Southampton
Management School

UNIVERSITY OF Southampton

Modelling the Collections Policy

Christophe Mues   Mee Chi So   Lyn Thomas
University of Southampton

Adiel T. De Almeida Filho
Federal University of Pernambuco

Debt Collections

- A multi-billion dollar industry:
  - £12 billion of loans to corporate and individuals were being written off by UK financial institutions in 2012 (Bank of England, 2013)
- Actions: formal letters, persistent phone calls, legal procedures, etc. (Coleman, 2004)
- No return on actions: ordered in terms of their perceived harshness
- Many problem aspects to consider: How long? In what sequence? Who should be contacted first?

Outline of the Talk

- Current practice and related literature
- Dynamic programming model
- Numeric example; results
- Conclusions and possible extensions

Current Practice & Related Literature

- Using **collection scorecards** (e.g. Experian, 2006)
- Score could reflect how likely is a defaulter to pay back a "satisfactory" percentage of the defaulted debt
- Segment the defaulted population based (in part) on score band they are in
- Different actions for different segments
- Choice of strategy may be based on expert judgement, experimentation, mathematical optimisation (e.g. also taking into account resource constraints)
- Little if any work reported in the academic literature though

Related Literature: LGD

- Growing number of papers on estimating **Loss-Given-Default** (**LGD**) or **Recovery Rate** (**RR**)
- Only a few of them look at the interaction between policy and LGD, e.g.:
  - Matuszyk et al. (2010): when and whether to recover "in house" for consumer loan
  - De Almeida Filho et al. (2010): at portfolio level
  - Weber (2012): self-exciting point process
    - Probability of paying back some percentage of balance
    - Stochastic intensity of repayment arrival times allowed to depend on actions of the lender
  - Han and Jang (2013): corporate credit and whether the lender's actions can impact LGD

Bayesian Dynamic Programming

- In this paper, we present current work on using **Bayesian dynamic programming** to optimise the collections strategy at the individual loan level
- Approach introduced to credit granting models by Bierman and Hausman (1970)
- Uncertainty about a parameter value (here: repayment probability, assumed to be a Bernoulli random variable) is described by a Beta distribution
  - Allows us to work at the individual defaulter level and take into account previous payment performance of that defaulter; i.e., the collector's belief about the repayment probability is updated at the end of each time period (e.g. calendar month)

Proposed Collections Model and Notation

- Performance history (by defaulter)
  - i: the current action
  - s: no. of periods under action i
  - m: no. of repayments under action i
  - r: the RR when the collector started using action i
- $V(r, s, m, i)$: the future net discounted RR
- At the beginning of each time period, two possible decisions for the lender:
  - Stay in action i
  - Move to action $i + 1$
- How to choose the optimal decision (i.e. the one that maximises the resulting RR)?

Move to Action $i + 1$

- $V(r, s, m, i) \rightarrow V(., 0,0, i + 1)$
- Define
  - $f_i(m)$ to be the RR of the m^{th} repayment under action i
    (i.e., pct. of debt outstanding at start of using action i that is repaid in the m^{th} actual repayment under action i)
  - $F_i(m) = \sum_{j=1}^{m} f_i(m)$ to be the cumulative RR in the m^{th} repayment under action i
- Therefore, if the lender moves to action i +1, the future net discounted RR will be:

$$V(r + (1 - r)F_i(m), 0,0, i + 1)$$

Stay in Action i

- What is the expected recovery rate from this point onward?
  - $Repayment$: $(1-r)f_i(m+1) + \ \beta V(r, s+1, m+1, i)$
  - $No\ repayment$: $0 + \beta V(r, s+1, m, i)$
- Repayment probability $B(s, m)$; expected value: m/s
- For action i, introduce prior of the repayment probability $B(s_0^i, m_0^i)$
- Hence, if the lender keeps in action i, the future net discounted RR will be:

$$\frac{(m+m_0^i)}{(s+s_0^i)} Repayment + \left(1 - \frac{(m+m_0^i)}{(s+s_0^i)}\right) No\ repayment\ - c_i$$

The Model and Some Optimality Results

- Therefore, the Bayesian dynamic program model is:

$$V(r,s,m,i)=\max\begin{cases}\frac{(m+m_0^i)}{(s+s_0^i)}\left[(1-r)f_i(m+1)+\beta V(r,s+1,m+1,i)\right]+\left(1-\frac{(m+m_0^i)}{(s+s_0^i)}\right)[0+\beta V(r,s+1,m,i)]-c_i & (1)\\ V(r+(1-r)F_i(m),0,0,i+1) & (2)\end{cases}$$

$$P(r,s,m,i)=\begin{cases}1,\text{if (1) is chosen}\\ 2,\text{otherwise}\end{cases}$$

