



Regression Markets for Energy Systems Operation

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Acknowledgements

Joint work with

- Pierre Pinson (DTU) and Jalal Kazempour (DTU)



Main collaborators:

- Ricardo Bessa (INESC TEC) and Carla Gonçalves (INESC TEC)

Objectives

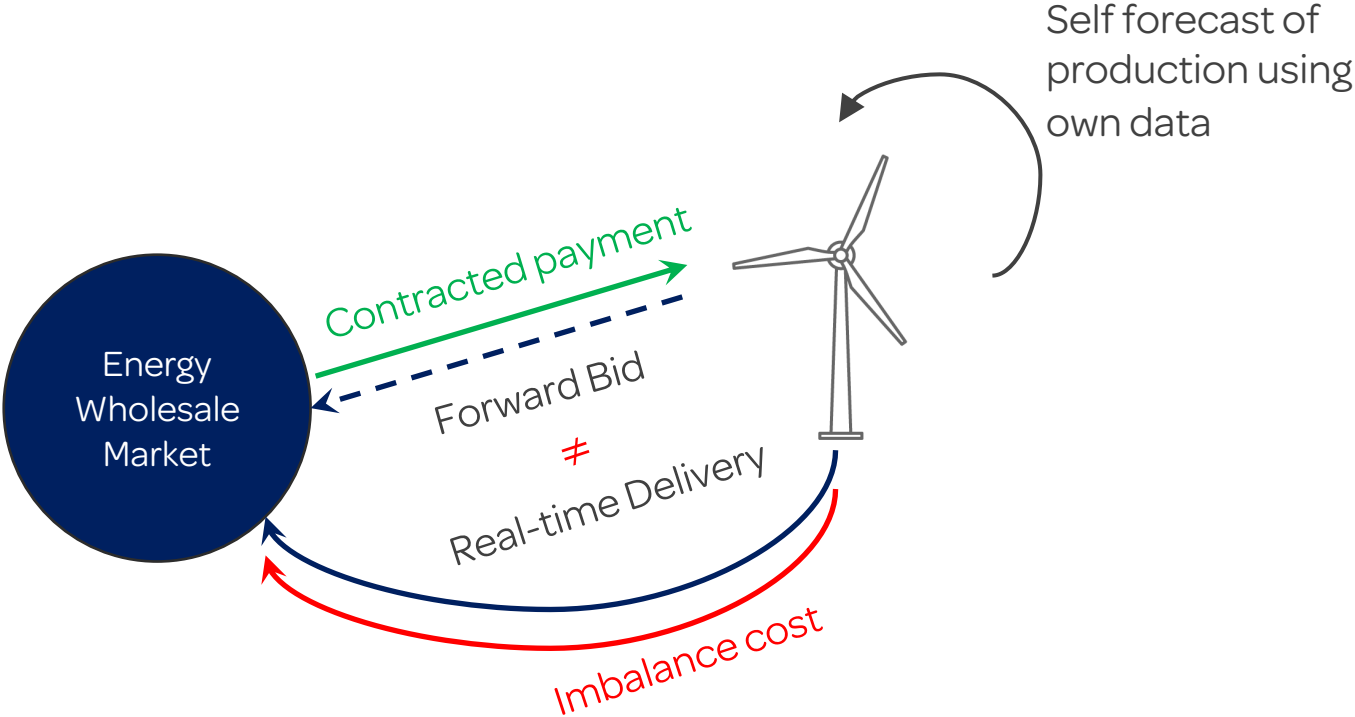


We would like to propose a regression market that

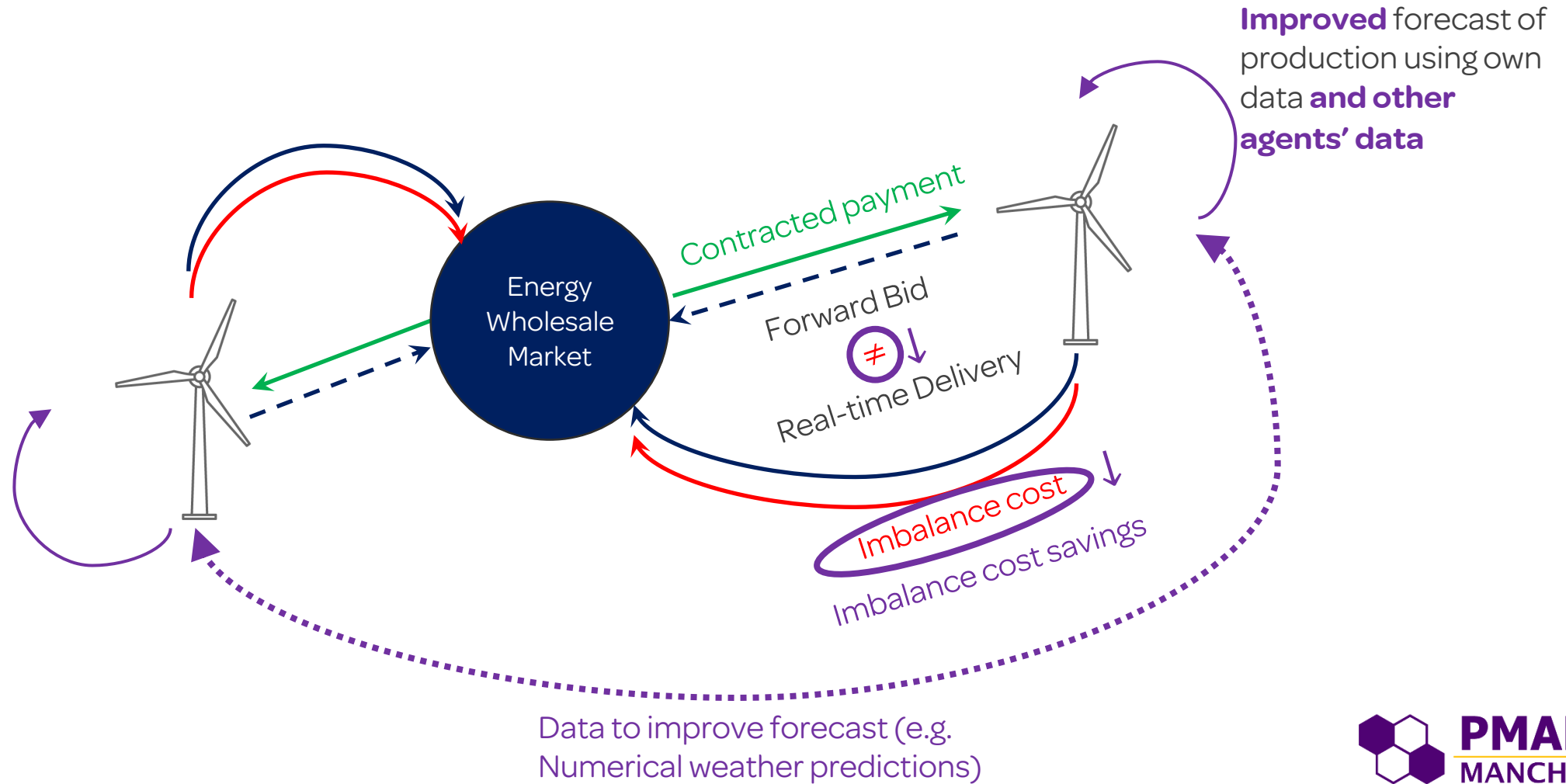
- Encourages data exchange that helps **improve the forecasting tasks of the data buyers** while providing **financial compensation for the data sellers**;
- Allocates the **payments based on the contribution** of each seller's data to the task of the buyers.
- Takes into account both **in-sample** and **out-of-sample** improvements of the forecasting task.



