Monetary Policy, Bank Heterogeneity, and the Marginal Propensity to Lend

Angel Fernández Rojas

Central Reserve Bank of Peru

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The views expressed herein are those of the author and not necessarily those of the Central Reserve Bank of Peru.

Introduction

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- Monetary policy affects the price and quantity of deposits.
- Response of deposits to MP is heterogeneous across banks.
- **This paper**: Deposit heterogeneity affects the monetary transmission.
  - Those who lose more deposits from a monetary tightening have lower MPLs.

This Paper

How deposit heterogeneity affects the monetary transmission?

- Banking model with heterogeneous banks
  - Banks provide loans using deposits and wholesale funding.
  - Key friction: Increasingly costly to substitute deposits with wholesale funding.
  - Banks face different degrees of financial frictions.
  - Endogenous positive covariance of MPLs and resp. of deposits to MP.

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  - Target cross-sectional distribution of frictions.
  - Using OLS and IV estimates of the average MPL.

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  - Using OLS and IV estimates of the average MPL.

- Findings
  - Bank heterogeneity dampens monetary policy by 17%.
    - Aggregate deposits reduce lending by 0.62%.
    - Heterogeneity increases bank lending by 0.11%.

Model

- Bank balance sheet
  - Invest in liquid assets b and loans l using deposits d and wholesale funding w.
  - Liquid assets are subject to a liquidity constraint, i.e. $b_j \geq \bar{b}$.

$$b_j + l_j = d_j + w_j \tag{1}$$

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- Key friction: Quadratic cost to use wholesale funding, $\frac{\phi_j}{2} w^2$.
- Banks have market power in loan and deposit markets.

$$\log l_j = -\varepsilon_j^l i_j^l + \gamma_j^l i + v_j^l \tag{3}$$

$$\log d_j = \varepsilon_j^d i_j^d - \gamma_j^d i + v_j^d \tag{4}$$

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- Banks maximize their net income

$$\max_{b_j, l_j, d_j, w_j} i b_j + i_j^l l_j - i_j^d d_j - i w_j - \frac{\phi_j}{2} w_j^2 \tag{5}$$
$$\text{s.t.} \quad (1) - (4)$$

Frictions increase interest rates

- Lending and deposit rates are increasing in the degree of frictions.

$$i_j^l = i + \phi_j w_j + \frac{1}{\varepsilon_j^l} \tag{6}$$

$$i_j^d = i + \phi_j w_j - \frac{1}{\varepsilon_j^d} \tag{7}$$

- **Without frictions**, deposits are not important for bank lending, i.e. $\phi_j = 0$.

Frictions increase deposit pass-through

- Loan and deposit pass-through are increasing in the degree of frictions.

$$\frac{\mathrm{d}i_j^l}{\mathrm{d}i} = \frac{\mathrm{d}i_j^d}{\mathrm{d}i} = 1 + \phi_j w_j \frac{\mathrm{d}\log w_j}{\mathrm{d}i} \tag{8}$$

- A higher policy rate increases deposit rates.
- **Higher frictions** increase deposit rates and the quantity of deposits by more.
  - Banks that need more deposits increase deposit rates by more.
  - Without frictions, banks do not need deposits.

Frictions expose lending to deposit shocks

$$\frac{\mathrm{d}\log l_j}{\mathrm{d}i} = \underbrace{\frac{\varepsilon_j^l \phi_j d_j}{1+\varepsilon_j^l \phi_j l_j}}_{\lambda_j^{MPL}} \frac{\mathrm{d}\log d_j}{\mathrm{d}i} + \Big[1 - \underbrace{\frac{\varepsilon_j^l \phi_j l_j}{1+\varepsilon_j^l \phi_j l_j}}_{MPL_j}\Big](\gamma_j^l - \varepsilon_j^l) \tag{9}$$

- MPL: Measures the increase in lending after an idiosyncratic deposit shock.
- **Higher frictions** increase MPLs.
  - More difficult to substitute deposits with wholesale funding.
  - Higher exposure of lending to deposit changes.

