Supplementary Material for

# Division of Labor by Dual Feedback Regulators Controls JAK2/STAT5 Signaling over Broad Ligand Range

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# Contents



# <span id="page-2-0"></span>1 Supplementary Data



Figure S1: Additional time series of negative regulators of JAK-STAT signaling.

Top panel: Control time series in cells without Epo stimulation. Primary CFU-E cells were starved and left untreated over the period of 8 h. After 8 h the time course was stopped due to increase of CFU-E cell death without Epo stimulation. RNA was extracted at 8 different time-points and subjected to microarray analysis. Middle and bottom panel: Time course of expression profiling of other Epo-induced negative regulators of JAK-STAT signaling. Primary CFU-E cells were starved and stimulated with 0.5 U/ml Epo. RNA was extracted at 12 different time-points and subjected to microarray analysis. Log2-fold change of mRNA levels were calculated relative to the time-point  $t = 0$ .



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Freshly isolated primary erythroid progenitor cells of the colony-forming unit erythroid stage (CFU-E) were stimulated with 5 U/ml Epo and samples were taken up to 240 min. Representative examples are shown for (a) CFU-E cells treated with either 1  $\mu$ g/ml actinomycin D or with vehicle (0.1 % dimethylsulfoxide) alone for 10 min prior to Epo stimulation and (b) CFU-E cells. At the indicated time points cellular lysates were subjected to immunoprecipitation (IP) and separated by SDS-PAGE order followed by quantitative immunoblotting (IB) based on chemiluminescence detection. SBP-JAK2, GST-EpoR, GST-STAT5, SBP-CIS were added prior to IP acting as calibrators to normalise the data. To prevent correlated errors in neighboring lanes due to inhomogenities in the polyacrylamide gel and the transfer to the membrane, samples were loaded in a randomized order on the gel [\(Schilling](#page-94-0) et al., [2005\)](#page-94-0).



## Figure S3: Quantification of molecules per cells of pathway components

Endogenous protein levels of JAK/STAT pathway components were estimated in cellular lysates of CFU-E cells by means of dilution series  $(n = 3)$  of added recombinant calibrator proteins. To determine CIS and SOCS3 levels, cells were stimulated with 5 U/ml Epo for 2 h. After lysis proteins were immunoprecipitated and analyzed by quantitative immunoblotting based on chemiluminescence detection. Dilution series of recombinant proteins were plotted with respective linear regression functions (solid lines) for SHP1 in  $1 \cdot 10^7$  CFU-E cells, for CIS in  $1 \cdot 10^7$  CFU-E cells and for SOCS3 in  $5 \cdot 10^6$  CFU-E cells. Molecules per cell were calculated by means of the respective regression function.



Table S1: Molecules per cell of JAK2/STAT5 pathway components estimated in CFU-E cells The concentrations were calculated considering the volumes and surface areas for CFU-E cells (cytoplasm: 400  $\mu$ m<sup>3</sup>, nucleus; 275  $\mu$ m<sup>3</sup>, surface area: 372  $\mu$ m<sup>2</sup>). Cytoplasmic and nuclear volume was estimated from z-stack data by measuring the whole cell area or nuclear area of each slice in ImageJ and calculating the respective volume by summing up the voxels per slice [\(Pfeifer](#page-94-1) et al., [2010\)](#page-94-1). The number of molecules per cell for EpoR on the surface of CFU-E cells was reported previously [\(Landschulz](#page-94-2) et al.,

[1989\)](#page-94-2).



Figure S4: Determination of STAT5B phosphorylation degree by mass spectrometry

Phosphorylation degree determination of STAT5B at Tyr694. Primary CFU-E cells were starved and stimulated with 5 Units/ml Epo for 10 min. Lysates were subjected to immunoprecipitation and SDS-PAGE with STAT5 antibody. STAT5 corresponding bands were analyzed by UPLC-ESI-MS/MS using homologue and isotopically labelled standards, each for the phosphopeptide (-P\*) and nonphosphorylated peptide (-OH\*) added at a -P\*:-OH\* molar ratio of 1:1. The chromatograms (left hand panels) show elution of cell-derived peptides (-P and -OH) and their homologue isotopically labelled analogues and demonstrate the Epo-induced phosphorylation. The corresponding mass spectra (right hand panels) in addition show the mass shift of 34 Da between analytes and standards. Data represents one representative example of 4 independent replicates.