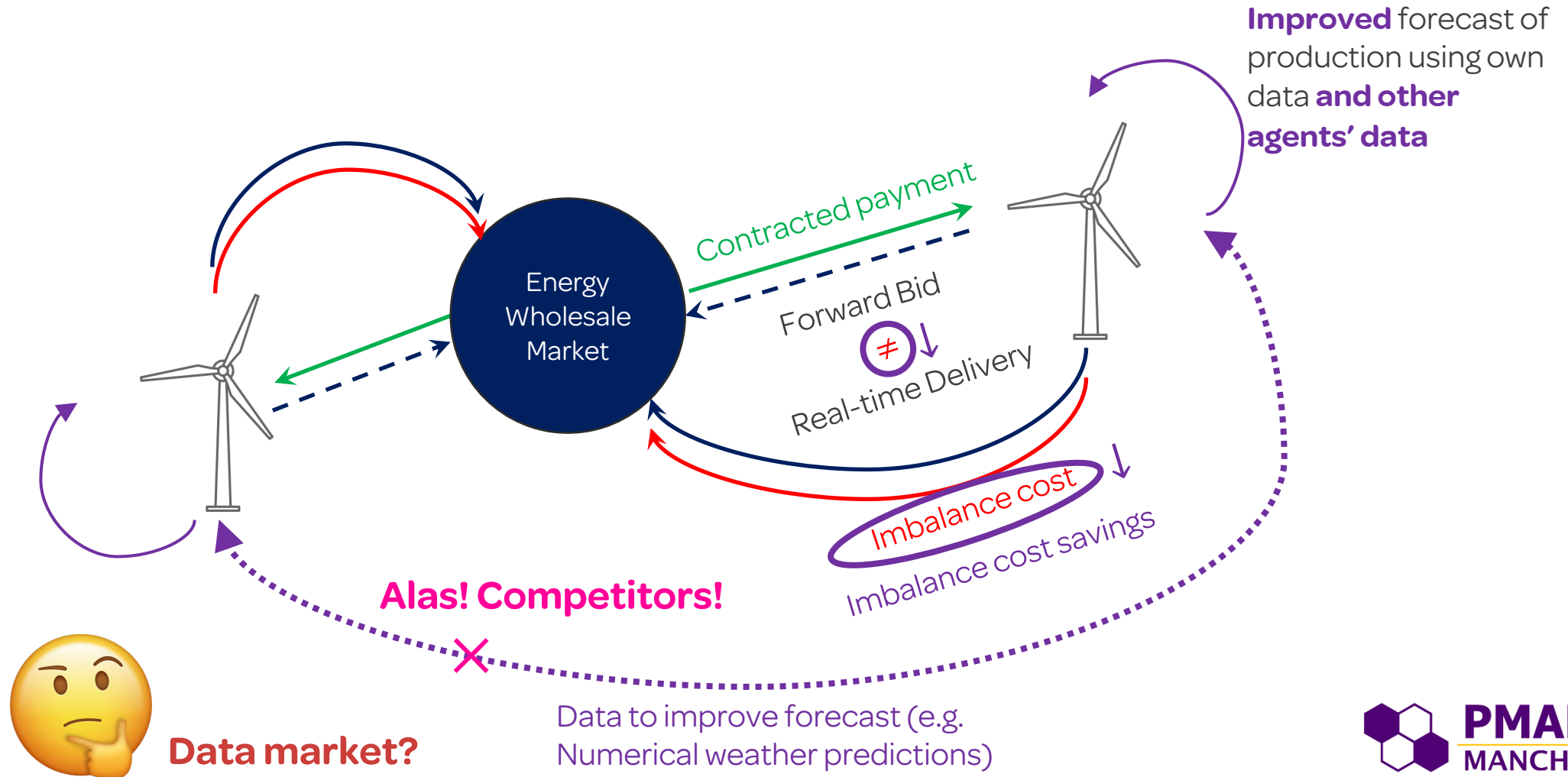
Motivating Case – Wind Forecasting



Motivating Case – Wind Forecasting

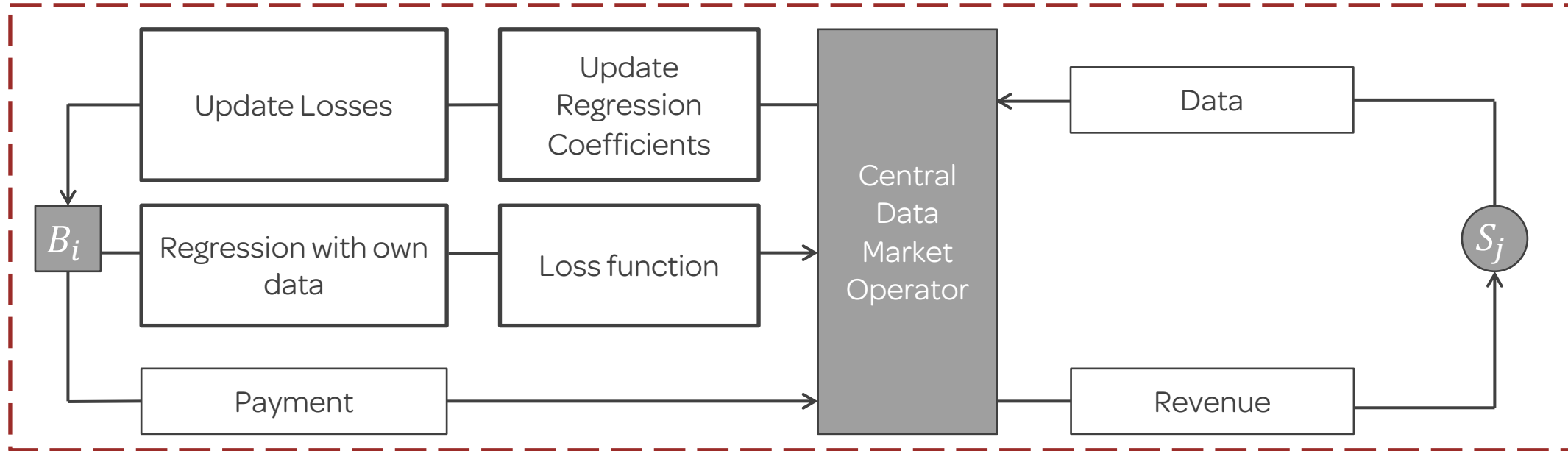


Motivating Case – Wind Forecasting