The deposit heterogeneity channel dampens MP

- Aggregate response of loans

$$\frac{\mathrm{d}\log l}{\mathrm{d}i} = \underbrace{\lambda^{MPL}\frac{\mathrm{d}\log d}{\mathrm{d}i}}_{\textbf{AD}\text{ channel}} + \underbrace{\sum \frac{l_j}{l}\lambda_j^{MPL}\left(\frac{\mathrm{d}\log d_j}{\mathrm{d}i} - \frac{\mathrm{d}\log d}{\mathrm{d}i}\right)}_{\text{DH channel}} + \underbrace{(1 - MPL)(\gamma^l - \varepsilon^l)}_{\text{Aggregate loan demand (}\textbf{ALD}\text{) channel}} \tag{10}$$

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- DH channel **dampens** monetary policy
  - Banks that lose more deposits after a monetary tightening have lower MPLs.
  - Endogenous **positive** covariance.

Empirical Framework

- Data
  - Quarterly bank-level data from U.S. banks.
  - Period: 1994 to 2007.
  - Monetary shocks from Miranda-Agrippino and Ricco (2019).

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- Bank-level regressions for loans and deposits

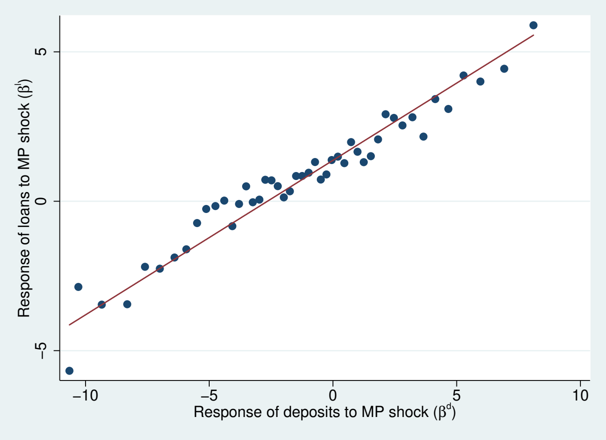
$$\frac{x_{j,t+3} - x_{j,t-1}}{x_{j,t-1}} = \alpha_j^x + \beta_j^x \mu_t^m + \nu_{jt}^x \tag{11}$$

  - μ_t^m is a monetary shock normalized to have a 1% effect on the Fed funds rate.
  - $x \in \{l, d\}$.

- Bank-level regressions for deposit rates

$$i_{j,t+3}^d - i_{j,t-1}^d = \alpha_j^{i^d} + \beta_j^{i^d} \mu_t^m + \nu_{jt}^{i^d} \tag{12}$$

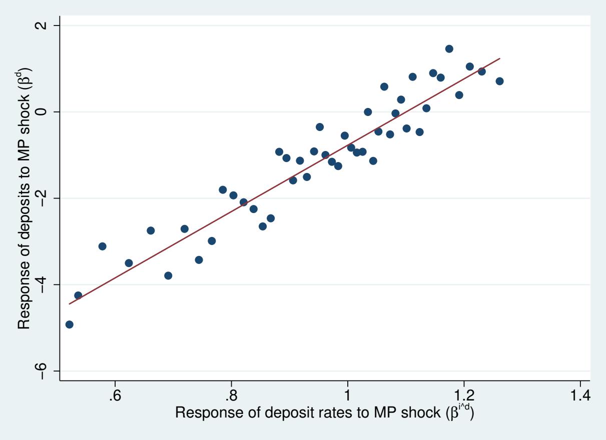
Banks that lose more deposits reduce lending by more.



- OLS regression of β_j^l on β_j^d

$$\lambda^{OLS} = \mathrm{E}[\lambda_j^{MPL}] + \text{Bias} \tag{13}$$

Banks that lose more deposits have lower pass-through.



