frac{\Lambda}{2} \int_0^T \phi_t^2 dt, \end{aligned}$$

$\leadsto$  mark to market stock positions at time 0 and  $T$

Natural class of **admissible strategies**:

$$\mathcal{A}^\Delta = \left\{ \phi = (\phi_t)_{t \in [0, T]} \text{ } \mathcal{G}^\Delta\text{-optional with } \int_0^T \phi_t^2 dt < \infty \text{ a.s.} \right\}$$

Exponential **utility maximization**:

$$\text{Maximize } \mathbb{E} \left[ u(V_T^{\Phi_0, \phi}) \right] = \mathbb{E} \left[ -\exp \left( -\alpha V_T^{\Phi_0, \phi} \right) \right] \text{ over } \phi \in \mathcal{A}^\Delta$$

## Related work

- ▶ enlargement of filtrations and small investor: Karatzas/Pikovsky '96, Amendinger/Imkeller/Schweizer '98, Amendinger/Becherer/Schweizer '03, Imkeller '03, . . . , Jeanblanc '05–'21
- ▶ insider trading with equilibrium prices: Kyle '85, Back '92, . . . Cetin '18, Back/Cocquemas/Ekren/Lioui '21
- ▶ insider trading with temporary price impact: Ankircher/BlanchetScalliet/Eyraud-Loisel '16, Barger/Donnelly '20
- ▶ control with infinite-dimensional state space: Ji/Wang/Yang '13, Fabbri/Gozzi/Swiech '17, Saporito/Zhang '19
- ▶ short-term inside information: B./Körber '21+  $\rightsquigarrow$  2nd part of this talk; B./Besslich '20

# Main result: Optimal Policy

$$\text{Maximize } \mathbb{E} \left[ u(V_T^{\Phi_0, \phi}) \right] = \mathbb{E} \left[ -\exp \left( -\alpha V_T^{\Phi_0, \phi} \right) \right] \text{ over } \phi \in \mathcal{A}^\Delta$$

## Theorem

The **optimal turnover rate** at time  $t \in [0, T]$  is

$$\hat{\phi}_t = \frac{d}{dt} \hat{\Phi}_t = \frac{1}{\Lambda} \left( \bar{S}_t^\Delta - S_t \right) + \frac{\Upsilon^\Delta(T-t)}{\Delta} \left( \frac{\mu}{\alpha \sigma^2} - \hat{\Phi}_t \right),$$

where  $\bar{S}^\Delta$  denotes the **stock price average**

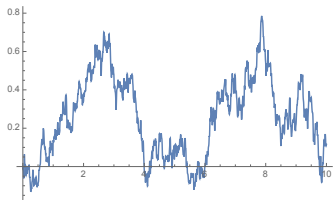
$$\bar{S}_t^\Delta := \left( 1 - \Upsilon^\Delta(T-t) \right) S_{(t+\Delta) \wedge T} + \Upsilon^\Delta(T-t) \frac{1}{\Delta} \int_0^\Delta S_{t+s} ds$$

with

$$\Upsilon^\Delta(\tau) = \frac{\Delta \sqrt{\rho} \tanh(\sqrt{\rho}(\tau - \Delta)^+)}{1 + \Delta \sqrt{\rho} \tanh(\sqrt{\rho}(\tau - \Delta)^+)}, \quad \tau \geq 0,$$

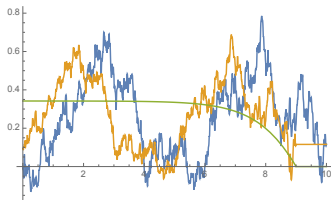
where  $\rho$  is the risk/liquidity ratio  $\rho = \frac{\alpha \sigma^2}{\Lambda}$ .