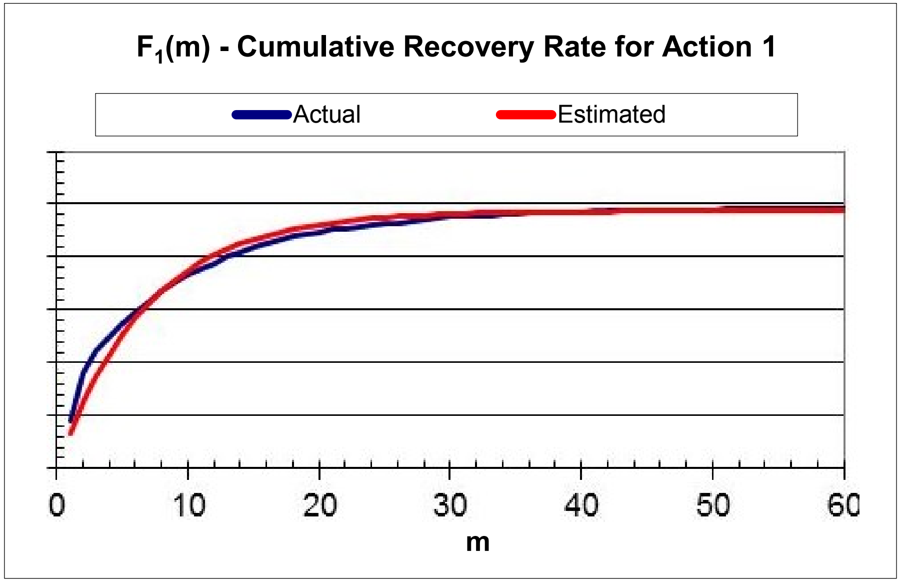
- Solving the model with value iteration (Puterman, 2005)
- Some optimality results:
  - One keeps on with action i if $s < s^*(r,m,i)$; One moves to action *i+1* if $s \geq s^*(r,m,i)$.
  - If RR is a constant under action i, i.e. $f_i(m) = f_i$, then $s^*(r,m,i) \leq s^*(r,m+1,i)$

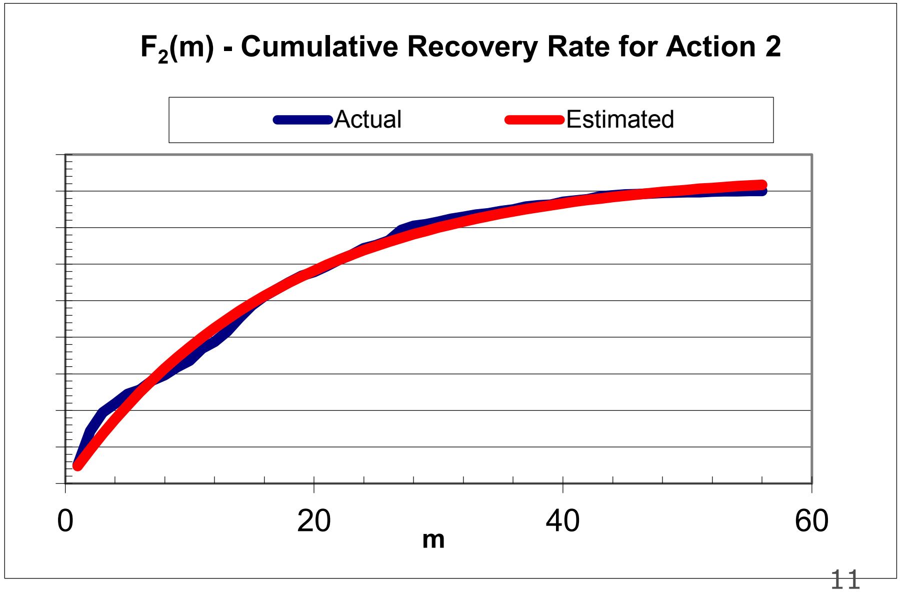
A Numeric Example

- Collection data from a European bank
- 3,000+ defaulted consumer unsecured loans
- Using data, exponential function fits well with $f_i(m)$

  Therefore, we define:

$$f_i(m) = a_i e^{-b_i m}. \text{ Hence } F_i(m) = \sum_{j=1}^{j=m} f_i(j) = \frac{a_i(1-e^{-b_i m})}{(1-e^{-b_i})}$$