IV regression to recover an estimate of the average MPL.

- Up to second order, in the model with full heterogeneity:

$$\lambda^{OLS} = \mathrm{E}[\lambda_j^{MPL}] + \text{Bias} \tag{14}$$
$$\lambda^{IV} = \mathrm{E}[\lambda_j^{MPL}] + \psi\text{Bias} + \tau \tag{15}$$

  - $\psi = \frac{1}{\theta\varepsilon^d}$, $\theta = \frac{\mathrm{Cov}(\beta_j^{i^d}, \beta_j^d)}{\mathrm{Var}(\beta_j^d)}$, $\varepsilon^d = \mathrm{E}[\varepsilon_j^d]$.
  - τ captures the covariance between deposit demand parameters and MPLs.
  - In the model with full heterogeneity, $\tau \geq 0$ and $1 > \theta\varepsilon^d$.

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- Up to second order:

$$\mathrm{E}[\lambda_j^{MPL}] \geq \tilde{\lambda}^{MPL} = \lambda^{OLS} + \frac{\theta\varepsilon^d}{1 - \theta\varepsilon^d}\left(\lambda^{OLS} - \lambda^{IV}\right) \tag{16}$$

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- Lower bound for the covariance

$$\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^d) \geq \mathcal{C} \tag{17}$$

Estimation Procedure

- Eight moments to target eight parameters.
- Define vector F

$$F = \begin{bmatrix} (\mathrm{E}[i_j^l] - mean(i_j^l))/std(i^l) \\ (\mathrm{E}[i_j^d] - mean(i_j^d))/std(i^d) \\ (\mathrm{E}[\beta_j^l] - mean(\beta_j^l)/std(\beta_j^l) \\ (\mathrm{E}[\beta_j^d] - mean(\beta_j^d)/std(\beta_j^d) \\ (\mathrm{E}[l_j] - mean(l_j)/std(l_j) \\ (\mathrm{E}[d_j] - mean(d_j))/std(d_j) \\ (\mathrm{E}[\lambda_j^{MPL}] - \tilde{\lambda}^{MPL})/std(\tilde{\lambda}^{MPL}) \\ (\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^d) - \mathcal{C})/std(\mathcal{C}) \end{bmatrix} \tag{18}$$

- The value of $F'F$ is minimized with $J = 20,000$.

Estimated parameters

Parameter	Description	Value	Standard error
ε^l	Loan demand elasticity	49.6971	1.9511
γ^l	Exposure of loan demand to the policy rate i	56.3458	0.1198
v^l	Loan demand shock	2.8899	0.1831
ε^d	Deposit demand elasticity	27.9970	0.6276
γ^d	Exposure of deposit demand to the policy rate i	32.4598	1.8782
v^d	Deposit demand shock	0.9206	0.2382
μ	Mean of log of the degree of financial frictions ϕ_j	-3.5958	0.2663
σ	Std of log of the degree of financial frictions ϕ_j	1.8757	0.8221

- Loan demand increases by 6.6% (=56.3-49.7).
- Deposit demand decreases by 4.5% (=32.5-28.0).

Model and data moments

Moment	Data	Model
Mean (i^l)	0.0845	0.0876
Mean (i^d)	0.0287	0.0318
Mean (β^d)	-1.1525	-1.5027
Mean (β^l)	0.7731	1.3942
Mean (l_j)	2.5810	2.5849
Mean (d_j)	2.4663	1.6902
$\tilde{\lambda}^{MPL}$	0.7237	0.7217
$\mathcal{C}$	0.7854	0.4424

- Covariance with heterogeneity only in financial frictions is not high enough.
- If shares are unrelated to betas, DH channel dampens MP by 94%.