## Discussion: Optimal policy illustration



- ▶  $S_0 = 0$ ,  $\mu = .1$ ,  $\sigma = .3$ ,  
 $\alpha = .03$ ,  $T = 10\Delta$ ,  $\Lambda = .01$
- ▶ stock price  $S$

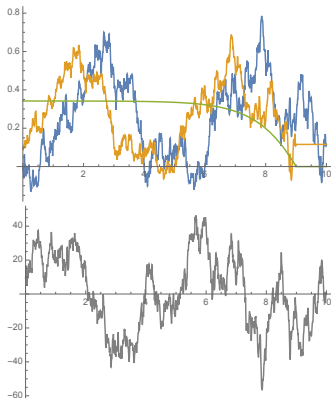
# Discussion: Optimal policy illustration



- ▶  $S_0 = 0, \mu = .1, \sigma = .3,$   
 $\alpha = .03, T = 10\Delta, \Lambda = .01$
- ▶ stock price  $S$
- ▶ stock price average  $\bar{S}^\Delta$
- ▶ weight  $\gamma^\Delta$

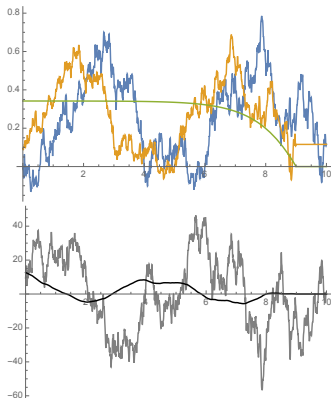


# Discussion: Optimal policy illustration



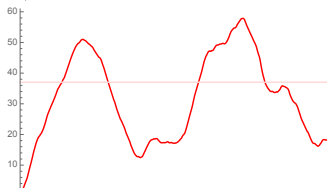
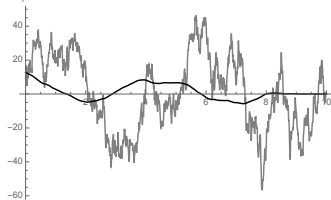
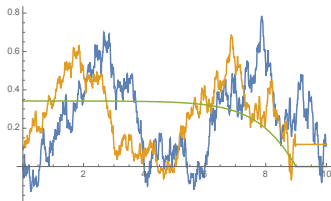
- ▶  $S_0 = 0, \mu = .1, \sigma = .3,$   
 $\alpha = .03, T = 10\Delta, \Lambda = .01$
- ▶ stock price  $S$
- ▶ stock price average  $\bar{S}^\Delta$
- ▶ weight  $\gamma^\Delta$
- ▶ inside trades  $(\bar{S}^\Delta - S)/\Lambda$

# Discussion: Optimal policy illustration



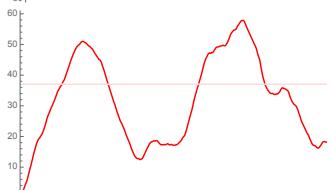
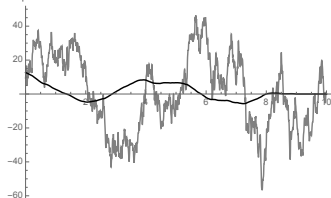
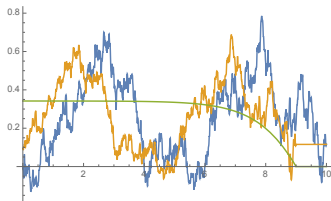
- ▶  $S_0 = 0, \mu = .1, \sigma = .3,$   
 $\alpha = .03, T = 10\Delta, \Lambda = .01$
- ▶ stock price  $S$
- ▶ stock price average  $\bar{S}^\Delta$
- ▶ weight  $\gamma^\Delta$
- ▶ inside trades  $(\bar{S}^\Delta - S)/\Lambda$
- ▶ trades tracking Merton ratio

# Discussion: Optimal policy illustration

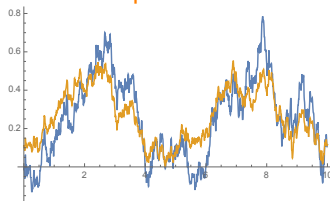


- ▶  $S_0 = 0, \mu = .1, \sigma = .3,$   
 $\alpha = .03, T = 10\Delta, \Lambda = .01$
- ▶ stock price  $S$
- ▶ stock price average  $\bar{S}^\Delta$
- ▶ weight  $\Upsilon^\Delta$
- ▶ inside trades  $(\bar{S}^\Delta - S)/\Lambda$
- ▶ trades tracking Merton ratio
- ▶ optimal total positions  $\hat{\phi}$
- ▶ Merton ratio  $\mu/(\alpha\sigma^2)$

