

# Bounds for Expected Occupation Densities and Applications



Paul Eisenberg (Krühner ) based on work with: **Shijie Xu**, **David Baños** and **Julia Eisenberg**

Vienna, 2026



- Occupation Measures and Local Times
- Expected Occupation bounds
- Applications

# Outline

- Occupation Measures and Local Times
- Expected Occupation bounds
- Applications

# Occupation Measure

## Definition (Occupation Measure)

Let  $(X_t)_{t \geq 0}$  be a continuous sample paths stochastic process on  $(\Omega, \mathcal{F}, \mathbb{P})$ . For  $t \geq 0$ , define the *occupation measure* by

$$\begin{aligned}\Lambda_t(A) &:= \int_0^t \mathbf{1}_A(X_s) ds, \quad A \in \mathcal{B}(\mathbb{R}^d), \\ \mu_t(A) &:= \int_0^t \mathbf{1}_A(X_s) d[X]_s, \quad A \in \mathcal{B}(\mathbb{R}^d)\end{aligned}$$

where the latter is only defined provided that the process  $X$  admits finite quadratic variation  $[X]_t$  a.s.

# Occupation Measure

## Definition (Occupation Measure)

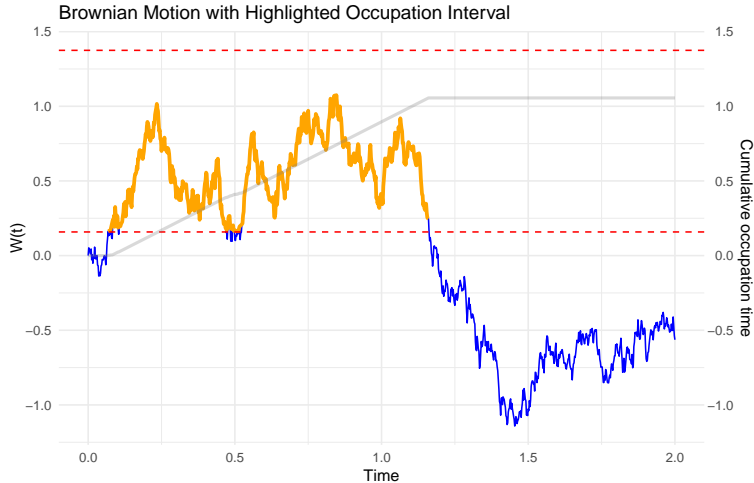
Let  $(X_t)_{t \geq 0}$  be a continuous sample paths stochastic process on  $(\Omega, \mathcal{F}, \mathbb{P})$ . For  $t \geq 0$ , define the *occupation measure* by

$$\Lambda_t(A) := \int_0^t \mathbf{1}_A(X_s) ds, \quad A \in \mathcal{B}(\mathbb{R}^d),$$
$$\mu_t(A) := \int_0^t \mathbf{1}_A(X_s) d[X]_s, \quad A \in \mathcal{B}(\mathbb{R}^d)$$

where the latter is only defined provided that the process  $X$  admits finite quadratic variation  $[X]_t$  a.s.

- Measures how much time the process spends in set  $A$  up to time  $t$ .
- Naturally depends on sample path  $\omega$ .

# BM with highlighted occupation interval



# Occupation Density

## Definition ((Expected) Occupation Density)

- If there exists a measurable function  $\lambda_t(x)$  such that

$$\Lambda_t(A) = \int_A \lambda_t(x) dx, \quad A \in \mathcal{B}(\mathbb{R}^d),$$

then  $\lambda_t(x)$  is called the *occupation density* at time  $t \geq 0$ ,  $x \in \mathbb{R}^d$ .

- If there exists a measurable function  $\ell_t(x)$  such that

$$\int_0^t P(X_s \in A) ds = E[\Lambda_t(A)] = \int_A \ell_t(x) dx, \quad A \in \mathcal{B}(\mathbb{R}^d),$$

then  $\lambda_t(x)$  is called the **expected occupation density** at time  $t \geq 0$ ,  $x \in \mathbb{R}^d$ .