<span id="page-6-0"></span>

Figure S5: Quantification of CIS and SOCS3 overexpression and correlation analysis of npSTAT5 and survival data.

(A) Overexpression levels of CIS and SOCS3 determined by immunoblotting for TUNEL assay experiments. CFU-E cells were lysed and samples were subjected to immunoblotting with CIS and SOCS3 antibodies to determine overexpression levels. (B) Comparison of the agreement of experimental obtained survival data and the integral npSTAT5 response predicted by the model in terms of log-likelihood for varying integration times. As the duration of nuclear activated STAT5 presence that is necessary to induce a survival response is unknown, we tested which integration time showed the strongest relationship to the experimentally determined survival rates. The integral npSTAT5 response correlates best with the survival rate for an integration time of about 60 minutes. The grey shaded region displays the 95% confidence interval for the determined integration time.



#### Figure S6: Calculation of increase of ratio pJAK2 relative to pEpoR

The four phosphorylated receptor complex variables were plotted for two different Epo concentrations: Epo  $log_{10} = -7$ and −8 Units/ml. At the higher Epo concentration the quantity EpoR pJAK2 increases relative to the variables where the receptor is phosphorylated as well, see e.g. at  $t = 30$  min. The observable pJAK2 is the sum of the four model variables p1EpoR pJAK2, p2EpoR pJAK2, p1p2 EpoRpJAK2 and EpoR pJAK2. The observable pEpoR is represented by p1EpoR pJAK2, p2EpoR pJAK2 and p1p2 EpoRpJAK2.

<span id="page-8-3"></span>

variable	parameter	value	p-value	standardized coefficients	contribution $[\%]$
pEpoRauc	$p_1$	$12.34 \cdot 10^{-14}$	$0.5\,$	$1.50 \cdot 10^{-11}$	$2.31 \cdot 10^{-24}$
pJAK2auc	$p_{2}$	$+4.60 \cdot 10^{-10}$	$0.5\,$	$1.20 \cdot 10^{-9}$	$1.50 \cdot 10^{-16}$
npSTAT5auc	$p_3$	0.0621	$\cdot 10^{-6}$	0.9765	99.32
CISauc	$p_{4}$	$3.71 \cdot 10^{-5}$	0.38	0.0053	$2.99 \cdot 10^{-3}$
SOCS3auc	$p_{5}$	0.0011	$1 \cdot 10^{-5}$	0.0805	0.67

Table S2: Results of regression statistics for contribution to survival signal

#### <span id="page-8-0"></span>1.1 Contributions to survival signal

In order to infer the contributions to the survival signal shown in Fig. 5 of the main text the following function was considered:

 $[\text{survival}] = p_0 + p_1 \cdot [\text{pEpoRauc}] + p_2 \cdot [\text{pJAK2auc}] + p_3 \cdot [\text{npSTAT5auc}] + p_4 \cdot [\text{CISauc}] + p_5 \cdot [\text{SOCS3auc}],$  (1)

where  $p_0$  is an offset parameter and 'auc' denotes the integrated signal of the respective species until 60 minutes, see in Fig. [S5.](#page-6-0) We apply standard regression statistics for linear models, see in Table [S2](#page-8-3) and in [Backhaus](#page-93-0) *et al.* [\(1996\)](#page-93-0). The p-value of the one-sided t-test indicated that only the parameters  $p_3$  and  $p_5$  do have statistically significant non-zero contributions. Via the standardized regression coefficients we can translate the values of the parameters to percentage contributions of explained variance.  $p_3$  and its corresponding variable, the integrated npSTAT5 response, contribute more than 99%.

## <span id="page-8-1"></span>1.2 Insufficient siRNA knockdown efficiency of SOCS members in primary murine CFU-E cells

We tested different techniques to generate siRNA knockdowns of the SOCS family members in primary erythroid progenitor cells. Retro-, lenti- and adenoviral vectors were used expressing different shRNA constructs targeting the mRNA of one of the SOCS family members in primary erythroid cells at the CFU-E stage. However, the knockdown efficiencies achieved with these experimental techniques were insufficient. A potential explanation for these results is the time period available for experiments of 12-20 h after transduction that may be too short to observe siRNA-mediated knockdown in these cells. The time frame of the experiments, however, can not be extended since erythroid progenitor cells start to terminally differentiate after 12 h. The study of Yu [et al.](#page-95-0) [\(2003\)](#page-95-0), reviewed in [Alexander and Hilton](#page-93-1) [\(2004\)](#page-93-1), generated stable Th2 cell lines overexpressing SOCS3 antisense constructs in the lymphoid lineage, a method that cannot be applied to primary cells.