DH channel dampens MP by 17%

AD channel	-0.6248
DH channel	0.1062
Aggregate MPL elasticity	0.4875
Aggregate MPL	0.5741
Aggregate resp. of dep.	-1.2815
Aggregate resp. of loans	2.3131

- After a 1% higher policy rate, deposits fall by 1.28%
- Lending falls by 0.62% due to the fall in deposits.
- Lending increases by 0.11% due to heterogeneity.

Conclusion

- I study how deposit heterogeneity affects the monetary transmission.
- Develop a banking model with heterogeneous banks.
  - Banks that lose more deposits after a monetary tightening have lower MPL.
- Main Finding: Bank heterogeneity dampens monetary policy by at least 17%.

Extra Slides

Microfoundation of loan demand

- A consumer lives for two periods and decides to borrow from bank j.

$$U(C_0, C_1) = \ln C_0 + \beta \ln C_1 \tag{19}$$
$$C_0 = \tilde{L}_j$$
$$C_1 = \overline{Y} - (1 + i_j^l)\tilde{L}_j$$

- The indirect utility conditional on borrowing from bank j is.

$$v_j = (1+\beta)(\ln \overline{Y} - \ln(1+\beta)) + \beta \ln(\beta) - \ln\big(1 + i_j^l\big) \tag{20}$$

- Assume stochastic utility approach with ε_j iid with Gumbel distribution:

$$V_j = v_j + \frac{1}{\varepsilon^l - 1}\varepsilon_j \tag{21}$$

- Loan demand is:

$$L_j = \frac{\overline{Y}}{1+\beta} \frac{1}{\left(\int_0^1 (1+i_i^l)^{1-\varepsilon^l} di\right)^{\frac{1}{1-\varepsilon^l}}} \left(\frac{1+i_j^l}{\left(\int_0^1 (1+i_i^l)^{1-\varepsilon^l} di\right)^{\frac{1}{1-\varepsilon^l}}} \right)^{-\varepsilon^l} \tag{22}$$

Model

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$$C_1 = (1 + i_j^d)\tilde{D}_j$$

- Assume stochastic utility approach with ε_j iid with Gumbel distribution:

$$V_j = v_j + \frac{\beta}{\varepsilon^d}\varepsilon_j \tag{24}$$

- Deposit demand is:

$$D_j = \frac{\beta \overline{Y}}{1+\beta}\left(\frac{1 + i_j^d}{\left(\int_0^1 (1 + i_i^d)^{\varepsilon^d} di\right)^{\frac{1}{\varepsilon^d}}}\right)^{\varepsilon^d} \tag{25}$$

Model

Microfoundation of loan demand II

- A consumer decides to borrow from bank j at rate i_j^l and nonbanks at rate i.
- CES constraint

$$\left(\alpha_j^{\frac{1}{\varepsilon_j^l}} L_j^{\frac{\varepsilon_j^l-1}{\varepsilon_j^l}} + (1-\alpha_j)^{\frac{1}{\varepsilon_j^l}} B_j^{\frac{\varepsilon_j^l-1}{\varepsilon_j^l}}\right)^{\frac{\varepsilon_j^l}{\varepsilon_j^l-1}} \geq \tilde{L} \tag{26}$$

- Loan demand is:

$$L_j = \tilde{L}\left(\frac{1+i_j^l}{\left(\alpha_j(1+i_j^l)^{1-\varepsilon_j^l} + (1-\alpha_j)(1+i)^{1-\varepsilon_j^l}\right)^{\frac{1}{1-\varepsilon_j^l}}}\right)^{-\varepsilon_j^l} \tag{27}$$

Model

Assumptions

Assumption 1 (Bound for bank liquidity). *For all banks, the aggregate liquidity constraint is sufficiently low such that* $\overline{b} < b^* = \min_{\phi_j}\{\frac{1}{\phi_j \varepsilon^l} + d(\phi_j)\}$.

Assumption 2 (Elasticities). *Exposure of loan demand to the policy rate is higher than loan demand elasticity, i.e.* $\gamma^l > \varepsilon^l$, *and exposure of deposit demand to the policy rate is higher than deposit demand elasticity, i.e.* $\gamma^d > \varepsilon^d$.