# Discussion: Optimal policy illustration



- ▶  $S_0 = 0, \mu = .1, \sigma = .3,$   
 $\alpha = .03, T = 10\Delta, \Lambda = .01$
- ▶ stock price  $S$
- ▶ stock price average  $\bar{S}^\Delta$
- ▶ weight  $\Upsilon^\Delta$
- ▶ inside trades  $(\bar{S}^\Delta - S)/\Lambda$
- ▶ trades tracking Merton ratio
- ▶ optimal total positions  $\hat{\phi}$
- ▶ Merton ratio  $\mu/(\alpha\sigma^2)$
- ▶ execution prices:



# Main result (ctd): Value of frontrunning

## Theorem

*The certainty equivalent of extra information is*

$$\begin{aligned} C(\Delta) &= -\frac{1}{\alpha} \log \frac{\max_{\phi \in \mathcal{A}^\Delta} \mathbb{E} \left[ -\exp \left( -\alpha V_T^{\Phi_0, \phi} \right) \right]}{\max_{\phi \in \mathcal{A}^0} \mathbb{E} \left[ -\exp \left( -\alpha V_T^{\Phi_0, \phi} \right) \right]} \\ &= \frac{1}{2\alpha} \int_0^T \frac{(s \wedge \Delta) \rho}{1 + (s \wedge \Delta) \sqrt{\rho} \tanh(\sqrt{\rho}(T-s))} ds. \end{aligned}$$

- ▶ independent of risk premium  $\mu$
- ▶ governed by risk/liquidity ratio  $\rho = \alpha \sigma^2 / \Lambda$  and ability to peek ahead  $\Delta$

# Proof proceeds via duality

Theorem (cf. Guasoni, Rasonyi '15)

Denoting by  $\mathcal{Q}$  the set of all probability measures  $\mathbb{Q} \sim \mathbb{P}$  with finite entropy  $\mathbb{E}_{\mathbb{Q}} \left[ \log \left( \frac{d\mathbb{Q}}{d\mathbb{P}} \right) \right] < \infty$  relative to  $\mathbb{P}$ , we have

$$\begin{aligned} & \max_{\phi \in \mathcal{A}} \left\{ -\frac{1}{\alpha} \log \mathbb{E} \left[ \exp \left( -\alpha V_T^{\Phi_0, \phi} \right) \right] \right\} \\ &= \inf_{\mathbb{Q} \in \mathcal{Q}} \mathbb{E}_{\mathbb{Q}} \left[ \frac{1}{\alpha} \log \left( \frac{d\mathbb{Q}}{d\mathbb{P}} \right) + \Phi_0(S_T - S_0) + \frac{1}{2\Lambda} \int_0^T \left| \mathbb{E}_{\mathbb{Q}}[S_T | \mathcal{G}_t^{\Delta}] - S_t \right|^2 dt \right] \end{aligned}$$

There is a minimizer  $\hat{\mathbb{Q}}$  and it yields via

$$\hat{\phi}_t = \frac{\mathbb{E}_{\hat{\mathbb{Q}}} [S_T | \mathcal{G}_t^{\Delta}] - S_t}{\Lambda}, \quad t \in [0, T],$$

the unique optimal turnover rates for the primal problem.

**Note:** This holds for **any**  $\mathcal{G}$  and **any** càdlàg  $S$  with finite exponential moments:  $\sup_{t \in [0, T]} \mathbb{E} \exp(\varepsilon S_t^2) < \infty$  for some  $\varepsilon > 0$ .

## Step 1: Rewrite the dual target value

Without loss of generality:  $S = W$  (rescale parameters).

## Step 1: Rewrite the dual target value

Without loss of generality:  $S = W$  (rescale parameters).