Another possible explanation of the insufficient knockdown in the primary cells is the rapid turnover of SOCS mRNA that could limit siRNA efficacy. [Larsson](#page-94-3) *et al.* [\(2010\)](#page-94-3) have shown that high pre-existing mRNA turnover rate is associated with reduced susceptibility to silencing by siRNAs.

## <span id="page-8-2"></span>1.3 Expression of anti-apoptotic STAT5 target gene Pim-1

To further analyze the direct correlation between the integral response of phosphorylated STAT5 in the nucleus and the survival decision of erythroid progenitor cells (Fig. 6C of the main text), we investigated the induction of anti-apoptotic target genes. Global gene expression demonstrated that exclusively Pim-1 is rapidly induced compared to untreated control cells (Fig. [S7A](#page-9-0)). Because it was also previously identified as STAT5-modulated anti-apoptotic effector [\(Menon](#page-94-4) et al., [2006;](#page-94-4) [Sathyanarayana](#page-94-5) et al., [2008\)](#page-94-5), we selected Pim-1 as representative candidate for further experiments. In contrast, Bcl-xL, which was discussed earlier to be important for survival in erythroid cell lines (Silva *[et al.](#page-95-1)*, [1999;](#page-95-1) [Socolovsky](#page-95-2) *et al.*, [1999\)](#page-95-2), showed upregulation only very late after 15-20 h and Bcl-2 showed no significant modulation. BIM as pro-apoptotic factor was repressed upon Epo stimulation. These results are in line with the expression pattern of pro-survival factors observed by [Sathyanarayana](#page-94-5) et al. [\(2008\)](#page-94-5) who investigated Epo-dependent

<span id="page-9-0"></span>

Figure S7: Epo-dependent expression of anti-apoptotic factors in primary erythroid progenitor cells at the CFU-E stage.

(A) Time series of Pim-1, BIM, BCL-2 and Bcl-xL with 0.5 Units/ml and without Epo stimulation as control. Freshly isolated and MACS sorted primary CFU-E cells from murine fetal livers were starved, stimulated or left untreated over a period of 8h or 24h. After 8h the untreated time course was stopped due to increase of CFU-E cell death without Epo stimulation. RNA was extracted at different time-points and subjected to microarray analysis. Log2-fold change of mRNA levels were calculated relative to the time-point  $t = 0$ . (B) Quantitative RT-PCR analysis of Pim-1 expression stimulated with various Epo concentrations at 2h. Freshly isolated CFU-E cells were starved and stimulated with the indicated Epo concentrations, prepared RNA was reverse transcribed and used in qRT-PCR analysis. Values represent means with SD for n = 3 independent reverse transcription samples. Relative concentrations were normalized using HPRT as a reference gene.

regulation of pro-survival factors in primary murine Kit<sup>(+)</sup>CD71<sup>(high)</sup>Ter119<sup>(-)</sup> erythroblasts. To examine if Pim-1 follows the integrated nuclear STAT5 response over the entire range of Epo concentrations, the upregulation of Pim-1 was determined after 2h for various Epo concentrations (Fig. [S7B](#page-9-0)). The dosedependent expression of Pim-1 mirrors the behavior of the integral pSTAT5 response (Fig. 6C of the main text), implying that the integral STAT5 response is directly proportional to transcriptional responses of direct target genes.