# Remarks on (expected) occupation measure and density

- The occupation measure  $\Lambda_t$  is a finite random measure with total mass  $t$  and its expectation  $E[\Lambda_t(\cdot)]$  is a finite measure with total mass  $t$ .
- If  $X$  is a 1-dimensional diffusion  $dX_t = b_t dt + \sigma_t dW_t$  with  $\sigma_t \geq \sigma_{\min} > 0$ , then for any  $t \geq 0$  the occupation density has a locally bounded version.
- If  $X$  is a 1-dimensional process such that  $X_t$  has density  $\rho_t$ , then

$$\int_0^t \rho_s(x) ds = l_t(x).$$



# Remarks on (expected) occupation measure and density

- The occupation measure  $\Lambda_t$  is a finite random measure with total mass  $t$  and its expectation  $E[\Lambda_t(\cdot)]$  is a finite measure with total mass  $t$ .
- If  $X$  is a 1-dimensional diffusion  $dX_t = b_t dt + \sigma_t dW_t$  with  $\sigma_t \geq \sigma_{\min} > 0$ , then for any  $t \geq 0$  the occupation density has a locally bounded version.
- If  $X$  is a 1-dimensional process such that  $X_t$  has density  $\rho_t$ , then

$$\int_0^t \rho_s(x) ds = l_t(x).$$

The main reason to be interested in expected occupation densities is the following formula which holds for any measurable  $f : \mathbb{R} \rightarrow [0, \infty)$ :

$$E \left[ \int_0^t f(X_s) ds \right] = \int_{-\infty}^{\infty} f(x) l_t(x) dx.$$

## Usage of expected occupation densities

Let  $X$  be a continuous sample path process which has expected occupation density  $\ell_t(x)$  and  $\gamma$  measurable with  $\ell_t(x) \leq \gamma_t(x)$ , that is  $\gamma$  is some upper bound for the expected occupation density.

- For measurable  $f : \mathbb{R} \rightarrow [0, \infty)$ :

$$\mathbb{E} \left[ \int_0^t f(X_s) ds \right] \leq \int_{-\infty}^{\infty} f(x) \gamma_t(x) dx.$$

- Upper bounds are usually easier to obtain than the expected occupation density itself.
- If an upper bound is known up to some constants (implicit upper bound), then it can be used to get qualitative upper bounds as appear in stability schemes for SDEs.

## Relation with expected values

### Lemma

Let  $X$  be a Markovian diffusion  $dX_t = b(X_t)dt + \sigma(X_t)dW_t$  and  $f : \mathbb{R} \rightarrow \mathbb{R}$  be a  $C^2$ -function with  $b, \sigma$  bounded measurable. Then

$$\begin{aligned} \mathbb{E}[f(X_t)] &= \mathbb{E}[f(X_0)] + \int_0^t \mathbb{E}[\mathcal{A}f(X_s)]ds \\ &\leq \mathbb{E}[f(X_0)] + \int_{-\infty}^{\infty} \max\{\mathcal{A}f(x), 0\} l_t(x) dx \end{aligned}$$

where  $\mathcal{A}$  is the generator  $\mathcal{A}f(x) = b'(x)f(x) + \frac{1}{2}\sigma^2(x)f''(x)$ .

- The formula is a useful tool for bounds, control and sensitivity analysis.

# Outline

- Occupation Measures and Local Times
- Expected Occupation bounds
- Applications

# Kernel based bounds (Strook Varadhan, 1979)

**Setting.** Let  $(X_t)_{t \geq 0}$  solve the SDE

$$dX_t = b(X_t) dt + \sigma(X_t) dW_t,$$

where  $b, \sigma \in C_b^\infty(\mathbb{R}^d)$  and the diffusion matrix  $a = \sigma\sigma^\top$  is *uniformly elliptic*:

$$m_1|\xi|^2 \leq \xi^\top a(x)\xi \leq m_2|\xi|^2.$$

**Gaussian heat kernel bounds.** There exist **unknown constants**  $c_i > 0$  such that **density**  $\rho_t$  of  $X_t$  admits

$$\rho_t(x) \leq c_1 t^{-d/2} \exp\left(-c_2 \frac{|x - X_0|^2}{t}\right), \quad t \in (0, T].$$