### Lemma

*The dual infimum coincides with the one taken over  $\mathbb{Q}$  with*

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = \exp \left( - \int_0^T \theta_t dW_t - \frac{1}{2} \int_0^T \theta_t^2 dt \right)$$

*for some bounded and adapted  $\theta$  changing values only at finitely many deterministic times. For such  $\theta$ , the induced  $\mathbb{Q}$ -Brownian motion  $W_s^{\mathbb{Q}} = W_s + \int_0^s \theta_r dr$ ,  $s \geq r$  generates the same filtration as  $W$  and so we get, for any  $t \in [0, T]$ , the Itô-representations*

$$\theta_t = a_t + \int_0^t l_{t,s} dW_s^{\mathbb{Q}}$$

*for a suitable constant  $a_t$  and square-integrable predictable  $l_{t,\cdot}$ .*



## Step 1: Rewrite the dual target value (ctd)

### Lemma

*With the previous notation the dual target value reads*

$$\begin{aligned} & \mathbb{E}_{\mathbb{Q}} \left[ \frac{1}{\alpha} \log \left( \frac{d\mathbb{Q}}{d\mathbb{P}} \right) + \Phi_0(S_T - S_0) + \frac{1}{2\Lambda} \int_0^T \left| \mathbb{E}_{\mathbb{Q}}(S_T | \mathcal{G}_t^\Delta) - S_t \right|^2 dt \right] \\ &= \frac{1}{2\alpha} \int_0^T a_t^2 dt - \Phi_0 \int_0^T a_t dt + \frac{1}{2\Lambda} \int_0^T \left( \int_t^T a_u du \right)^2 dt \\ &+ \int_0^T \mathbb{E}_{\mathbb{Q}} \left[ \frac{1}{2\alpha} \int_s^T l_{t,s}^2 dt + \frac{1}{2\Lambda} \int_s^T \left( \int_t^T l_{u,s} du \right)^2 dt \right. \\ &\quad \left. + \frac{s \wedge \Delta}{2\Lambda} \left( 1 - \int_s^T l_{u,s} du \right)^2 \right] ds. \end{aligned}$$

↪ **family of deterministic (!) variational problems:**

Minimize separately over  $a$  and over  $l_{\cdot,s}$  for each  $s \in [0, T]$ !

## Step 2: Solve deterministic variational problems

### Lemma

*The minimum of the functional*

$$\frac{1}{2\alpha} \int_0^T a_t^2 dt - \Phi_0 \int_0^T a_t dt + \frac{1}{2\Lambda} \int_0^T \left( \int_t^T a_u du \right)^2 dt$$

*over  $a \in L^2([0, T], dt)$  is attained for  $\hat{a}\Phi_0$  where*

$$\hat{a}_t = \frac{\alpha \cosh(\sqrt{\rho}(T-t))}{\cosh(\sqrt{\rho}T)}, \quad t \in [0, T].$$

*The resulting minimum value is  $-\hat{A}_T \Phi_0^2$  where*

$$\hat{A}_T = \Lambda \sqrt{\rho} \tanh(\sqrt{\rho}T)/2.$$

## Step 2: Solve deterministic variational problems

### Lemma

For any  $s \in [0, T]$ , the minimum of the functional

$$\frac{1}{2\alpha} \int_s^T l_t^2 dt + \frac{1}{2\Lambda} \int_s^T \left( \int_t^T l_u du \right)^2 dt + \frac{s \wedge \Delta}{2\Lambda} \left( 1 - \int_s^T l_u du \right)^2$$

over  $l \in L^2([s, T], dt)$  is attained at

$$\hat{l}_{t,s} = \frac{\rho(s \wedge \Delta) \cosh(\sqrt{\rho}(T-t))}{\cosh(\sqrt{\rho}(T-s)) + \sqrt{\rho}(s \wedge \Delta) \sinh(\sqrt{\rho}(T-s))}, \quad t \in [s, T].$$

The corresponding minimum value is

$$\hat{L}_s = \frac{1}{2\Lambda} \frac{s \wedge \Delta}{1 + (s \wedge \Delta) \sqrt{\rho} \tanh(\sqrt{\rho}(T-s))}.$$