OLS estimate

Table: OLS estimation

	Estimate
Average MPL elasticity	0.52 $[0.49, 0.55]$

Notes: This table shows an OLS estimate of the average MPL elasticity. In brackets: 95% bootstrap confidence intervals.

OLS and IV estimates

$$\lambda^{OLS} = \mathrm{E}[\lambda_j^{MPL}] + \Big(1 - \mathrm{E}[MPL_j]\Big)\frac{\mathrm{Cov}(\gamma_j^l - \varepsilon_j^l, \beta_j^d)}{\mathrm{Var}(\beta_j^d)}$$
$$+ \mathrm{E}[\beta_j^d]\frac{\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^d)}{\mathrm{Var}(\beta_j^d)} - \mathrm{E}[(\gamma_j^l - \varepsilon_j^l)]\frac{\mathrm{Cov}(MPL_j, \beta_j^d)}{\mathrm{Var}(\beta_j^d)} \tag{28}$$
$$+ \frac{\mathrm{E}[(\widehat{\lambda}_j^{MPL})(\widehat{\beta}_j^d)^2]}{\mathrm{Var}(\beta_j^d)} - \frac{\mathrm{E}[(\widehat{MPL}_j)(\widehat{\gamma}_j^l - \widehat{\varepsilon}_j^l)(\widehat{\beta}_j^d)]}{\mathrm{Var}(\beta_j^d)}$$

$$\lambda^{IV} = \mathrm{E}[\lambda_j^{MPL}] + \Big(1 - \mathrm{E}[MPL_j]\Big)\frac{\mathrm{Cov}(\gamma_j^l - \varepsilon_j^l, \beta_j^{i^d})}{\mathrm{Cov}(\beta_j^d, \beta_j^{i^d})}$$
$$+ \mathrm{E}[\beta_j^d]\frac{\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^{i^d})}{\mathrm{Cov}(\beta_j^d, \beta_j^{i^d})} - \mathrm{E}[(\gamma_j^l - \varepsilon_j^l)]\frac{\mathrm{Cov}(MPL_j, \beta_j^{i^d})}{\mathrm{Cov}(\beta_j^d, \beta_j^{i^d})} \tag{29}$$
$$+ \frac{\mathrm{E}[(\widehat{\lambda}_j^{MPL})(\widehat{\beta}_j^d)(\widehat{\beta}_j^{i^d})]}{\mathrm{Cov}(\beta_j^d, \beta_j^{i^d})} - \frac{\mathrm{E}[(\widehat{MPL}_j)(\widehat{\gamma}_j^l - \widehat{\varepsilon}_j^l)(\widehat{\beta}_j^{i^d})]}{\mathrm{Cov}(\beta_j^d, \beta_j^{i^d})}$$

Lower bound for covariance of MPLs and deposit exposure.

- Up to second order

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- Bias 1 ≥ 0
- Lower bound for the covariance

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- Bias 1 ≥ 0
- Lower bound for the covariance

$$\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^d) \geq \mathcal{C} = \frac{\Big(\lambda^{OLS} - \mathrm{E}[\lambda_j^{MPL}] + z\Big(\gamma^l - \varepsilon^l\Big)\mathrm{E}[\lambda_j^{MPL}]\Big)\mathrm{Var}(\beta_j^d)}{\Big(\mathrm{E}[\beta_j^d] - (\gamma^l - \varepsilon^l)\mathrm{E}\Big[\frac{l_j}{d_j}\Big]\Big)} \tag{31}$$

where $z = \frac{\mathrm{Cov}\left(\frac{l_j}{d_j}, \beta_j^d\right)}{\mathrm{Var}(\beta_j^d)}$, $\gamma^l = \mathrm{E}[\gamma_j^l]$, and $\varepsilon^l = \mathrm{E}[\varepsilon_j^l]$.

