Screening and Self-Selection in Moving Pictures

Evidence from Brazilian Public Funding

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Introduction

- Brazilian federal public funding for audiovisual is substantial, $\approx$ \$200M USD in 2022
  - French movie subsidies were \$761M in 2022
  - US NEA budget was \$162M in 2020[1]
- Different public funding **sources**: some is **direct funding**; some **indirectly** via tax breaks.
- For each source, funding decision-makers are different.
- Significant **heterogeneity** in the performance of box-office revenues per funding source.

[1] In 2020, public funding for Arts and Culture at all levels was \$1.47 billion in the US and \$1.52 billion in Brazil.

Motivation & Research Question

- **Research question**: What drives the differences in box-office performance across funding sources?
- We see three main (non-rival) explanations:
  - Self-selection;
  - Screening;
  - Different goals.
- Goal: quantify the relative role of each.
- Model deals with relative role of **first** and **second** explanations.
- This presentation, set aside the **third** explanation.

Relevance

Why is this project of interest more broadly?

- General problem of two-sided matching under (high) uncertainty
- Many other settings with similar structure:
  - Venture capital [Sørensen, 2007];
  - R&D funding [Bergemann and Hege, 2005];
  - Publishing industry.
- Our setting: detailed data and relatively rigid structure
  - Allows us to isolate the effects of signal quality
- Resurgent interest in industrial policy
- Furthermore, public funding for audiovisual is widespread
  - In US, Section 181 of Tax Code, state incentives;
  - In 2009, Europe had 280 audiovisual public funding bodies [Newman-Baudais, 2011]

Contribution to the Literature

- **Role of information and uncertainty in two-sided matching**: Kaplan and Schoar [2005], Sørensen [2007], Lerner [1999]
  - Relative role of private information from applicants and DMs to explain performance
- **Industrial policy**: Juhász et al. [2023], Pack [2006], Becker [2015], Lerner [2002]
  - Policy recommendations change substantially depending on who possesses information
- **Effects of movie subsidies**: Thom [2017], Mastellone [2021], Tannenwald [2010]
  - Consider how to best allocate money, conditional on some level of funding

Regulatory Framework

- Brazilian public funding is divided into two main categories:
  - **Direct funding (DF)**: mainly FSA, 70% of total funding
  - **Indirect funding (IF)**: tax breaks, investment is fully deducted from federal tax bill
- Types of funding are **heterogeneous**:
  - **Revenue sharing** differs
  - Investment **caps** per project vary
  - **Speed**
- Most importantly, who picks projects:
  - **DF**: government officials
  - **Specialized IF**: firms in the audiovisual business
  - **General IF**: any firm or individual

Data

- Main data sources, from ANCINE:
  1. Dataset of all commercial film releases in Brazil, from 1995 to 2022.
  2. Administrative datasets of application information for public funding.
  3. Plus, auxiliary datasets with covariates on firms involved.

Descriptive Statistics: Brazilian Film Releases Between 1995-2022

- **Market Overview:**
  - 2,269 movies released; 1,458 unique directors, 418 distributors, 1,284 producers
  - 72% of movies received public funding
  - Genre split: 63% fiction, 35% documentary, 2% animation
- **Market Concentration:**
  - Low concentration on pooled sample: HHI for directors (0.001), distributors (0.021), producers (0.0021)
  - Yearly concentration measures are low as well
- **Performance Trends:**
  - Publicly funded projects generally outperform non-funded ones in sample
  - Privately funded movies are usually very small and/or documentaries
- **Regional Dynamics:** Production concentrated in RJ (64%) and SP (42%), followed by RS, PE, MG