Data Market under a Regression Framework

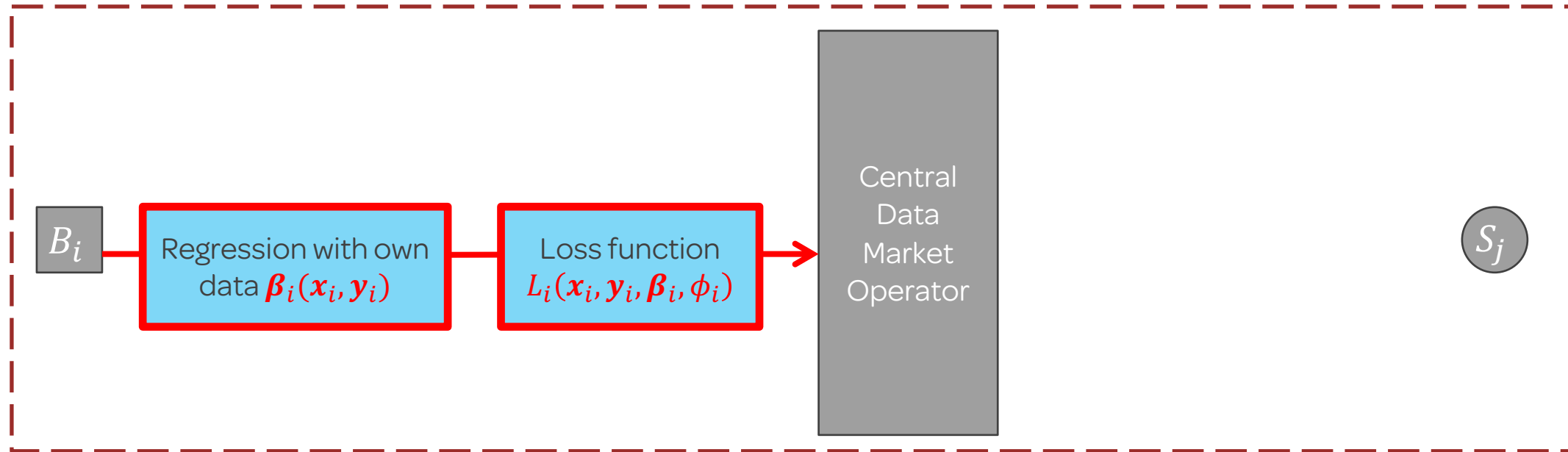
$$i \in \mathcal{B} = \{1, 2, \dots, b\}, j \in \mathcal{S} = \{1, 2, \dots, s\}$$