## <span id="page-10-0"></span>1.4 Impact of stochasticity on nuclear phosphorylated STAT5

Intrinsic stochasticity was simulated using the Stochastic Simulation Algorithm [\(Gillespie,](#page-93-2) [1977\)](#page-93-2), see Fig. [S8.](#page-10-1) To mimic the effect of extrinsic stochasticity of a cell population, we simulated the ODE model for multiple protein initial concentrations drawn from a normal distributed centered around the estimated value with  $10\%$  variation, see Fig. [S9](#page-11-0) and also in [\(Spencer](#page-95-3) *et al.*, [2009\)](#page-95-3). If the variability in the STAT5 response in single cells simulated by intrinsic or extrinsic stochasticity is the main source to explain the all-or-none survival decision, a bi-stable behavior would be expected. However, in both cases, the trajectory of npSTAT5 is rather negligibly affected by noise and does not show bi-stability. We therefore suggest that other individual cell-to-cell differences cause the all-or-none response of cell death or survival.

<span id="page-10-1"></span>



The effect of intrinsic noise on the model dynamics were calculated by the Stochastic Simulation Algorithm [\(Gillespie,](#page-93-2) [1977\)](#page-93-2). Ten realizations are displayed. As the profile likelihood analysis shows, see in Section [2.5,](#page-53-0) the upper bound for the parameters SOCS3Turn and CISRNATurn is not determined. To reduce the computation time for SSA these parameter were set to  $10<sup>1</sup>$ , which is in agreement with the experimental data. The dynamics of npSTAT5 is affected by intrinsic noise only negligibly.

<span id="page-11-0"></span>

#### Figure S9: Simulation of the effect of extrinsic noise on the model dynamics.

The figure shows the effect of extrinsic noise on the model dynamics. For the computation, the parameters accounting for the concentration level of the modeled components, CISEqc, CISRNAEqc, SOCS3Eqc, SOCS3RNAEqc, init EpoRJAK2, init SHP1 and init STAT5 where varied by 10% in logarithmic space around their estimated values. Ten realizations are displayed. The qualitative behaviour of the model dynamics, especially the STAT5 activation, is not affected by extrinsic noise, e.g. bi-stability does not occur in the parameter ranges that are determined by the experimental data.

# <span id="page-12-0"></span>2 Supplementary Model Results

In the following, the mathematical model describing the dynamics of the biological system by ordinary differential equations (ODEs), the mapping of the model outputs to the experimental data for each of the different experimental conditions, and the estimation of the unknown model parameters from the experimental data is described in detail. Furthermore, an analysis of the uncertainties in the estimated parameters due to the limited quality of the experimental data is presented in terms of identifiability and confidence intervals. Finally, the remaining parameter uncertainties are in turn translated to uncertainties in the model predictions in terms of confidence intervals of the model trajectories. This procedure allows for a realistic reasoning about the biological questions that should be addressed by the modeling approach.

On demand, we can supply MATLAB code that disburdens the re-implementation of the project by supplying the ODE model, the connection of model outputs to the data sets, the efficient ODE solver and the parameter estimation procedure itself.

## <span id="page-12-1"></span>2.1 Modeling concept

Cellular processes can be modeled using a system of ordinary differential equations (ODEs), see e.g. in [Wolkenhauer](#page-95-4) [\(2008\)](#page-95-4). To adequately describe the underlying biological process with this mathematical framework spatial effects have to be neglected by assuming that diffusion is fast compared to the reaction rates of the protein interactions and the spatial extend of a cell. Intrinsic stochasticity of the discrete dynamics of molecular reactions can be neglected, if the copy number of molecules is sufficiently large, i.e. for a protein copy number  $> 10$  [\(Taniguchi](#page-95-5) *et al.*, [2010\)](#page-95-5). In Fig. [S8,](#page-10-1) intrinsic stochasticity was simulated ten times, using the Stochastic Simulation Algorithm [\(Gillespie,](#page-93-2) [1977\)](#page-93-2) for the parameters values estimated by the ODE framework. The dynamics of npSTAT5, the quantity of interest for the biological question, are affected by intrinsic noise only negligibly. Extrinsic noise due to cell to cell variability, can be illustrated by simulating the ODE dynamics for varying parameter values, such as initial protein concentration. In Fig. [S9,](#page-11-0) extrinsic stochasticity was simulated ten times, using parameters values estimated by the ODE framework with normally distributed variations in the initial protein concentrations of 10% in logarithmic space. The qualitative behaviour of the model dynamics, especially the STAT5 activation, is not affected by extrinsic noise, e.g. bi-stability does not occur for the parameter ranges that are determined by the experimental data. Moreover, stochastic effects are suppressed, if the dynamics of protein concentration is modeled as average over a cell population using experimental data obtained from averaging over many cells. This applies for many measurement techniques such as immunoblotting or quantitative RT-PCR. The experimental data used here contains an average over  $\approx 4 \cdot 10^7$  cells. Consequently, the resulting ODE framework describes the average behaviour of a cell.