**Expected occupation density bound.** Consequently,

$$l_t(x) \leq \int_0^t c_1 s^{-d/2} \exp\left(-c_2 \frac{|x - X_0|^2}{s}\right) ds.$$

## Failure of densities (McNamura 1983)

**Counterexample.** There exists a one-dimensional diffusion

$$dX_t = \sigma(t, X_t) dW_t, \quad X_0 = 0,$$

with

$$\sigma(t, x) \in \{\sigma_1, \sigma_2\},$$

such that for some fixed  $T > 0$  the random variable  $X_T$  *does not admit a density* with respect to Lebesgue measure.

### Key properties.

- Uniform ellipticity holds.
- The diffusion coefficient is bounded and measurable.
- The process is well defined for all  $t \geq 0$ .

### Consequences.

- No classical heat kernel estimate exists at time  $T$ .
- Pointwise or Gaussian density estimates are impossible.
- Occupation bounds cannot rely on kernel estimates.

# Krylov occupation bounds (Krylov Röckner 2008)

**Setting.** Let  $(X_t)_{t \geq 0}$  be a diffusion

$$dX_t = \beta_t dt + \sigma_t dW_t,$$

where

$a_t = \sigma_t \sigma_t^\top$  is uniformly elliptic and bounded,

and  $b$  is progressively measurable unbounded.

**Krylov estimate.** Let  $f \in L^p([0, T] \times \mathbb{R}^d)$  with  $p > \frac{d}{2} + 1$ . Then there exists a **unknown constant**  $C = C(d, p, \lambda, \Lambda, T)$  such that

$$\mathbb{E} \left[ \int_0^T |f(t, X_t)| dt \right] \leq C \|f\|_{L^p([0, T] \times \mathbb{R}^d)}.$$

## Key features.

- No pointwise heat kernel bounds required (or possible).
- Coefficients need only be measurable.
- Applies equally to time-inhomogeneous diffusions.

## K. Xu upper bound (explicit)

**Setting.** Let  $(X_t)_{t \geq 0}$  be a 1-dimensional diffusion

$$dX_t = \beta_t dt + \sigma_t dW_t,$$

where  $\sigma_t \in [\sigma_{\min}, \sigma_{\max}]$  with  $0 < \sigma_{\min} \leq \sigma_{\max}$  and  $|\beta_t|$  is bounded by  $K$ .



## K. Xu upper bound (explicit)

**Setting.** Let  $(X_t)_{t \geq 0}$  be a 1-dimensional diffusion

$$dX_t = \beta_t dt + \sigma_t dW_t,$$

where  $\sigma_t \in [\sigma_{\min}, \sigma_{\max}]$  with  $0 < \sigma_{\min} \leq \sigma_{\max}$  and  $|\beta_t|$  is bounded by  $K$ .

### Theorem (K., Xu (2025))

*Let  $X$  be as above. Then its expected local time  $\ell_t$  exists and*

$$\alpha_t(x) \leq \ell_t(x) \leq \gamma_t(x)$$

*for some continuous functions  $\alpha, \gamma$   
with explicit form given by ...*

## Explicit upper bound

### Theorem

*Let  $X$  be as above. Then its expected local time  $\ell_t$  exists and a version satisfies*

$$\ell_t(x) \leq \gamma_t(x)$$

*where*

$$\gamma_t(x) = \frac{\sigma_{\max}}{\sigma_{\min}^2} \int_0^t \left( \frac{1}{\sqrt{s}} \varphi(v(|x - X_0|, s)) + K \Phi(v(|x - X_0|, s)) \right) ds,$$