Data Market under a Regression Framework

Market Inputs

$$i \in \mathcal{B} = \{1, 2, \dots, b\}, j \in \mathcal{S} = \{1, 2, \dots, s\}$$



STEP 1. Buyer shares analytics task with central market operator

Buyer B_i has an **analytics task**, in the form of a **regression with linear parameters** with an eventual **forecasting** job

\mathbf{x}_i : own data, $\mathbf{y}_i \in \mathbb{R}^T$: forecasting target of length T , $\boldsymbol{\beta}_i$: regression coefficients, ϕ_i : willingness to pay.

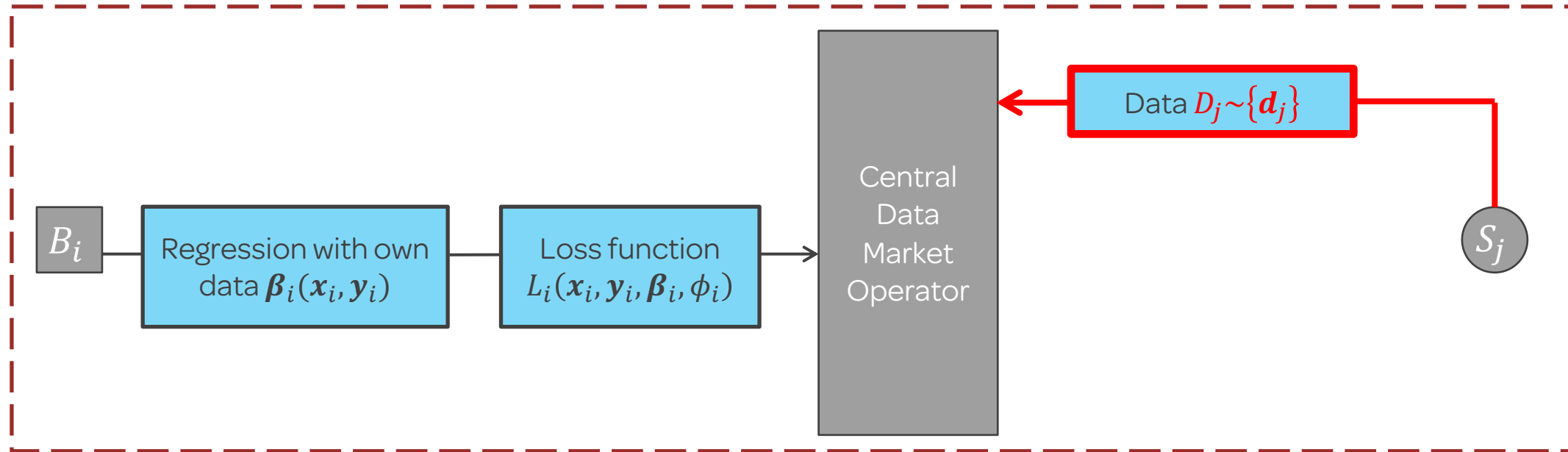
In-sample mean squared error (MSE) to measure losses: $L_i = \phi_i \frac{1}{T} \|\mathbf{y}_i - \mathbf{x}_i \boldsymbol{\beta}_i\|_2^2$

$$\Rightarrow \boldsymbol{\beta}_i = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \|\mathbf{y}_i - \mathbf{x}_i \boldsymbol{\beta}\|_2^2.$$

Data Market under a Regression Framework

Market Inputs

$$i \in \mathcal{B} = \{1, 2, \dots, b\}, j \in \mathcal{S} = \{1, 2, \dots, s\}$$