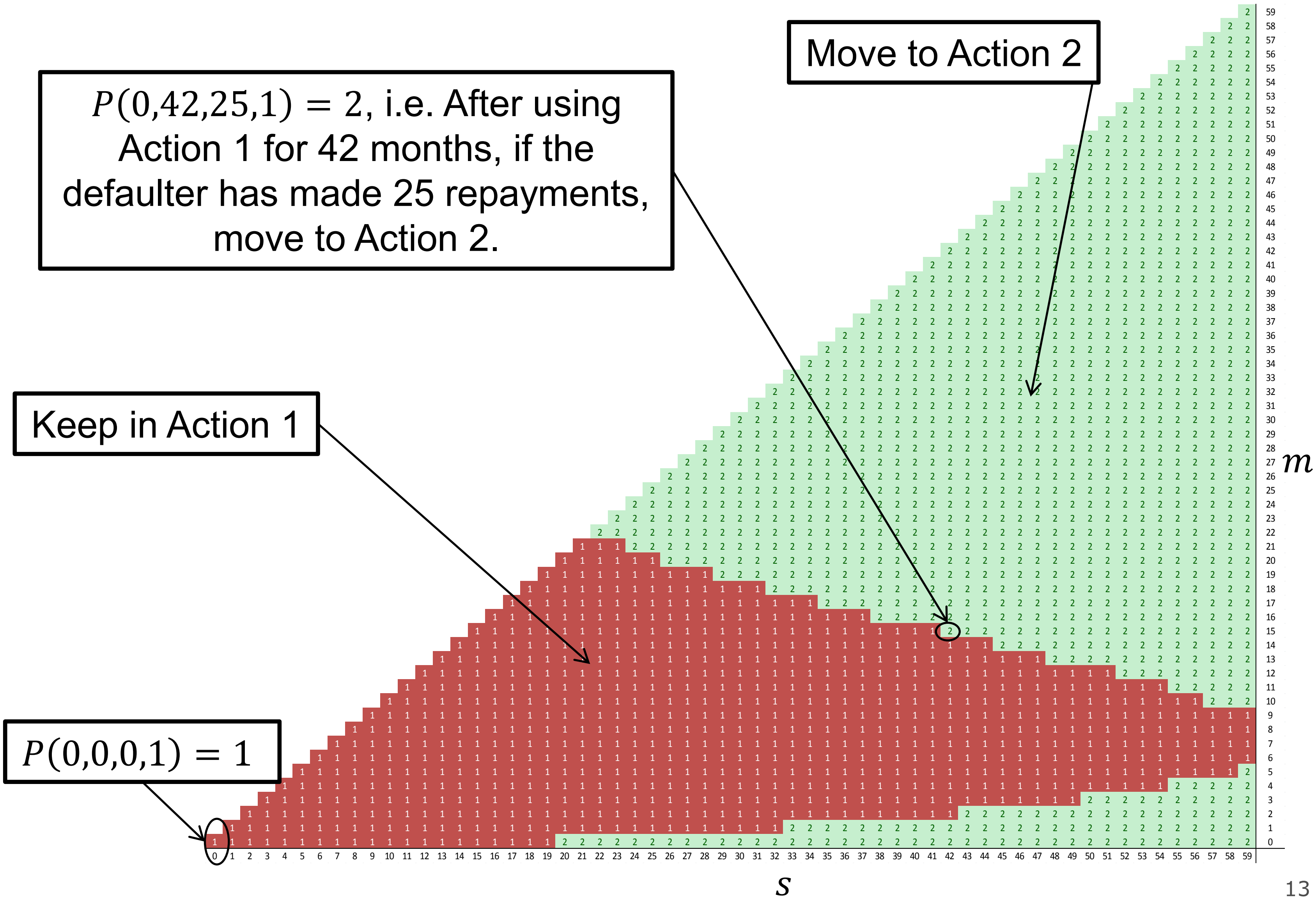


A Numeric Example: Parameters

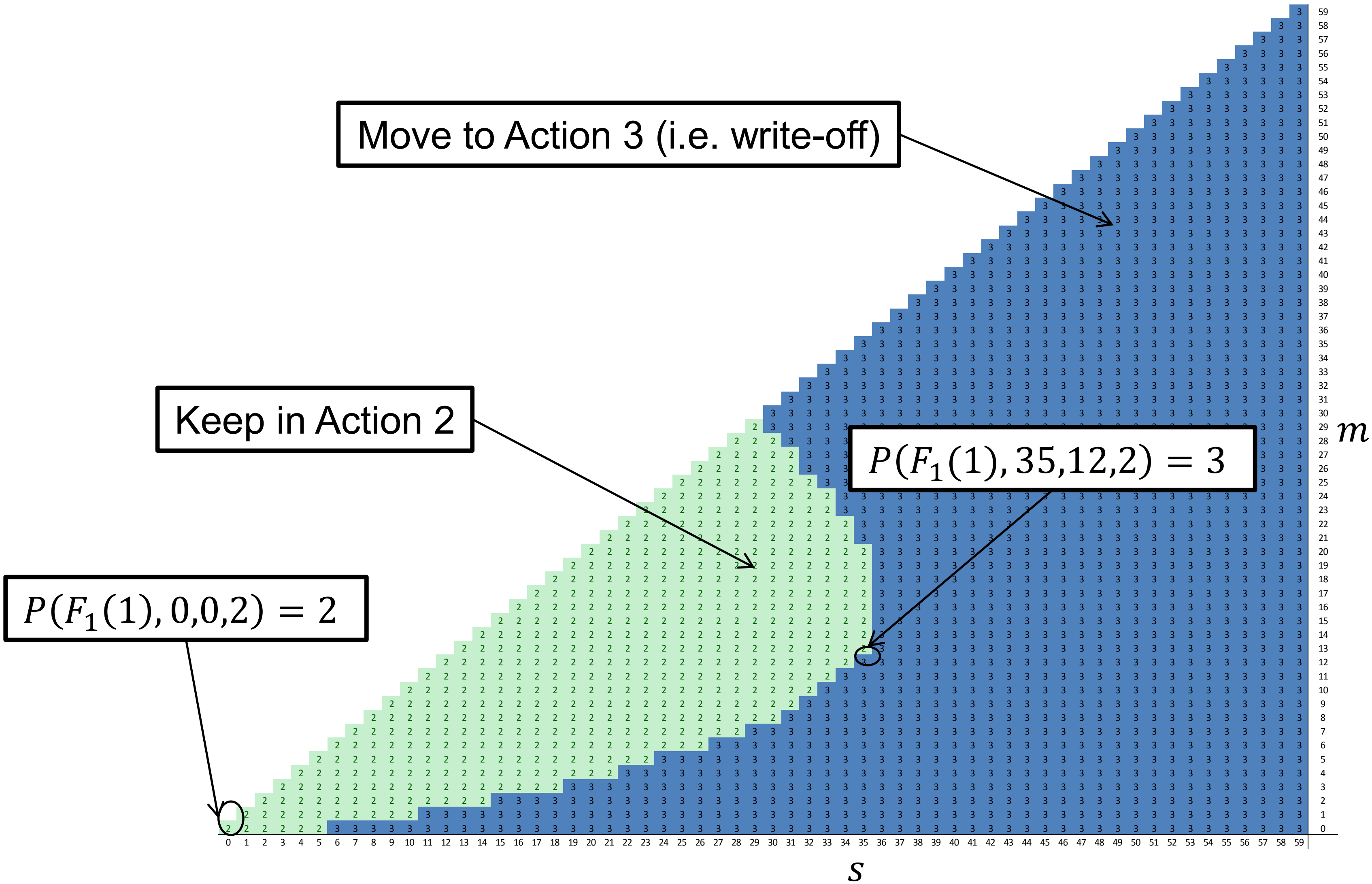
Actions	a_i	b_i	Monthly Cost (c_i)	s_0^i	m_0^i
1 – General communication	0.035721	0.1470	0.00048656	2	1
2 – Legal procedure	0.024522	0.0577	0.00398703	2	1
3 – Write-off (The boundary condition)	-	-	0	-	-

- Solving the model with value iteration
- Maximum $m = 60$ (5 years)
- Find the optimal policy for different (r, s, m, i)