## Step 3: Deal with Gaussian stochastic Volterra equation

Candidate for dual solution:  $\hat{\mathbb{Q}} \sim \mathbb{P}$  with density represented by

$$\hat{\theta}_s = \hat{a}_s \Phi_0 + \int_0^s \hat{l}_{s,r} d\hat{W}_r^{\hat{\mathbb{Q}}}, \quad s \in [0, T].$$

For the associated Brownian motion  $\hat{W} = W^{\hat{\mathbb{Q}}} = W + \int_0^\cdot \hat{\theta}_r dr$  this implies the **Gaussian Volterra-type integral equation**

$$\hat{W}_t = W_t + \int_0^t \hat{a}_s \Phi_0 ds + \int_0^t \int_0^s \hat{l}_{s,r} d\hat{W}_r ds, \quad t \in [0, T].$$

## Step 3: Deal with Gaussian stochastic Volterra equation

Theorem (Hitsuda '68, Hida, Hitsuda '93)

*The Gaussian Volterra-type integral equation has the unique solution*

$$\begin{aligned}\hat{W}_t &= W_t + \Phi_0 \int_0^t \hat{a}_s ds - \int_0^t \int_0^s \hat{k}_{s,r} (dW_r + \Phi_0 a_r dr) ds \\ &= W_t - \int_0^t \int_0^s \hat{k}_{s,r} dW_r ds + \Phi_0 \left( \int_0^t \hat{a}_s ds - \int_0^t \int_0^s \hat{k}_{s,r} \hat{a}_r dr ds \right)\end{aligned}$$

where  $\hat{k}$  is the associated resolvent kernel characterized by

$$\hat{k}_{t,s} + \hat{l}_{t,s} = \int_s^t \hat{l}_{t,u} \hat{k}_{u,s} du, \quad 0 \leq s \leq t \leq T,$$

and this  $\hat{W}$  is the  $\hat{\mathbb{Q}}$ -Brownian motion induced by  $W$ .

**Remark:** Result used previously in math finance by Cheridito '01.

# Solution to the dual problem

## Lemma

For our  $\hat{I}$ , the resolvent kernel is

$$\hat{k}_{t,s} = -\exp\left(\int_s^t \hat{I}_{u,u} du\right) \hat{I}_{t,s}, \quad 0 \leq s \leq t \leq T,$$

and the dual infimum is attained by  $\hat{\mathbb{Q}} \sim \mathbb{P}$  with density

$$\frac{d\hat{\mathbb{Q}}}{d\mathbb{P}} = \exp\left(-\int_0^T \hat{\theta}_t dW_t - \frac{1}{2} \int_0^T \hat{\theta}_t^2 dt\right)$$

for  $\hat{\theta}$ ,  $\hat{W}$  as constructed above; this  $\hat{W}$  coincides with the  $\hat{\mathbb{Q}}$ -Brownian motion induced by the  $\mathbb{P}$ -Brownian motion  $W$  via Girsanov's theorem. The value of the dual problem is

$$-\frac{\Lambda \Phi_0^2 \sqrt{\rho}}{2 \coth(\sqrt{\rho} T)} + \int_0^T \frac{1}{2\Lambda} \frac{(s \wedge \Delta)}{1 + (s \wedge \Delta) \sqrt{\rho} \tanh(\sqrt{\rho}(T-s))} ds.$$

# From dual to primal solution: Optimal open loop control

Recall from general duality: Optimal primal turnover policy is

$$\hat{\phi}_t = \frac{\mathbb{E}_{\hat{\mathbb{Q}}} [S_T | \mathcal{G}_t^\Delta] - S_t}{\Lambda}, \quad t \in [0, T],$$

when  $\hat{\mathbb{Q}}$  is the dual solution. Using the relation between  $S = W$  and  $\hat{W}$ , we find

$$\mathbb{E}_{\hat{\mathbb{Q}}} [S_T | \mathcal{G}_t^\Delta] = \int_0^{(t+\Delta) \wedge T} \left( 1 - \int_s^T \hat{l}_{u,s} du \right) d\hat{W}_s - \int_0^T \hat{a}_u du \Phi_0$$

which readily yields an **“open loop”** description of the optimal policy.