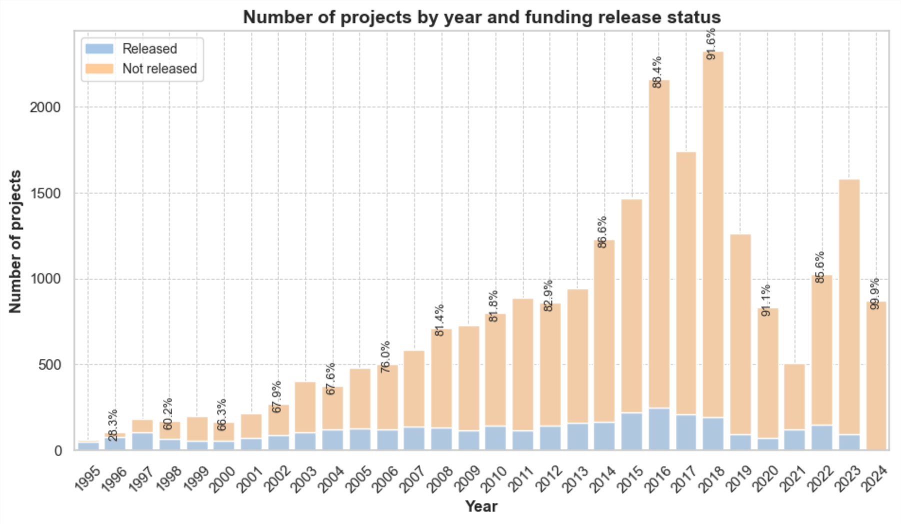
Descriptive Statistics: Public Funding

- Publicly funded released movies, 60% raised funds from at least 2 different sources
- Median movie has raised money from 2 different types of public funds (75th pct has three)
- Median HHI of funding composition is 7000 (0.7)

Number of Sources	Proportion
1	0.40
2	0.27
3	0.19
4	0.10
5	0.03
6	0.01

Table 1: Distribution of Movies by Number of Different Funding Sources Projects per Funding Category

Descriptive Statistics: How Many Projects Get Done?



Spending and Revenue by Type of Funding

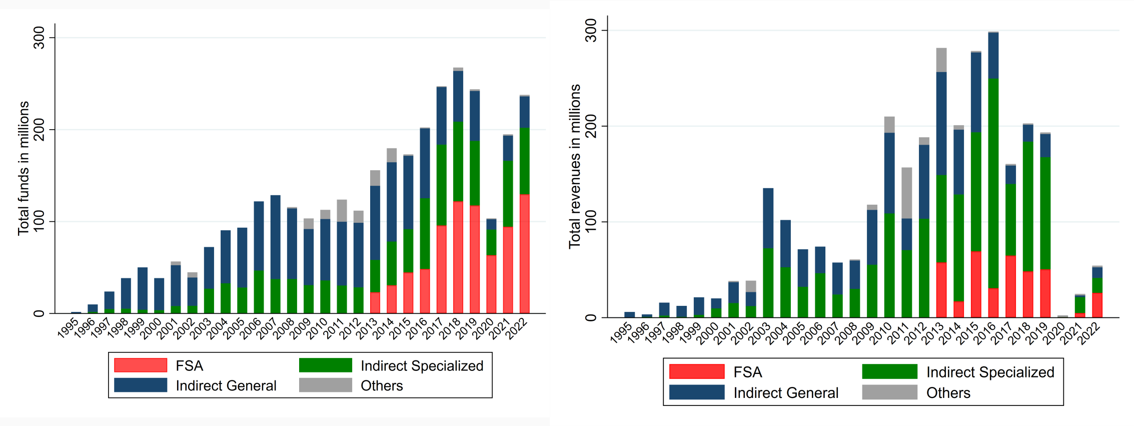


Figure 1: Total Spending and Revenue. Revenues are apportioned for each movie in proportion to the fraction of that type of funding in the total budget.

Correlation Between Sources of Funds and Revenues

Table 2: Revenue: Movies (1995 to 2022)

Dep. Variable:	Revenue			
Direct	-0.234	-0.156	-0.689*	-0.627
	(0.269)	(0.268)	(0.394)	(0.384)
Indirect specialized	2.309***	2.404***	1.590***	1.725***
	(0.321)	(0.318)	(0.493)	(0.478)
Indirect general	0.041	0.151	-0.091	0.030
	(0.205)	(0.222)	(0.245)	(0.262)
Others	1.638**	1.740**	0.854	0.962
	(0.809)	(0.809)	(0.722)	(0.713)
Year FE	Yes	Yes	Yes	Yes
Genre FE	Yes	Yes	Yes	Yes
Dist FE	No	No	Yes	Yes
Approved/raised	No	Yes	No	Yes
Observations	2242	2242	2242	2242
R-squared	0.13	0.13	0.29	0.29