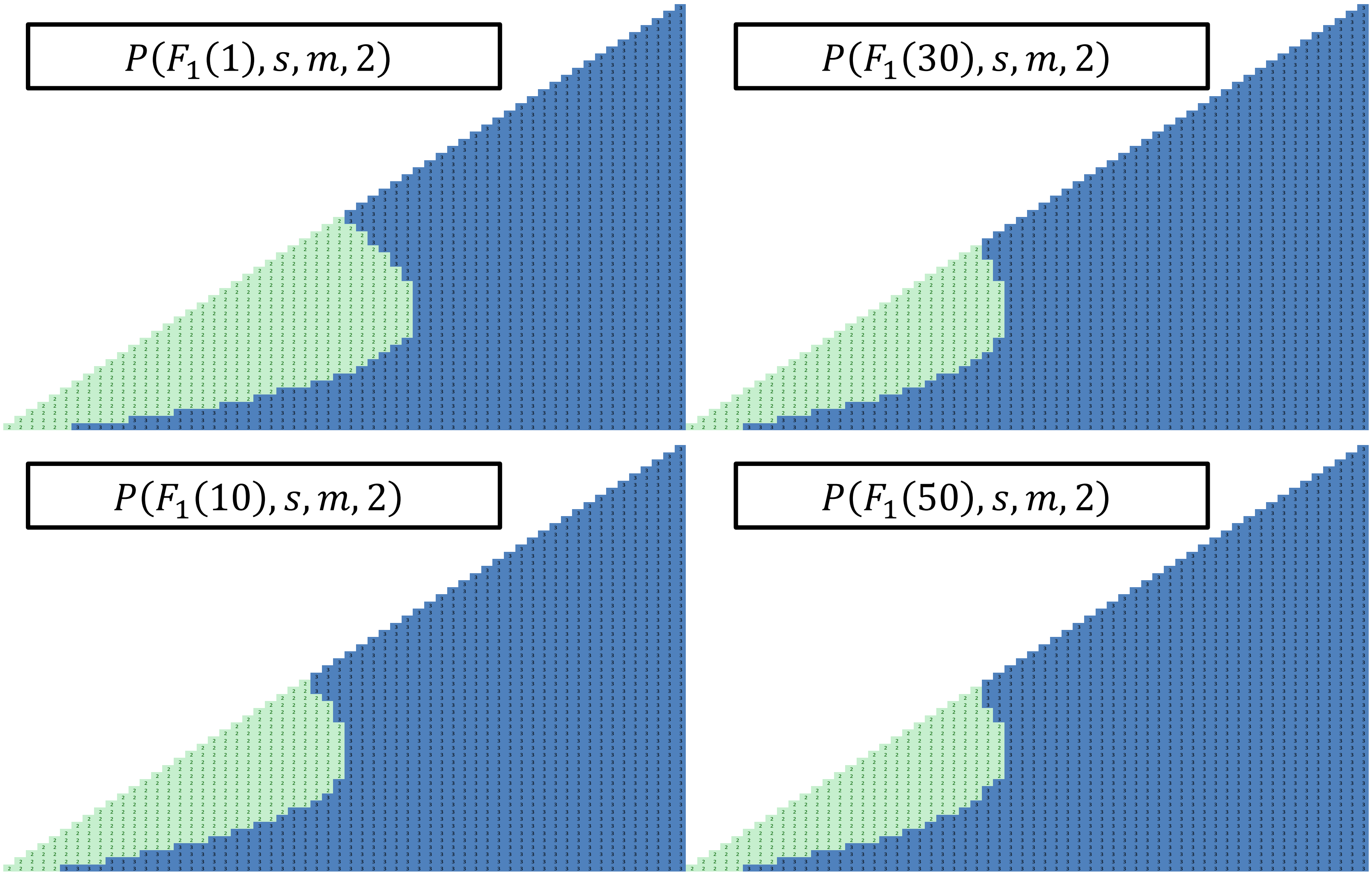
Optimal Policies for $(0, s, m, 1)$



Optimal Policies for $(F_1(1), s, m, 2)$



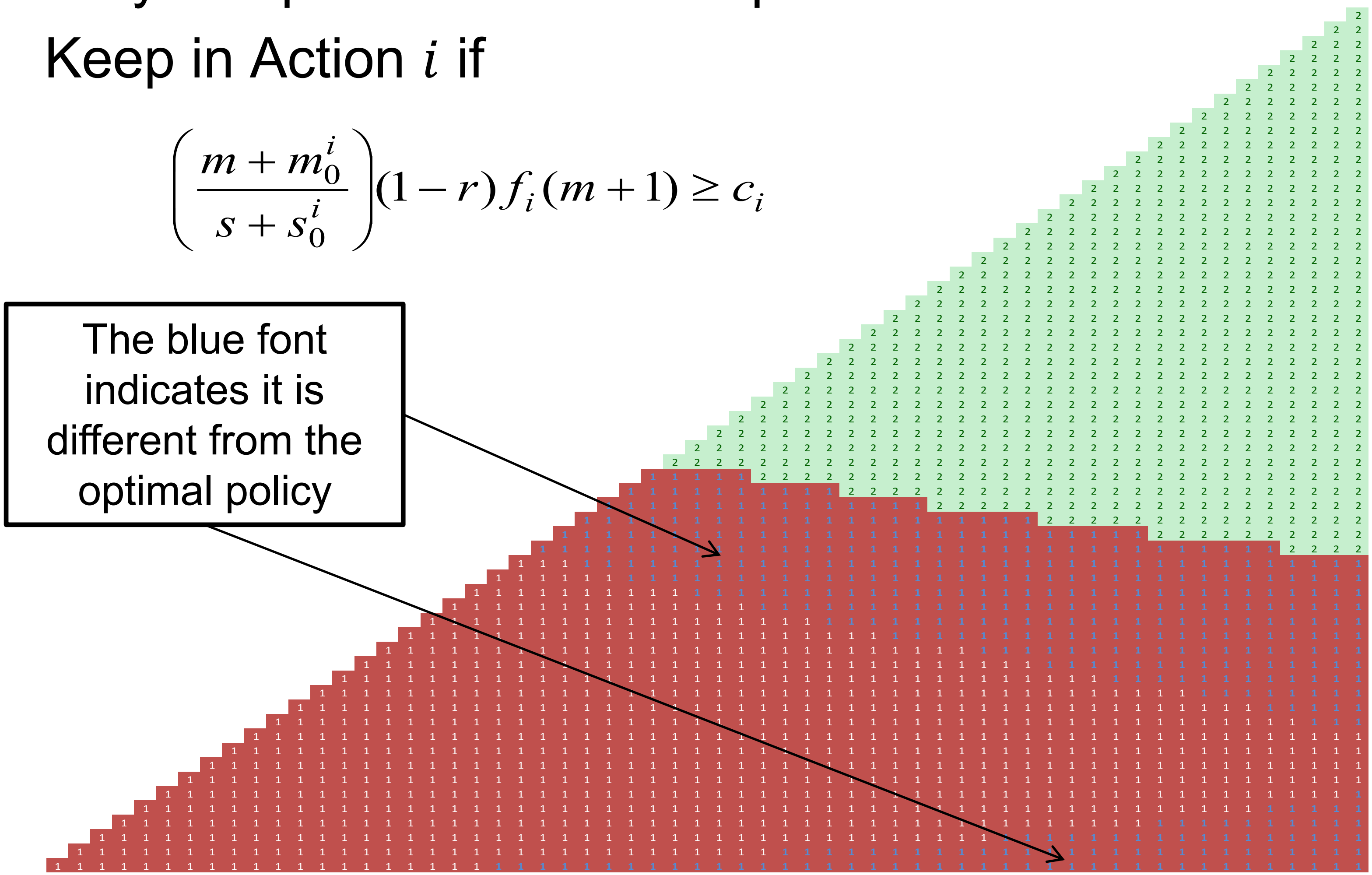
Optimal Policies for $(F_1\,(.), s, m, 2)$