This is clearly explicit

# From dual to primal solution: Optimal open loop control

Recall from general duality: Optimal primal turnover policy is

$$\hat{\phi}_t = \frac{\mathbb{E}_{\hat{\mathbb{Q}}} [S_T | \mathcal{G}_t^\Delta] - S_t}{\Lambda}, \quad t \in [0, T],$$

when  $\hat{\mathbb{Q}}$  is the dual solution. Using the relation between  $S = W$  and  $\hat{W}$ , we find

$$\mathbb{E}_{\hat{\mathbb{Q}}} [S_T | \mathcal{G}_t^\Delta] = \int_0^{(t+\Delta) \wedge T} \left( 1 - \int_s^T \hat{l}_{u,s} du \right) d\hat{W}_s - \int_0^T \hat{a}_u du \Phi_0$$

which readily yields an **“open loop”** description of the optimal policy.

This is clearly explicit, **but** not really expressive . . .



## From open loop to closed loop: Getting feedback

Proving that dynamic programming holds in the primal optimization problem, allows us to back out the feedback form of the optimal policy from its open loop description.

A rather tedious computation finally leads to the initially described optimal feedback policy:

$$\hat{\phi}_t = \frac{1}{\Lambda} \left( \bar{S}_t^\Delta - S_t \right) + \frac{\Upsilon^\Delta (T - t)}{\Delta} \left( \frac{\mu}{\alpha \sigma^2} - \hat{\Phi}_t \right)$$

What if we **sort of** knew what the future brings?

# What if we **sort of** knew what the future brings?

Bachelier stock price dynamics, zero interest rate:

$$S_t = s_0 + \mu t + \sigma(\gamma W_t + \sqrt{1 - \gamma^2} B_t), \quad t \geq 0$$

for two independent Brownian motions  $W, B, \gamma \in [0, 1]$ .

Information flow: at time  $t$  **noisy signal on stock price evolution** up to time  $\tau(t) \geq t$  with  $\tau : [0, T] \rightarrow [0, T]$  continuous, increasing:

$\leadsto$  **"frontrunning"**

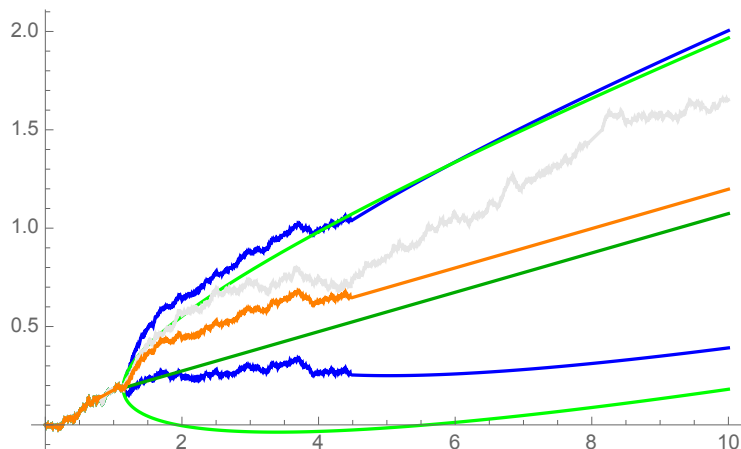
$$\mathcal{G}_t^\tau = \sigma(S_s, s \leq t) \vee \sigma(W_s, s \leq \tau(t)), \quad t \geq 0.$$

$S$  is *not* a  $\mathcal{G}^\tau$ -martingale  $\leadsto$  arbitrage opportunities curtailed by price impact because execution price is

$$S_t^\phi = S_t + \frac{\Lambda}{2} \phi_t$$

where  $\phi_t = \frac{d}{dt} \Phi_t$  is the frontrunner's turnover rate  $\leadsto$  **temporary price impact** à la Almgren-Chriss