Distribution of Intended Budget by Type of Funding

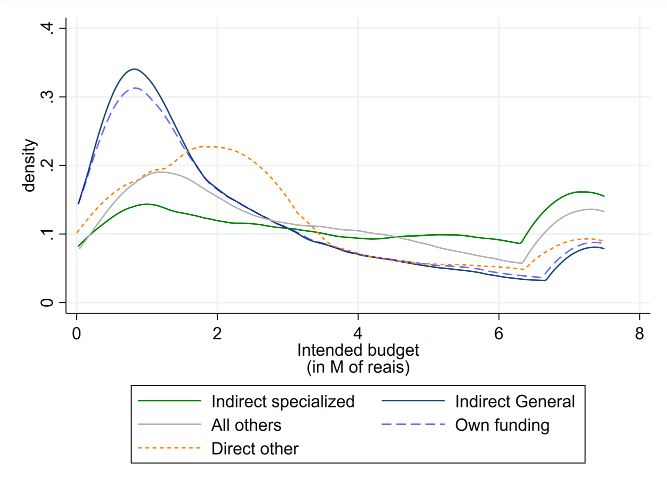


Figure 2: Intended budget KDE by category of funding capped at 7.5M BRL, excluding FSA

Modelling the Problem

- Movie projects set a total budget (exogenously)
- Two-step problem:
  1. Applicants first choose to apply to types of funding, choosing how much to request from each source
  2. Each funding source sees a pool of applicants/requests and picks projects
- Both applicants and funders get a noisy signal of movie type.
- Funders choose projects to maximize profits up to available funds, given applicant pool.
- Applicants maximize residual revenue streams, conditional on being funded.

Funding Model Setup

- Source j: total budget B_j, revenue share $r_j \in [0,1]$
- Applicant i has total budget b_i
- Private signal per movie $s_{ij} = m_i + \sigma_j \varepsilon_{ij}$, i.i.d. noise
- Budget request: δ_{ij}, actual funding: $d_{ij} \le \delta_{ij}$
- *Ex-post* profits:

$$\pi(m_i, d_{ij}) = \left(\frac{d_{ij}}{b_i}\right) r_j m_i$$

- Expected profit given signal s_{ij}, b_i and choice set $\mathcal{I}_i$: CEF derivation

$$\begin{aligned} E[\pi(m_i, d_{ij}) | s_{ij}, b_i, \mathcal{I}_i] &= \left(\frac{d_{ij}}{b_i}\right) r_j E(m_i | s_{ij}, b_i, \mathcal{I}_i) \\ &= \left(\frac{d_{ij}}{b_i}\right) r_j g_i(s_{ij}) \end{aligned}$$

Funders' Problem

$$\Pi_j(\boldsymbol{s}_j) = \max_{d_{1j},\dots,d_{w_j j}} \sum_{i \in w_j} E[\pi(m_i, d_{ij}) | s_{ij}, b_i, \mathcal{I}_i]$$

$$\text{s.t.} \sum_{i \in w_j} d_{ij} \leq B_j$$

$$d_{ij} \leq \delta_{ij}, \; \forall i$$

- Optimal strategy: Rank projects by CEF/budget $a_{ij} = \frac{g_i(s_{ij})}{b_i}$.
- Fund projects up to I-th project where $\sum_{i=1}^{I} \delta_{ij} = B_j$ (possibly fractional funding for last)
- Defines cut-off $a_j^* = a_{Ij}$ for last funded project I

Probability of Funding

Ex-ante probability of j funding project i is:

$$\begin{aligned} P(a_{ij} \geq a_j^* \mid m_i, b_i, \mathcal{I}_i) &= P(g_i(m_i + \sigma_j \varepsilon_{ij}) \geq b_i a_j^* \mid m_i, b_i, \mathcal{I}_i) \\ &= 1 - P(g_i(m_i + \sigma_j \varepsilon_{ij}) \leq b_i a_j^* \mid m_i, b_i, \mathcal{I}_i) \\ &\equiv 1 - q_{ij}(\sigma_j; a_j^*) \end{aligned}$$

Funder’s Likelihood

- We define a joint likelihood for the funding portfolio of source j:

$$\mathcal{L}(\sigma_j; a_j^*, I) = \prod_{i=1}^{I} \left[1 - q_{ij}(\sigma_j; a_j^*)\right] \prod_{i=I+1}^{w_j} \left[q_{ij}(\sigma_j; a_j^*)\right]$$