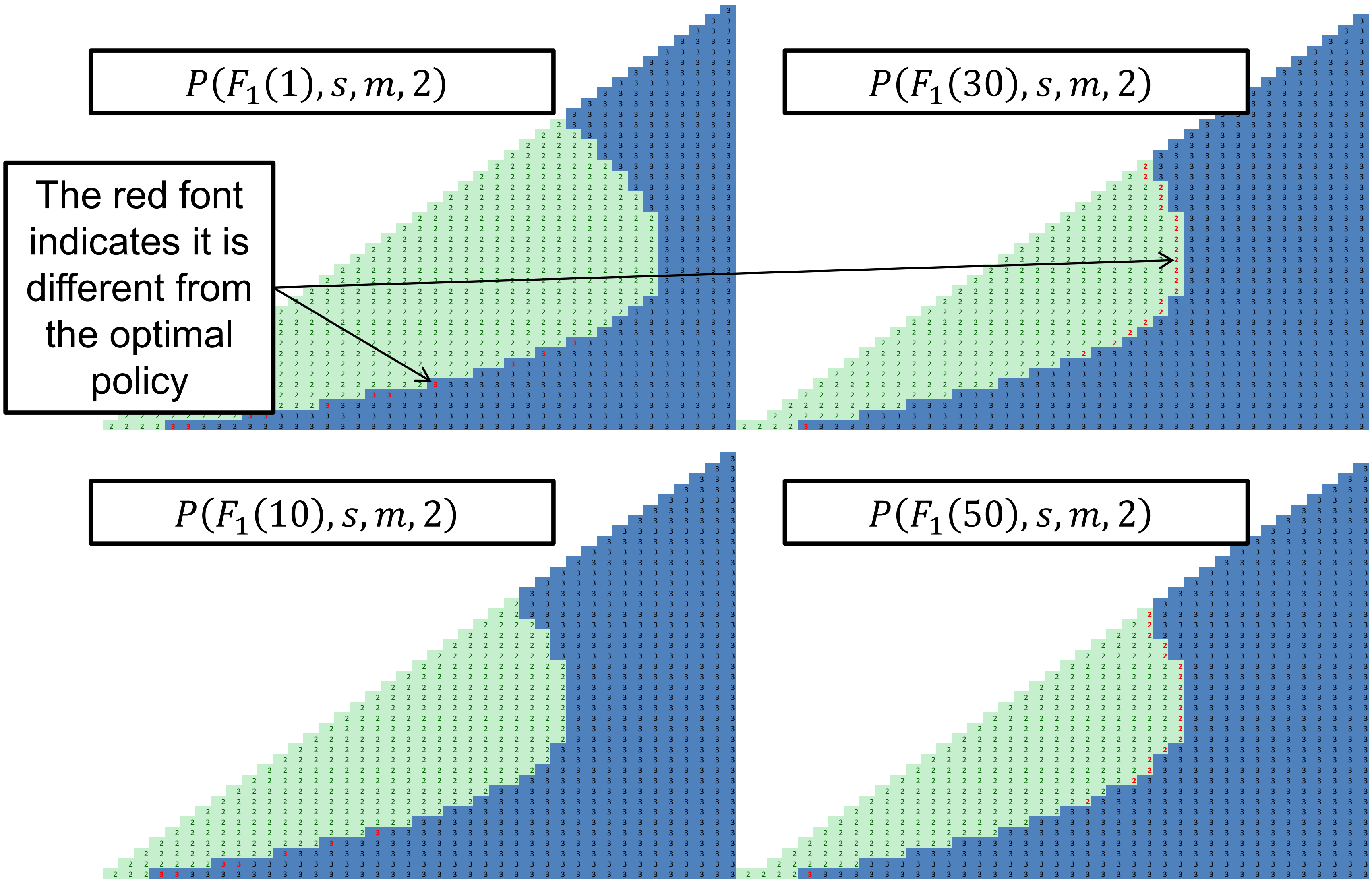
Myopic Policies for $(0, s, m, 1)$

- Only compare the current expected RR vs. the cost
- Keep in Action i if

$$\left(\frac{m+m_0^i}{s+s_0^i}\right)(1-r)f_i(m+1)\ge c_i$$

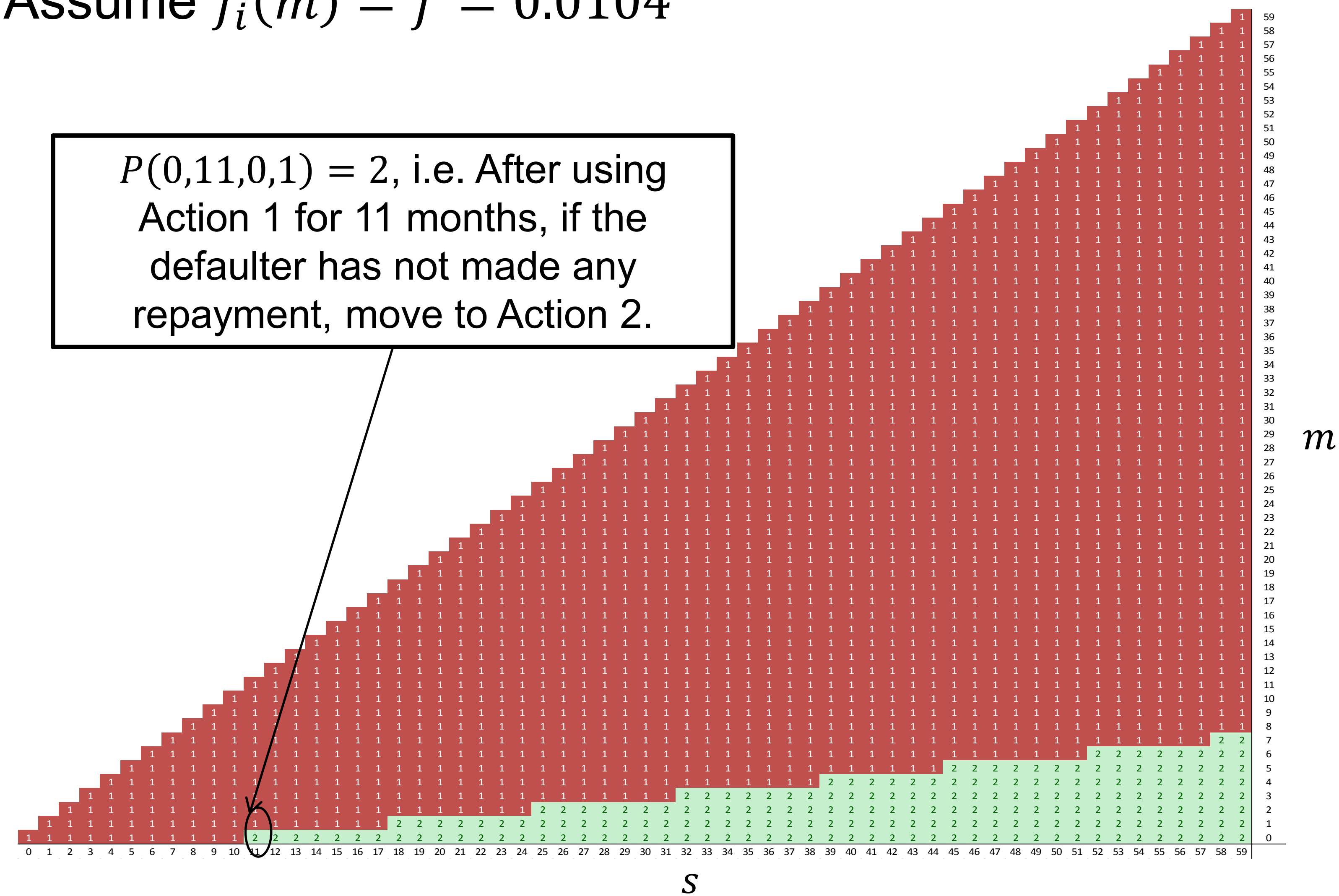


Myopic Policies for $(F_1(.), s, m, 2)$

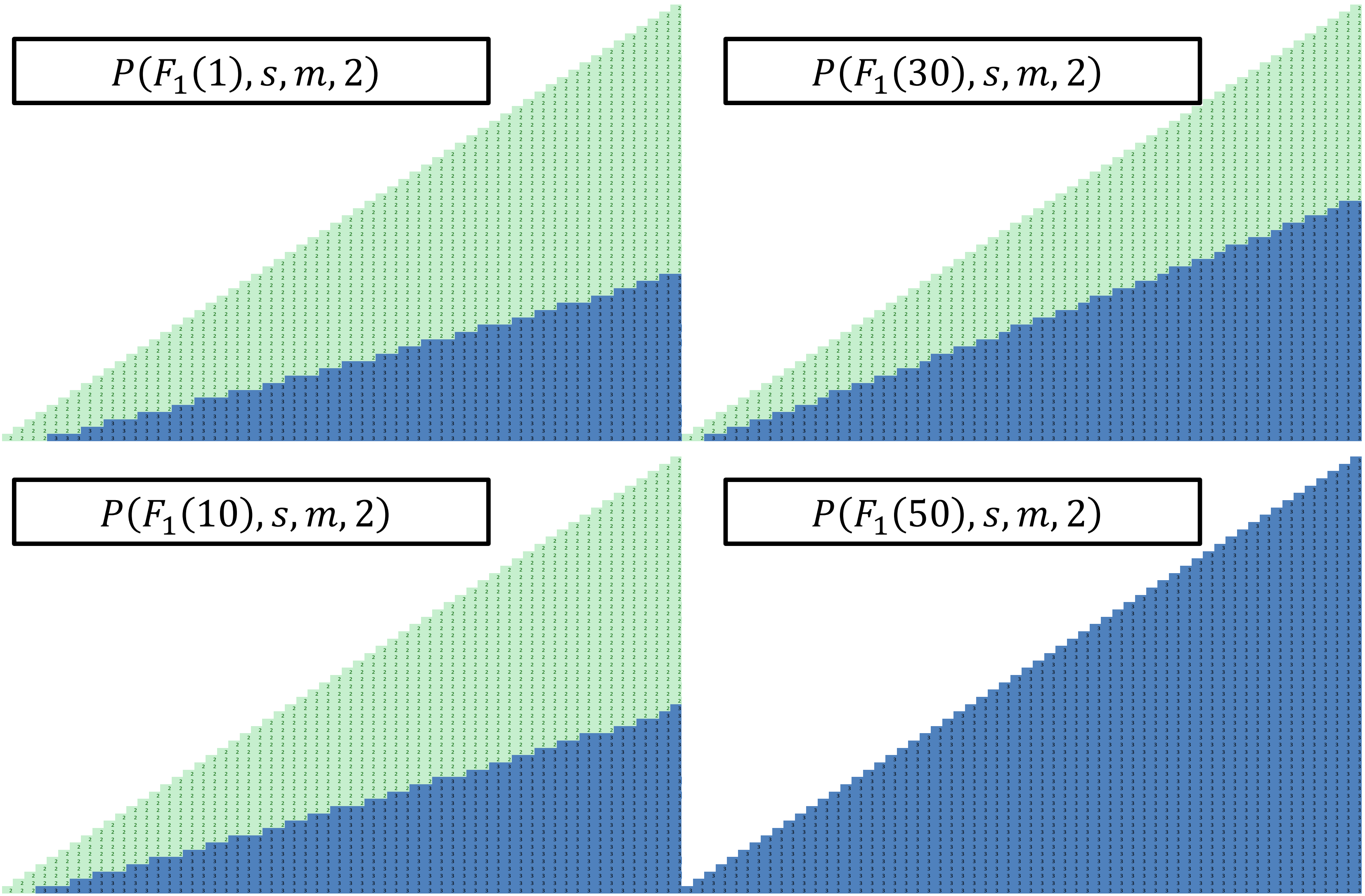


A Fixed Repayment Amount for $(0, s, m, 1)$

- Assume $f_i(m) = f = 0.0104$



A Fixed Repayment Amount for $(F_1\ (.), s, m, 2)$



Conclusions & Possible Extensions

- We argued the case for developing policies that:
  - Are based on performance of individual customer
  - Reassess course of action at end of each time period