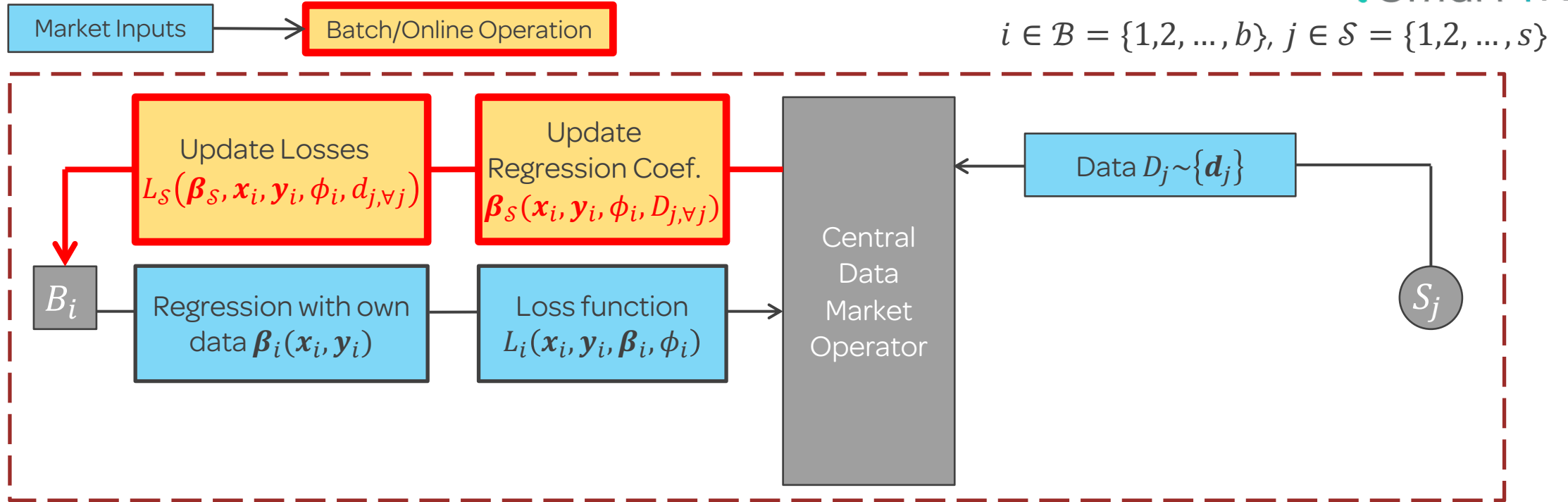


STEP 2. Sellers share data and reservation to sell with central market operator

Seller S_j offers **additional data** D_j into the data market, which include features \mathbf{d}_j :

$\mathbf{d}_j \in \mathbb{R}^T$: seller's offered feature of length T .

Data Market under a Regression Framework



STEP 3. Central market operator updates regression

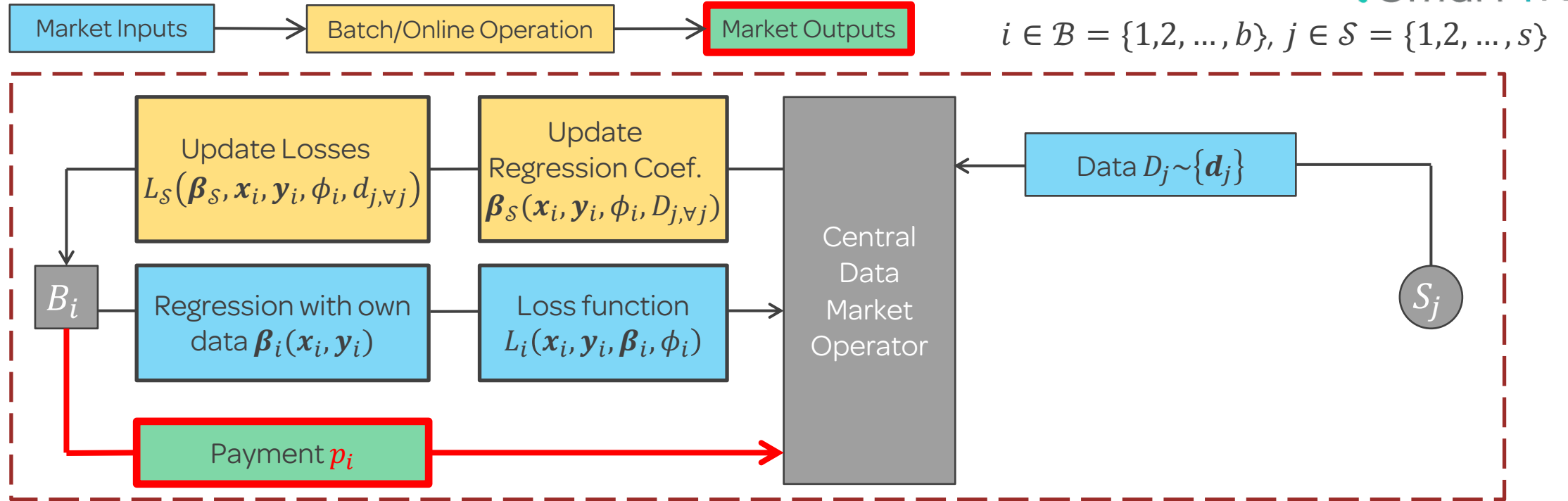
Given the buyer's **analytics task** and the **additional data** from sellers, the data market operator computes $\beta_{\mathcal{S}}$ and $L_{\mathcal{S}}$:

$\beta_{\mathcal{S}}$: regression coefficients with additional data from the sellers, $L_{\mathcal{S}}$: losses with additional data from the sellers.

Recall buyer **losses**: $L_{\mathcal{S}} = \phi_i \frac{1}{T} \|y_i - x_{\mathcal{S}} \beta_{\mathcal{S}}\|_2^2$, where $x_{\mathcal{S}} = [x_i \ d_1 \ \dots \ d_s]$. $\Rightarrow \beta_{\mathcal{S}} = \underset{\beta}{\operatorname{argmin}} \|y_i - x_{\mathcal{S}} \beta\|_2^2$ -- OLS?