The dynamics of the concentrations of n biological compounds  $\vec{x}$  such as proteins in different phosphorylation states that are involved in a biological system, described by an ODE framework, is given by

$$
\dot{\vec{x}}(t,\theta) = \vec{f}(\vec{x}(t,\theta),\vec{u}(t),\theta) \tag{2}
$$

<span id="page-12-2"></span>
$$
\vec{x}(0,\theta) = \vec{w}(\theta). \tag{3}
$$

The dynamical behavior may depend on an input function  $\vec{u}(t)$  such as a treatment with ligands and model parameters  $\theta = \{\theta_1 \dots \theta_l\}$  such as rate constants or initial concentrations that are usually unknown for in vivo systems and need to be estimated from experimental data. Each component of  $\vec{f}$  in Eq. [2](#page-12-2) is usually composed of a sum of several reaction fluxes  $v_j$  that correspond to the interactions present

<span id="page-12-3"></span>
$$
\dot{\vec{x}}(t,\theta) = \mathbf{N} \cdot \vec{v}(\vec{x}(t,\theta),\vec{u}(t),\theta)
$$
\n(4)

where  $N$  is the stoichiometry matrix, see e.g. in [Heinrich and Schuster](#page-93-3) [\(1996\)](#page-93-3). Eq. [3](#page-12-2) indicates that the initial conditions  $\vec{x}(0)$  for Eq. [2](#page-12-2) might also be dependent on the model parameters  $\theta$  that need to be estimated.

In order to compare the simulated model dynamics with experimental data, the dynamics given by Eq. [2](#page-12-2) are mapped by a function  $\vec{g}$  to m model outputs

<span id="page-13-0"></span>
$$
\vec{y}(t_i, \theta) = \vec{g}(\vec{x}(t_i, \theta), \theta) + \vec{\epsilon}(t_i). \tag{5}
$$

The model outputs are the quantities accessible by experiments measured at times  $t_i$ . They may depend on additional parameters such as scaling or offset parameters included in  $\theta$ .

The distribution of the measurement noise  $\vec{\epsilon}(t_i)$  is assumed to be known, e.g. being independently normally distributed with  $\epsilon_k(t_i) \sim \text{N}(0, \sigma_k^2(t_i))$ . For concentration measurements in biological applications it is reasonable, and was explicitly shown in the case of immunoblotting experiments [\(Kreutz](#page-94-6) et al., [2007\)](#page-94-6), that the measurement noise is log-normally distributed. Therefore, before proceeding with parameter estimation both experimental data and model outputs were transformed logarithmically.

**Parameter estimation** For the description of in vivo systems, commonly many model parameters  $\theta$ are unknown and have to be estimated from experimental data  $y^{\dagger}$ . The parameters are estimated by the Maximum Likelihood Estimation (MLE) approach. For normally distributed measurement noise in Eq. [5,](#page-13-0) it is more common and equivalent to MLE to minimize  $-2 \log(L)$ , where

<span id="page-13-3"></span>
$$
L(y^{\dagger}|\theta) = \prod_{k=1}^{m} \prod_{i=1}^{d_k} \frac{1}{\sigma_k(t_i)\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{y_k^{\dagger}(t_i) - y_k(t_i,\theta)}{\sigma_k(t_i)}\right)^2\right)
$$
(6)

is the likelihood function.  $d_k$  denotes the number of experimental data  $y_k^{\dagger}$  for each model output  $k =$ 1...m measured at time points  $t_i$  with  $i = 1...d_k$  and  $\sigma_k(t_i)$  is the corresponding magnitude of the measurement noise. The value of this *objective function* indicates the mismatch of experimental data  $y_k^{\dagger}(t_i)$  and the model outputs  $y_k(t_i, \theta)$  predicted by the model for parameters  $\theta$ . For a detailed discussion of MLE in the context of non-linear regression models, see e.g. in [Seber and Wild](#page-95-6) [\(2003\)](#page-95-6).