Calibration equations

$$\mathrm{E}[i_j^l - i] = \frac{1}{\varepsilon^l} + \mathrm{E}[\phi_j w_j] \tag{32}$$

$$\mathrm{E}[i - i_j^d] = \frac{1}{\varepsilon^d} - \mathrm{E}[\phi_j w_j] \tag{33}$$

$$\mathrm{E}[\beta_j^l] = \mathrm{E}[\lambda_j^{MPL}\beta_j^d] + (1 - \mathrm{E}[MPL_j])(\gamma^l - \varepsilon^l) \tag{34}$$

$$\mathrm{E}[\beta_j^d] = \mathrm{E}\left[\frac{\varepsilon^d\phi_j l_j(\gamma^l - \varepsilon^l) - (1 + \varepsilon^l\phi_j l_j)(\gamma^d - \varepsilon^d)}{1 + \varepsilon^l\phi_j l_j + \varepsilon^d\phi_j d_j}\right] \tag{35}$$

$$\mathrm{E}[l_j] = \mathrm{E}[\exp\left(-\varepsilon^l i_j^l + \gamma^l i + v^l\right)] \tag{36}$$

$$\mathrm{E}[d_j] = \mathrm{E}[\exp\left(\varepsilon^d i_j^d - \gamma^d i + v^d\right)] \tag{37}$$

$$\tilde{\lambda}^{MPL} = \lambda^{OLS} + \frac{\theta\varepsilon^d}{1 - \theta\varepsilon^d}\left(\lambda^{OLS} - \lambda^{IV}\right) = \mathrm{E}\left[\frac{\varepsilon_j^l\phi_j d_j}{1 + \varepsilon_j^l\phi_j l_j}\right] \tag{38}$$

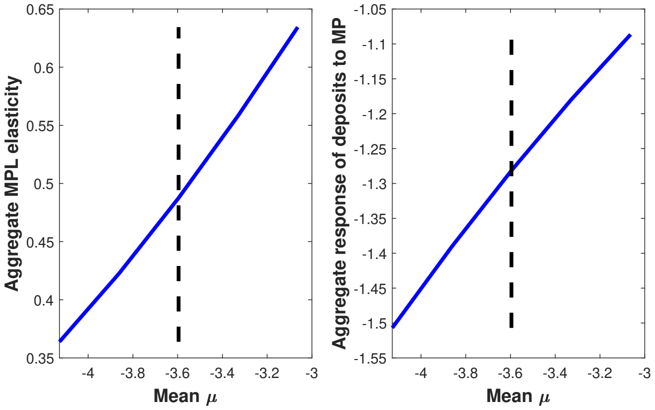
$$\mathrm{Cov}(\lambda_j^{MPL}, \beta_j^d) = \mathcal{C} = \frac{\left(\lambda^{OLS} - \tilde{\lambda}^{MPL} + z\left(\gamma^l - \varepsilon^l\right)\tilde{\lambda}^{MPL}\right)\mathrm{Var}(\beta_j^d)}{\left(\mathrm{E}[\beta_j^d] - (\gamma^l - \varepsilon^l)\mathrm{E}\left[\frac{l_j}{d_j}\right]\right)} \tag{39}$$