Or $\beta_{\mathcal{S}} = \underset{\beta}{\operatorname{argmin}} \{ \phi_i \frac{1}{T} \|y_i - x_{\mathcal{S}} \beta\|_2^2 + \lambda \|\beta\|_1 \}$ - Lasso Regression

Data Market under a Regression Framework

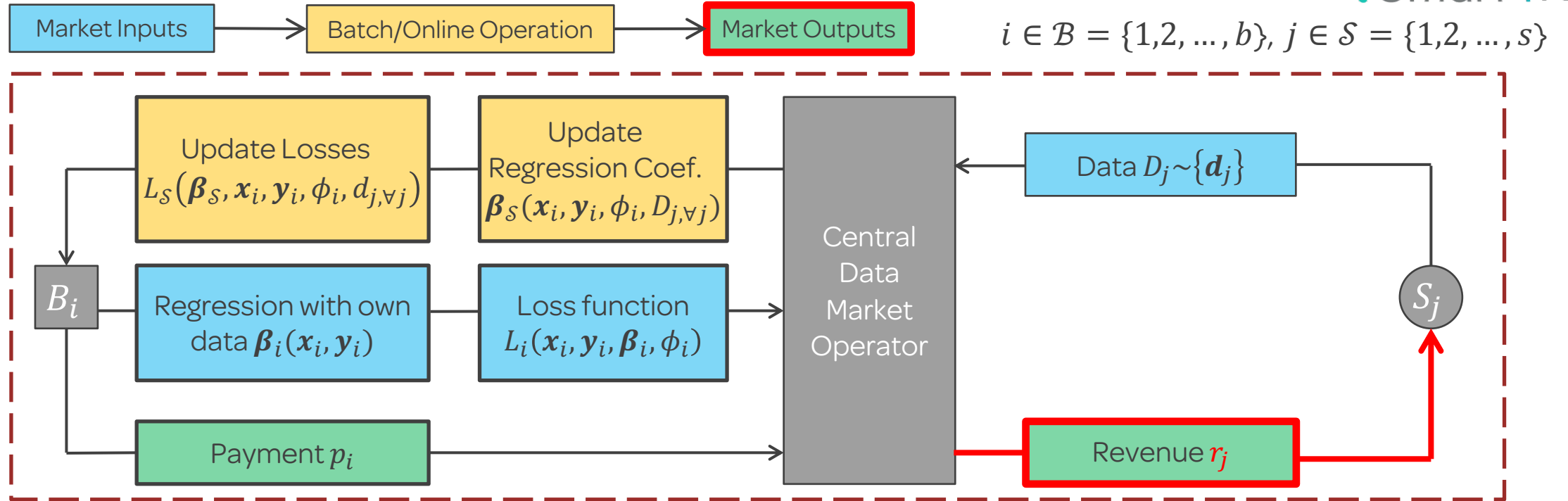


STEP 4. Central market operator determines buyer's payment

The data market operator evaluates the **reduced losses** of the buyer, which determines the **total payment** to the sellers:

$$p_i = L_i - L_S.$$

Data Market under a Regression Framework



STEP 5. Central market operator allocates the payment to sellers

then **allocates the payment** to the sellers based on certain rules^[1]. It needs to be **Budget Balanced**:

$$p_i = \sum_{j \in \mathcal{S}} r_j$$

[1] P. Pinson, L. Han, and J. Kazempour, "Regression markets and application to energy forecasting," in TOP, in press, May 2022, doi: 10.1007/s11750-022-00631-7. [Online].

Available: <https://link.springer.com/article/10.1007/s11750-022-00631-7>

Cooperative Game Based Payment Allocation

Recall the loss function of B_i with **own features** without the data market is

$$L_i(\boldsymbol{\beta}_i) = \phi_i \frac{1}{T} \|\mathbf{y}_i - \mathbf{x}_i \boldsymbol{\beta}_i\|_2^2$$

And the loss function of B_i with **own features and support features** from a set of sellers $\mathcal{S} (j \in \mathcal{S})$ is

$$L_{\mathcal{S}}(\boldsymbol{\beta}_{\mathcal{S}}) = \phi_i \frac{1}{T} \|\mathbf{y}_i - \mathbf{x}_{\mathcal{S}} \boldsymbol{\beta}_{\mathcal{S}}\|_2^2$$

Therefore, the **total payment** of B_i can be simply defined as the **value of cooperation** of **grand coalition** \mathcal{S}

$$p_i = v(\mathcal{S}) = L_i(\boldsymbol{\beta}_i) - L_{\mathcal{S}}(\boldsymbol{\beta}_{\mathcal{S}})$$

Cooperative Game Based Payment Allocation

Given $p_i = v(\mathcal{S}) = L_i(\boldsymbol{\beta}_i) - L_{\mathcal{S}}(\boldsymbol{\beta}_{\mathcal{S}})$

We define the value of each **coalition** $\mathcal{J} \subseteq \mathcal{S}$ as

$$v(\mathcal{J}) = L_i(\boldsymbol{\beta}_i) - L_{\mathcal{J}}(\boldsymbol{\beta}_{\mathcal{J}})$$

where, $L_{\emptyset}(\boldsymbol{\beta}_{\emptyset}) = L_i(\boldsymbol{\beta}_i)$, so $v(\emptyset) = 0$