**Measurement noise** The magnitude of the measurement noise  $\sigma_k(t_i)$  for each experimental technique is estimated simultaneously with the remaining parameters. Therefore, a parameterized *error model* of the form

<span id="page-13-4"></span>
$$
\vec{\sigma}(t_i, \theta) = \vec{s}(\vec{y}(t_i, \theta), \theta) \tag{7}
$$

describing the measurement noise for each model output is assumed. The additional parameters accounting for the magnitude of the measurement noise are estimated simultaneously with the remaining model parameters.

Parameter transformations Each ODE model that is realized as dimensional equations describing dimensional quantities has an intrinsic scaling invariance. This invariance originates from the free choice of units and can be exploited to reduce the number of free parameters and to disentangle dynamical parameters  $\theta^d$  from "static" parameters  $\theta^x$  like initial concentrations or others reflecting the concentration scale. The basic idea is to express a dynamical variable x in units of its corresponding  $\theta^x$ .

<span id="page-13-2"></span><span id="page-13-1"></span>
$$
X := \frac{x}{\theta^x}.\tag{8}
$$

The unique solution  $x(t, \theta^d, \theta^x)$  can then be expressed as

$$
x(t, \theta^d, \theta^x) = \theta^x X(t, \Theta^d),\tag{9}
$$

i.e. as the unique solution to the transformed system with transformed parameters  $\Theta^d$  that are disentangled from  $\theta^x$ . For most of the applied measurement techniques, the model output y is connected to the dynamical variable x by a scaling factor  $\theta^s$  by

$$
y(t_i) = \theta^s x(t_i). \tag{10}
$$

Eq. [\(9\)](#page-13-1) indicates that the scaling parameter  $\theta^s$  is directly correlated to  $\theta^x$ . This correlation is immediately resolved by the parameter transformation

<span id="page-14-1"></span>
$$
\theta^s \to \frac{\Theta^s}{\theta^x}.\tag{11}
$$

The resolution of this correlation facilitates a faster and more efficient parameter estimation. In some cases, such as for mRNA measurements of CIS and SOCS3, no experimental information was available about the absolute concentration scale that determines  $\theta^x$ . Consequently these  $\theta^x$  are structurally nonidentifiable. Due to the nature of the applied transformations these structurally non-identifiabilities can be resolved easily by setting the corresponding  $\theta^x$  to a constant value, e.g. to 1. Please note, this only fixes the scales of the dynamical variables without posing any restrictions on the shape of the dynamics. However, no prediction of absolute concentrations for the affected species can be made as long as no measurement of absolute concentration is available.

Identifiability and confidence intervals of the estimated model parameters In order to evaluate the identifiability of the model parameters and to assess confidence intervals the profile likelihood was evaluated, see in Sec. [2.5.](#page-53-0) Detailed instructions how to interpret the result are given in Raue *[et al.](#page-94-7)* [\(2009\)](#page-94-7). Briefly, the profile likelihood is sampled for each parameter individually in a manner that detects potential directions in parameter space that are not well determined by the experimental data. A profile likelihood resulting in a flat line indicates a parameter that is structurally non-identifiable, meaning that the parameter can not be inferred. A profile likelihood that rises but does not cross the desired threshold for 95% confidence intervals is practically non-identifiable, given the experimental data. A finite lower or upper confidence bound can still be available. If the profile likelihood exceeds the threshold on both sides the parameter is identifiable and can be determined with a confidence of 95% within its confidence intervals.

Confidence intervals of the predicted model dynamics In order to realistically assess the precision of model predictions, the remaining uncertainties in the parameter estimates have to be translated to the model trajectories, see in Sec. [2.6.](#page-83-0) In general, 95% time point-wise confidence intervals for the predicted dynamical model trajectories requires sampling of the respective point-wise 95% confidence region in the parameter space. Due to the high dimensionality sampling of a high-dimensional parameter space is only feasible in an approximative manner. In this work, the region of the parameter space has been sampled by evaluating the model predictions along the parameter vectors determined during the calculations of the profile likelihood, see in Raue *[et al.](#page-94-8)* [\(2010\)](#page-94-8) for details. This guarantees that the extreme points of the parameter confidence region for each parameter are sampled.