- Fit σ_j to maximize likelihood

Application Model Setup

- Project i observes private signal $s_i \equiv m_i + \sigma_i \varepsilon_i$, i.i.d. noise.
- Each source $j \in \mathcal{J}$ has a threshold of funding a_j^*, requires a share of revenues $r_j \in [0, 1]$
- Let $\gamma_j = 1 - \alpha_j$, be the residual applicant claims
- Project chooses source subset $J_i \in \mathcal{P}(\mathcal{J})$, and requests δ_{ij}, $\forall j \in J_i$
- Objective is to maximize residual stream of revenues conditional on being able to secure funding

Probability of Being Funded

For applicant i, given her private signal, the probability of getting funds from j is:

$$\begin{aligned} P(a_{ij} \geq a_j^* \mid s_i, b_i) &= P\left(g_i(s_{ij}) \geq b_j a_j^* \mid s_i, b_i\right) \\ &= P\left(g_i(s_i - \sigma_i + \sigma_j \varepsilon_{ij}) \geq b_j a_j^* \mid s_i, b_i\right) \\ &\equiv p_{ij}(\sigma_i, \sigma_{ij}; a_j^*) \end{aligned}$$

Gross Profits

- Applicants do not repay the funding they receive, just share revenues.
- Expected profits are:

$$
\begin{aligned}
E[\pi_i(J_i, \boldsymbol{\delta}_i) \,|\, s_i, b_i) &= \left(\prod_{j \in J_i} p_{ij}(\sigma_i, \sigma_{ij}; a_j^*)\right)\left(\frac{1}{b_i}\sum_{j \in J_i} \delta_{ij}\gamma_j\right) E(m_i | s_i, b_i) - \sum_{j \in J_i} f_j^K(\delta_{ij}) + \epsilon_i(J_i) \\
&= V_{ij}(J_i; \boldsymbol{\beta}_i) + \epsilon_i(J_i)
\end{aligned}
$$

- Applicants have idiosyncratic preferences for bundles $\epsilon_i(J_i)$, and a cost when increasing bids $f_j^K(.)$, a K-th order polynomial with random coefficients
- CEF can also be written as function of known objects CEF derivation

Applicant's Problem

- Objective is:

$$\Pi_i(s_i, \epsilon_i; \boldsymbol{\beta}_{ik}) = \max_{J_i \in \mathcal{P}(J); \{\delta_{ij}\}_{j \in J_i}} E[\pi_i(J_i, \boldsymbol{\delta}_i) \mid s_i, b_i]$$
$$\text{s.t.} \sum_{j \in J_i} \delta_{ij} = b_i$$

- FOCs set optimal $\boldsymbol{\delta}_i^*$ vector as a function of random coefficients and choice set J_i.

Applicant's Likelihood

- If shocks $\epsilon(J_i)$ are EVT1, then:

$$P(J_i, \boldsymbol{\delta}_i) = \int_{\boldsymbol{\beta}_i} \frac{e^{V_{ij}(J_i;\boldsymbol{\beta}_i)}}{\sum_{J_i' \in \mathcal{P}(J)} e^{V_{ij}(J_i';\boldsymbol{\beta}_i)}} \mathbb{I}\{\delta_i^*(J_i, \boldsymbol{\beta}_i) = \boldsymbol{\delta}_i\} dF(\boldsymbol{\beta}_i)$$

  Where $F(\boldsymbol{\beta}_i)$ is the CDF of the random coefficients. The probability depends on the model parameters as well, which we omitted for readability.

Joint Likelihood

- If we have $i \in \mathcal{I}$ projects and $j \in \mathcal{J}$ sources, the joint likelihood is:

$$\mathcal{L}(\boldsymbol{\delta}, \boldsymbol{J}; \boldsymbol{\sigma}, \boldsymbol{a}^*, \beta) = \prod_{i \in \mathcal{I}} P(J_i, \boldsymbol{\delta}_i) \prod_{j \in \mathcal{J}} \mathcal{L}(\sigma_j; a_j^*, I)$$

- Parameters to fit are:
  1. Signal variances σ_i, σ_j;
  2. Threshold (nuisance) parameters a_j^*;
  3. Random coefficient parameters (mean, variance)