  - Take into account there is usually a sequence of actions to consider and one needs to “look ahead”
- Flexible approach: possible extensions
  - Could include a fixed cost for starting a new action
  - The RR can be made a function of s as well: $F(m, s)$
  - Prior could use any available loan- or debtor-specific information (thus extending the idea of a collection score) or even a function of the economic conditions (estimate recovery rate or LGD in downturn conditions)

List of References

- Coleman, A. M. 2004. *Collection Management Handbook*, John Wiley, Hoboken.
- De Almeida Filho, A. T., C. Mues, L. C. Thomas. 2010. Optimizing the Collections Process in Consumer Credit. *Production and Operations Management*. 19 698-708.
- Experian. 2006. The value of implementing scoring in the collection process. *Experian White Paper*, Almondsbury Bristol.
- Han, C., Y. Jang. 2013. Effects of debt collection practices on loss given default. *Journal of Banking and Finance*. 37 21-31.
- Matuszyk, A., C. Mues, L. C. Thomas. 2010. Modelling LGD for unsecured personal loans: decision tree approach. *Journal of Operational Research Society*. 61 393-398.
- Weber, T. 2012. Dynamic valuation of delinquent credit card accounts, EPFL-CDM-MTEI, *Ecole Polytechnique Federale de Lausanne*

Thank you

We welcome any comments or suggestions.