Data moments

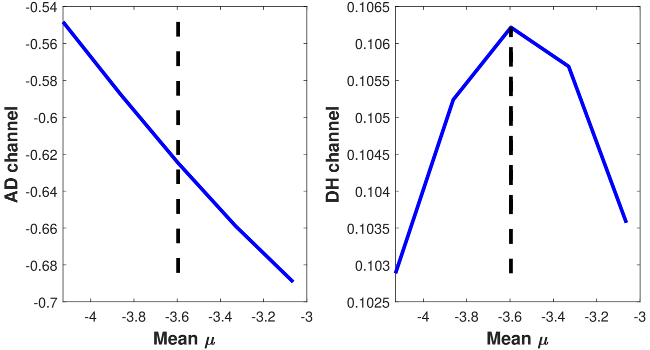
Table: Data moments

Moment	Value	Standard deviation
Mean (i^l)	0.0845	0.0088
Mean (i^d)	0.0287	0.0059
Mean (β^d)	-1.1525	4.9004
Mean (β^l)	0.7731	5.7155
Mean (l_j)	2.5810	33.7136
Mean (d_j)	2.4663	27.8293
$\tilde{\lambda}^{MPL}$	0.7237	0.0279
$\mathcal{C}$	0.7897	0.3527

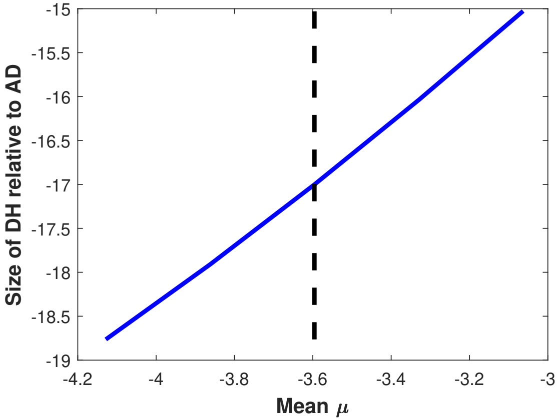
MPL and deposits



AD and DH channel



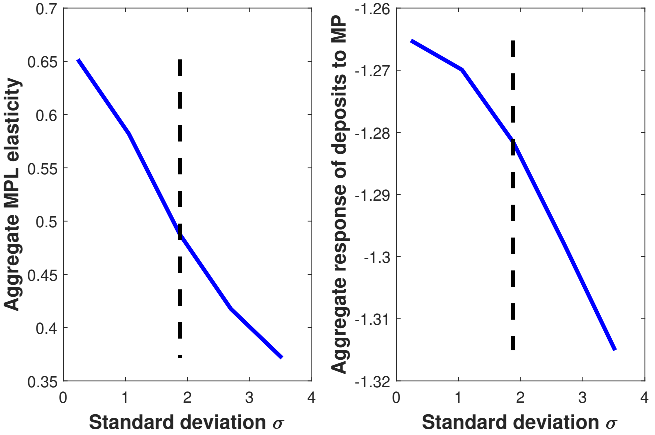
Relative size of DH channel



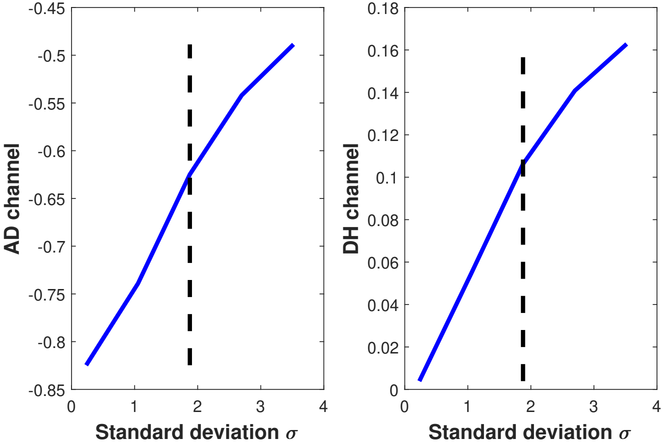
Model and data moments

Moment	Data	Model
Mean (i^l)	0.0845	0.0876
Mean (i^d)	0.0287	0.0318
Mean (β^d)	-1.1525	-1.5027
Mean (β^l)	0.7731	1.3942
Mean (l_j)	2.5810	2.5849
Mean (d_j)	2.4663	1.6902
$\tilde{\lambda}^{MPL}$	0.7237	0.7217
$\mathcal{C}$	0.7854	0.4424

MPL and deposits



AD and DH channel



Relative size of DH channel