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The **Leave-One-Out Payment** for each data seller $j \in \mathcal{S}$ can be defined as

$$LOO_j = v(\mathcal{S}) - v(\mathcal{S} \setminus \{j\}) = L_{\mathcal{S} \setminus \{j\}}(\boldsymbol{\beta}_{\mathcal{S} \setminus \{j\}}) - L_{\mathcal{S}}(\boldsymbol{\beta}_{\mathcal{S}})$$

Advantages:

- Computation Tractability

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Caveat: the Leave-One-Out Payment does **NOT** guarantee a **balanced budget**, leading to

$$\sum_{j \in \mathcal{S}} LOO_j \neq p_i \quad (\text{e.g., two data sellers that provide identical information})$$

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The **Shapley Value** for each data seller $j \in \mathcal{S}$ is defined as

$$\phi_j = \sum_{\mathcal{J} \subseteq \mathcal{S}, j \in \mathcal{J}} \frac{(|\mathcal{J}| - 1)! (|\mathcal{S}| - |\mathcal{J}|)!}{|\mathcal{S}|!} [v(\mathcal{J}) - v(\mathcal{J} \setminus \{j\})]$$

Advantages:

- **Budget Balance**
- Symmetry
- Zero-Element

Cooperative Game Based Payment Allocation

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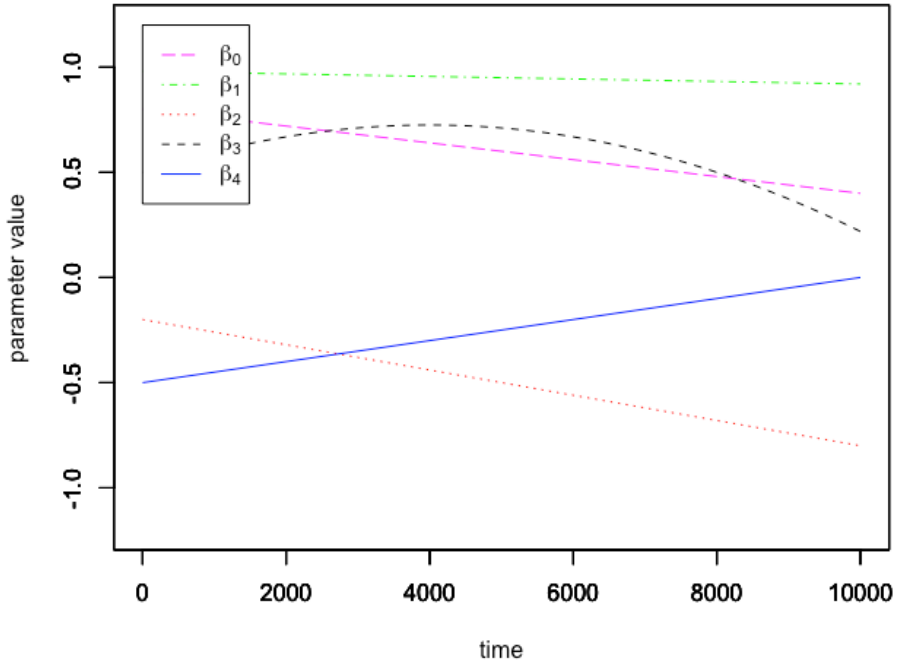
- **Budget Balance**
- Symmetry
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Caveat: The Shapley Value is computationally **intractable**, and it assumes no **revenue thresholds** from the sellers' perspective. → **Lasso regression**^[2]!

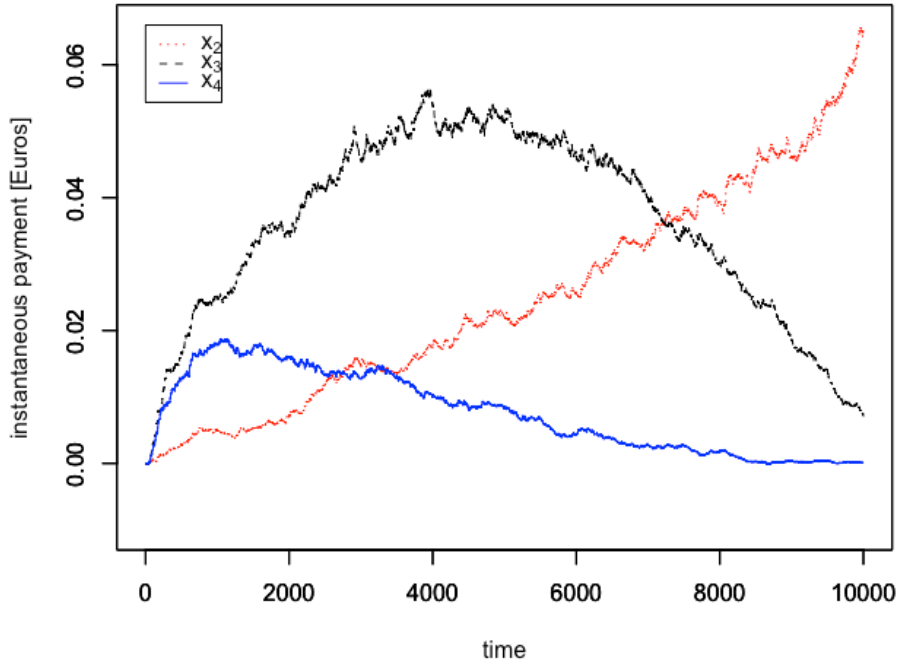
[2] L. Han, P. Pinson, and J. Kazempour, "Trading Data for Wind Power Forecasting: A Regression Market with Lasso Regularization," *accepted for PSCC 2022*, pp. 1-13, 2021. [Online]. Available: <https://arxiv.org/abs/2110.07432>