*where  $\varphi$ ,  $\Phi$  are the standard normal density and distribution function and*

$$v(r, s) := K\sqrt{s} - \frac{r}{\sigma_{\max}\sqrt{s}} \quad s > 0, r \geq 0$$

## Explicit upper bound

### Theorem

*Let  $X$  be as above. Then its expected local time  $\ell_t$  exists and a version satisfies*

$$\ell_t(x) \leq \gamma_t(x)$$

*where*

$$\gamma_t(x) = \frac{\sigma_{\max}}{\sigma_{\min}^2} \int_0^t \left( \frac{1}{\sqrt{s}} \varphi(v(|x - X_0|, s)) + K \Phi(v(|x - X_0|, s)) \right) ds,$$

*where  $\varphi$ ,  $\Phi$  are the standard normal density and distribution function and*

$$v(r, s) := K\sqrt{s} - \frac{r}{\sigma_{\max}\sqrt{s}} \quad s > 0, r \geq 0$$

## Further comments

- Optimal expected and path-wise **interval** occupation has been found in (Ankirchner, Wendt 25). The bound for

$$\int_0^t P(X_s \in [a, b]) ds = E[\Lambda_t([a, b])] \leq Q_t(a, b, \sigma_{\min}, \sigma_{\max}, K), \quad a < b, t \geq 0$$

looks quite different — they only coincide to our bound in a limiting sense. However, their bound was used to find the bound in (Krühner, Xu 25).

# Outline

- Occupation Measures and Local Times
- Expected Occupation bounds
- Applications

# Application: Pre-estimates for Control Problems

**Setting:** Let

$$X_t^\sigma = X_0 + \int_0^t \sigma(s, X_s) dW_s$$

where  $\sigma : \mathbb{R}^2 \rightarrow [a, b]$  measurable where  $0 < a \leq b$  is given. Denote the set of measurable functions  $\sigma$  where such a process  $X^\sigma$  exists by  $\mathcal{C}$ .

**Question:** How large is

$$\sup_{\sigma \in \mathcal{C}} \mathbb{E} \left[ f(X_t^\sigma) + \int_0^t g(X_s^\sigma) ds \right] \leq ?$$

# Application: Pre-estimates for Control Problems

**Setting:** Let

$$X_t^\sigma = X_0 + \int_0^t \sigma(s, X_s) dW_s$$

where  $\sigma : \mathbb{R}^2 \rightarrow [a, b]$  measurable where  $0 < a \leq b$  is given. Denote the set of measurable functions  $\sigma$  where such a process  $X^\sigma$  exists by  $\mathcal{C}$ .

**Question:** How large is

$$\sup_{\sigma \in \mathcal{C}} \mathbb{E} \left[ f(X_t^\sigma) + \int_0^t g(X_s^\sigma) ds \right] \leq ?$$

**A common numerical approach:** Find  $C^2$ -functions  $V_N(t, x)$  and **hope** that

$$V_N(u, x) \approx \mathbb{E} \left[ f(X_t^\sigma) + \int_u^t g(X_s^\sigma) ds \mid X_u^\sigma = x \right], \quad V_N(t, x) = f(x)$$

# Application: Pre-estimates for Control Problems, cont.

**A common numerical approach:** Need to find  $h_N : \mathbb{R} \rightarrow [0, \infty)$  such that

$$\sup_{m \in [a, b]} \left( \partial_1 V_N(s, x) + \frac{1}{2} \partial_2^2 V_N(s, x) m^2 + g(x) \right) \leq h(x)$$



# Application: Pre-estimates for Control Problems, cont.

**A common numerical approach:** Need to find  $h_N : \mathbb{R} \rightarrow [0, \infty)$  such that

$$\sup_{m \in [a, b]} \left( \partial_1 V_N(s, x) + \frac{1}{2} \partial_2^2 V_N(s, x) m^2 + g(x) \right) \leq h(x)$$

**Error control:** For some  $\sigma \in \mathcal{C}$  we find

$$\begin{aligned} E[f(X_t^\sigma)] &= E[V_N(t, X_t^\sigma)] \\ &= V_N(0, X_0) + E \left[ \int_0^t \partial_1 V_N(s, X_s^\sigma) + \frac{1}{2} \partial_2^2 V_N(s, X_s^\sigma) \sigma^2(X_s) ds \right] \\ &\leq V_N(0, X_0) + E \left[ \int_0^t h_N(X_s) ds \right] - E \left[ \int_0^t g(X_s) ds \right] \end{aligned}$$