Equilibrium

Given parameters $\boldsymbol{\sigma}_i, \boldsymbol{\sigma}_j, \boldsymbol{\alpha}_j, \boldsymbol{b}, \boldsymbol{B}, N$ and realizations of $s_i, s_{ij}, \beta_{ik}, \epsilon_i$ for all $i \in \mathcal{I}$, $j \in \mathcal{J}$:

1. Each project i chooses a subset J_i^* and bids δ_{ij}^* to maximize profits, given source thresholds $\boldsymbol{a}^*$.
2. Funders j select a subset of applicants to maximize objectives given their budgets B_j, resulting in funding decisions d_{ij}^* above a threshold t_j^*.
3. The expected thresholds $t_j^* = a_j^*$, i.e., the expected applicant decisions match the endogenous funder thresholds.

That is, applicants correctly anticipate the thresholds a^*. Parties have no incentive to change after all private information is obtained, but *before* uncertainty fully resolves.

Next Steps

- Missing data: types are not observed for most projects as they never get done (Heckman selecion model, IPW).
- Changes to the model:
  - Funders should consider probabilities peers fund the project.
  - Dynamics?
- First pass at estimation
- Think about simulation issues
- Disentangle $\neq$ optimization from bad optimization

Thank You!

Questions?

Policy Objectives

- What is gov't funding optimizing for?
- Exhibit 1: Call for Proposals BRDE/FSA – Film Production: Artistic Performance 2024

  1.2. OBJECTIVE To invest in the production of Brazilian audiovisual works [...] with artistic potential and contributing to the internationalization of Brazilian films [...].

- Exhibit 2: Call for Proposals BRDE/FSA – Film Production: Commercial Performance 2022

  To invest in audiovisual works in order to contribute to the expansion of Brazilian films' participation in the theatrical exhibition market and to strengthen Brazilian companies in the sector.

- For indirect funding, objectives are less clear.

Bad Optimizers vs. Else Optimizers

- Can we tell apart funders optimizing for box-office performance vs. something else?
- Box-office optimizers' performance should track at least how predictable performance is from public info.
- If predictability of project pool varies over time, then so should performance of box-office optimizers.
- Agents optimizing for something else should not have a performance that co-moves with predictability of project pool.
- We could test this in the data

Descriptive Statistics: Projects per Category of Funding

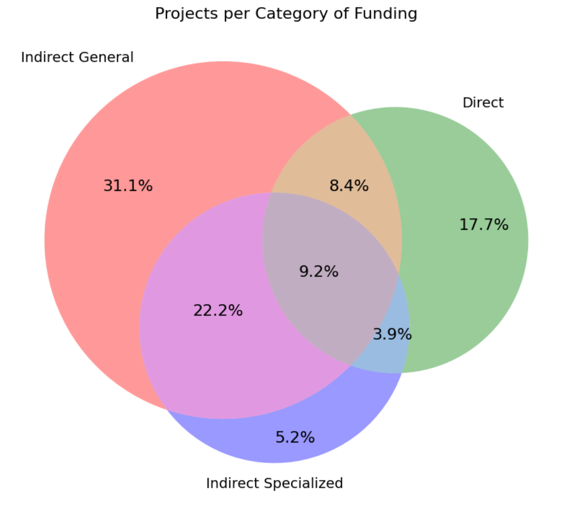


Figure 3: Projects per category of funding, out of 1625 receiving public funding.

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Conditional Expectation Function – Funder's Problem

$$E\left[m_i | s_{ij}, b_i, \mathcal{I}_i\right] = \int m_i \, f(m_i | s_{ij}, b_i, \mathcal{I}_i) \, dm_i$$

$$f(m_i | s_{ij}, b_i, \mathcal{I}_i) = \int_{s_i} f(m_i | s_{ij}, b_i, s_i) f(s_i | s_{ij}, b_i, \mathcal{I}_i) \, ds_i$$

$$f(m_i | s_{ij}, b_i, s_i) = \frac{h\left(\frac{s_{ij} - m_i}{\sigma_j}\right) h\left(\frac{s_i - m_i}{\sigma_i}\right) f(b_i | m_i) f(m_i)}{\int_{m_i} h\left(\frac{s_{ij} - m_i}{\sigma_j}\right) h\left(\frac{s_i - m_i}{\sigma_i}\right) f(b_i | m_i) f(m_i) \, dm_i}$$

$$f(s_i | s_{ij}, b_i, \mathcal{I}_i) = \frac{P(\mathcal{I}_i | s_i, b_i) \times \left[\int_{m_i} h\left(\frac{s_{ij} - m_i}{\sigma_j}\right) h\left(\frac{s_i - m_i}{\sigma_i}\right) f(b_i | m_i) f(m_i) \, dm_i\right]}{\int_{s_i} f(s_i, s_{ij}, b_i, \mathcal{I}_i) \, ds_i}$$