Case Studies (Synthetic Data)

$$Y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 x_{2,t-1} + \beta_3 x_{3,t-1} + \beta_4 x_{4,t-1} + \varepsilon_t$$



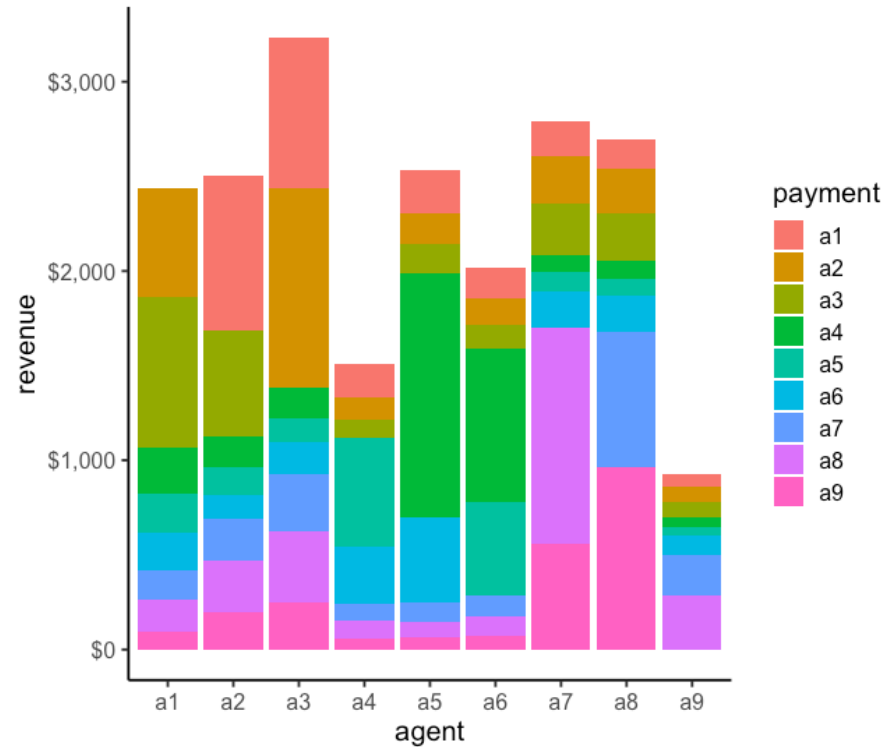
(a) True parameters



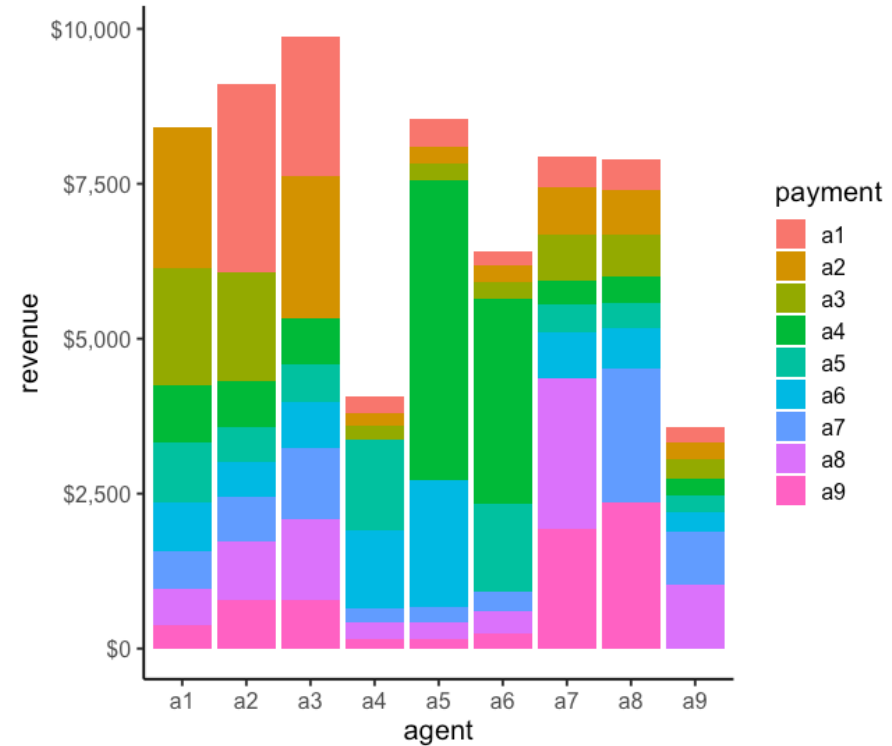
(b) Instantaneous Payments

Fig. 1. Temporal evolution of the regression parameters and the corresponding payments for the various features of the support agents over the period considered.

Case Studies (South Carolina, USA, 7 years)



(a) Batch regression market



(b) Out-of-sample regression market

Fig. 2. Cumulative revenues of all agents in both batch and out-of-sample regression markets for a span of 10,000 time instants.





THANK YOU !

Visit the project website at
www.smart4res.eu



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