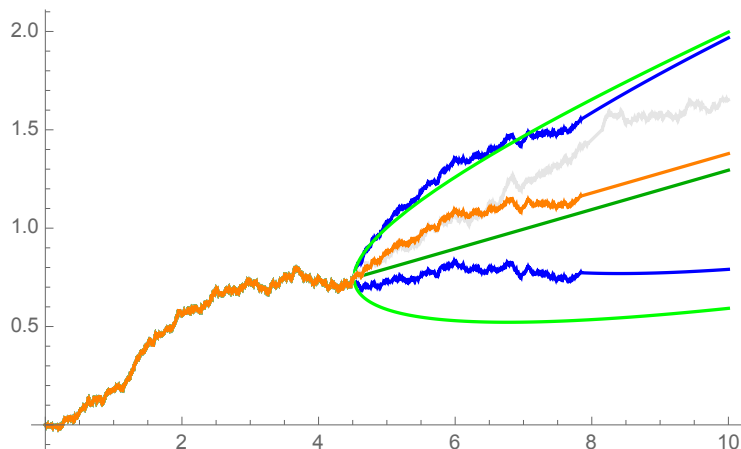
# Noisy information in the course of time



As of time  $t \in [0, T]$ , the standard deviation of  $S$  from  $\bar{S}^\tau$  for  $s \geq 0$  into the future is

$$\sigma\sqrt{s(1-\gamma^2)} \text{ if } s \leq \tau(t) - t \text{ and after that } \sigma\sqrt{s - \gamma^2(\tau(t) - t)}$$

# Noisy information in the course of time



As of time  $t \in [0, T]$ , the standard deviation of  $S$  from  $\bar{S}^\tau$  for  $s \geq 0$  into the future is

$$\sigma\sqrt{s(1-\gamma^2)} \text{ if } s \leq \tau(t) - t \text{ and after that } \sigma\sqrt{s - \gamma^2(\tau(t) - t)}$$

# Main result: Optimal Policy

The optimal policy takes a similar form as in the special case with perfect information corresponding to  $\gamma = 1$ ; the technique of proof still works, but computations and formulae are more involved:

- ▶ at any time  $t \in [0, T]$ , one considers the best guess of the future price evolution

$$\hat{S}_{t+s}^\tau = S_t + \mu s + \sigma \gamma (W_{(t+s) \wedge \tau(t)} - W_t), \quad s \geq 0.$$

- ▶ the guess  $\hat{S}^\tau$  is averaged over  $s \in [0, \tau[t] - t]$  with some explicitly given kernel  $\Upsilon(t, s)$  to yield an indicator  $\bar{S}_t^\tau$  to assess the earnings potential and hence optimal inside trades:  
 $(\bar{S}_t^\tau - S_t)/\Lambda$
- ▶  $\Upsilon(t, \tau(t))$  also yields urgency for trading towards Merton ratio  $\mu/(\alpha\sigma^2)$
- ▶ value of extra information as measured by certainty equivalent can be computed explicitly as well

# Conclusion and Outlook

- ▶ insider model with dynamic information advantages: frontrunning
- ▶ price impact keeps utility maximization viable: super-linear transaction costs
- ▶ explicit solution with financial-economic meaning: inside trades combined with standard optimal investment
- ▶ no dynamic programming, but dual approach
- ▶ convex duality result holds beyond Bachelier setting and frontrunning
- ▶ noisy inside information process
- ▶ Open: How to allow for more flexible signal quality deterioration (instead of abruptly no info beyond  $\tau(t)$ )? Stochastically changing signal quality?...

# Conclusion and Outlook

- ▶ insider model with dynamic information advantages: frontrunning
- ▶ price impact keeps utility maximization viable: super-linear transaction costs
- ▶ explicit solution with financial-economic meaning: inside trades combined with standard optimal investment
- ▶ no dynamic programming, but dual approach
- ▶ convex duality result holds beyond Bachelier setting and frontrunning
- ▶ noisy inside information process
- ▶ Open: How to allow for more flexible signal quality deterioration (instead of abruptly no info beyond  $\tau(t)$ )? Stochastically changing signal quality?...

**Thank you very much!**