Back

Conditional Expectation Function – Funder's Problem (II)

If the set $\mathcal{I}_i$ consists of the source applications J_i and the requests $\boldsymbol{\delta}_i = \{\delta_{ij}\}_{j \in J_i}$. Given the private signal s_i and the budget b_i, the probability that applicant i applies can be expressed as:

$$P(\mathcal{I}_i \mid s_i, b_i) = \int_{\boldsymbol{\beta}_i} \frac{e^{V_{ij}(s_i, b_i, J_i; \boldsymbol{\beta}_i)}}{\sum_{J_i' \in \mathcal{P}(J)} e^{V_{ij}(s_i, b_i, J_i'; \boldsymbol{\beta}_i)}} \mathbb{I}\{\delta_i^*(J_i, \boldsymbol{\beta}_i) = \boldsymbol{\delta}_i\} \, dF(\boldsymbol{\beta}_i)$$

Here, V_{ij} is the value function that depends on the signal s_i, budget b_i, and application bundle J_i, while $\mathbb{I}\{\cdot\}$ is an indicator function. Back

Conditional Expectation Function – Applicant

We have:

$$E\left[m_i | s_i, b_i\right] = \int m_i \, f\left(m_i | s_i, b_i\right) dm_i$$

Using Bayes' Theorem:

$$f\left(m_i | s_i, b_i\right) = \frac{f\left(s_i \mid m_i, b_i\right) f\left(m_i \mid b_i\right) f\left(b_i\right)}{f\left(s_i \mid b_i\right) f\left(b_i\right)} = \frac{h\left(\frac{s_i - m_i}{\sigma_j}\right) \; f\left(m_i \mid b_i\right)}{f\left(s_i \mid b_i\right)}$$

Where $h(.)$ is the pdf of the error term, since $\varepsilon_{ij} = \frac{s_i - m_i}{\sigma_j}$. Back

Conditional Expectation Function – Applicant (II)

Note that we can orthogonally decompose $m_i = E(m_i \mid b_i) + \xi_i$:

$$s_i = E(m_i \mid b_i) + \xi_i + \sigma_i \varepsilon_{ii}$$
$$\sigma_i \varepsilon_i = s_{ij} - E(m_i \mid b_i) - \xi_i$$

These error terms are independent, so:

$$f(m_i | s_i, b_i) = \frac{h\left(\frac{s_i - m_i}{\sigma_i}\right) f(m_i \mid b_i)}{p(\sigma_i \varepsilon_i + \xi_i = s_i - E[m_i \mid b_i])}$$

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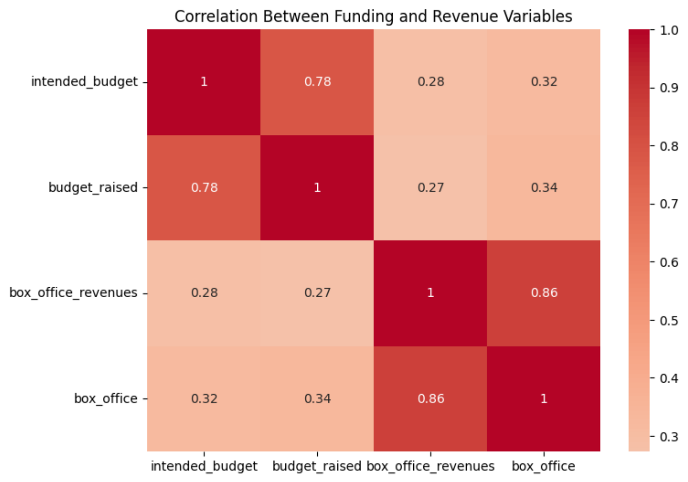
Correlation Heatmap Between Budget and Performance



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