So we get for any  $\sigma \in \mathcal{C}$ :

$$E \left[ f(X_t) + \int_0^t g(X_s) ds \right] \leq V_N(0, X_0) + \int_{-\infty}^{\infty} h(x) \gamma_t(x) dx.$$

- Expected occupation densities bounds  $\gamma$  allow for upper mean path integral bounds:

$$\mathbb{E}\left[\int_0^t f(X_s)ds\right] \leq \int_{-\infty}^{\infty} f(x)\gamma_t(x)dx$$

- When drift/diffusion are known to be smooth, then
- (Krühner Xu 2025) bounds give explicit upper estimates under bounded drift and diffusion in the elliptic regime under no further regularity assumption on the drift/diffusion.

## References: Classical heat kernel bounds

- D. Stroock and S. R. S. Varadhan, *Multidimensional Diffusion Processes*, Springer, 1979.
- D. G. Aronson, *Bounds for the fundamental solution of a parabolic equation*, Bull. Amer. Math. Soc. **73** (1967), 890–896.
- D. G. Aronson, *Non-negative solutions of linear parabolic equations*, Ann. Scuola Norm. Sup. Pisa, 1968.
- E. B. Davies, *Heat Kernels and Spectral Theory*, Cambridge University Press, 1989.

## References: Parametrix and regularity (more heat kernel bounds)

- A. Friedman, *Partial Differential Equations of Parabolic Type*, Prentice–Hall, 1964.
- O. Ladyzhenskaya, V. Solonnikov, N. Ural'tseva, *Linear and Quasilinear Equations of Parabolic Type*, AMS, 1968.

---

## References: Krylov-type occupation bounds

- N. Krylov, *Lectures on Elliptic and Parabolic Equations in Sobolev Spaces*, AMS, 2008.
- N. V. Krylov and M. Röckner, *Strong solutions of stochastic equations with singular time dependent drift*, Probab. Theory Relat. Fields **131** (2005), 154–196.

# References: 1D diffusions and occupation times

- J. McNamara, *Optimal control of the diffusion coefficient of a simple diffusion process*, Math. Oper. Res. **8**, 373–380, 1983.
- S. Ankirchner and J. Wendt, *A sharp upper bound for the expected interval occupation time of Brownian martingales*, Journal of theoretical Probability, **38**, 2025.
- P. Krühner and S. Xu, *Sharp bounds for the expected occupation density of Itô processes with bounded irregular drift and diffusion coefficients*, Electronic Journal of Probability. **30**, 2025.
- D. Baños and P. Krühner, *Hölder continuous densities of solutions of SDEs with measurable and path dependent drift coefficients*, Stochastic Processes and their Applications. **127**, 1785 – 1799, 2017.
- D. Baños and P. Krühner, *Optimal density bounds for marginals of Itô processes*, Communications in Stochastic Analysis, **10**, 131–150, 2016.

# References: Density bounds via Malliavin calculus

- D. Nualart and L. Quer-Sardanyons, *Optimal Gaussian density estimates for a class of stochastic equations with additive noise*, Infinite Dimensional Analysis, Quantum Probability and Related Topics **14**, 2009.
- I. Nourdin and F. G. Viens, *Density formula and concentration inequalities with Malliavin calculus*, Electron. J. Probab., **14**, 2287–2309, 2009.
- T. Nguyen, *Gaussian lower bounds for the density via Malliavin calculus*, Comptes Rendus Mathématique **358**, 79–87, 2020.
- B. Gess, C. Ouyang, and S. Tindel, *Density bounds for solutions to differential equations driven by Gaussian rough paths*, Journal of Theoretical Probability, **33**, 611–648, 2020.
- V. Bally, L. Caramellino and A. Kohatsu-Higa, *Upper bounds for the derivatives of the density associated to SDEs with jumps*, J. Math. Anal. Appl., **531**, 2024.

# Thank you for your attention!

# Thank you for your attention!

Questions?