### <span id="page-14-0"></span>2.2 Definition of dual negative feedback model of JAK2/STAT5 signaling

The general topology of the model was constructed based on prior biological knowledge and experimental data generated in this study. To achieve reliable model predictions, we tailored the model complexity to the requirements of our biological question and generated extensive time-resolved data, using different experimental approaches. After systematically eliminating short lived protein-protein complexes and fast reactions, the model comprised 25 dynamical variables representing the time course of species concentrations and 36 reactions involving 29 parameters that characterize the dynamical behavior. The model structure is depicted in Fig. [S10.](#page-15-0)

To explain the events at the plasma membrane EpoR and JAK2 were modeled as a protein complex since JAK2 modulates the expression of EpoR on the cell surface [\(Huang](#page-93-4) *et al.*, [2001\)](#page-93-4). Upon ligand binding to the EpoR, rearrangements of EpoR lead to the activation of JAK2 by transphosphorylation. Activated JAK2 then phosphorylates various tyrosine residues on the cytoplasmic domain of the receptor. This activation mechanism was reflected by considering different activation states of the receptor complex. It has been previously shown that CIS-GFP can bind unspecifically to the EpoR lacking the STAT5 recruitment site Y401 if expressed in high amounts [\(Ketteler](#page-93-5) *et al.*, [2003\)](#page-93-5). To include this information in

<span id="page-15-0"></span>

Figure S10: Network representation of dual negative feedback model of JAK2/STAT5 signaling

Diamond shaped nodes correspond to model inputs, see Eq. [12.](#page-17-0) Ellipsoid shaped nodes correspond to dynamical variables described by the ODE system, see Eq. [49](#page-18-0) – [73.](#page-18-0) Species npSTAT5, CISnRNA1–5 and SOCS3nRNA1–5 are located in the nuclear compartment, the remaining species in the cytoplasmatic compartment. Black arrows and box shaped nodes indicate reactions with corresponding rate equations given in Eq. [13](#page-17-1) – [48.](#page-17-1) Red T-shaped arrows indicated inhibitorial influence on a reaction and blue O-shaped arrows indicate catalyzing influence on a reaction. Reactions  $v_{18}$  to  $v_{22}$  and  $v_{28}$ to  $v_{32}$  account for a delay that reflects the processing steps of the mRNA.

the model, two subclasses of phosphorylated tyrosines at the receptor were incorporated into the model: (i) p1 EpoR pJAK2 represents the phosphorylated tyrosine sites Y343 and Y401 that serve as recruitment sites for STAT5 and thereby facilitate STAT5 phosphorlyation. CIS inhibits phosphorylation of STAT5 induced by this variable. (ii) p2 EpoR pJAK2 represents the remaining phosphorylated tyrosines sites of the EpoR that do not recruit STAT5. Phosphorylation of this variable can be inhibited by high levels of CIS due to unspecific binding of CIS to the unphosphorylated EpoR (EpoRJAK2 CIS). p12 EpoR pJAK2 represents the completely phosphorylated complex. It is important to note that the EpoR pJAK2 variable can also account for phosphorylated JAK2 that was dissociated from the EpoR.

In general, phosphatase activities were included in the model as dephosphorylation reactions that are proportional to the substrate with a time-independent kinetics. Ligand-dependent attenuation, for instance by receptor internalization and dephosphorylation was summarized by including SHP1-mediated deactivation of JAK2 and EpoR as described in a previous model of CFU-E cells [\(Schilling](#page-94-9) *et al.*, [2009\)](#page-94-9). The tyrosine phosphatase SHP1 has previously been shown to require binding to the specific phosphorylated tyrosine residue Tyr429 on the EpoR to activate phosphatase activity (Pei *[et al.](#page-94-10)*, [1996;](#page-94-10) Klingmüller [et al.](#page-93-6), [1995\)](#page-93-6). Therefore, SHP1 was considered to exist in two states in the model: one active and one inactive form. The transition of inactive to catalytically active SHP1 is mediated by phosphorylated EpoR that reflects the recruitment to the specific phosphotyrosine residue. The activated form of SHP1 then catalyzes dephosphorylation of JAK2 and EpoR ( $pEpoR \rightarrow EpoR$ , catalyzed by SHP1Act).

Phosphorylation of STAT5 by JAK2 is mediated by recruiting STAT5 to phosphotyrosine 343 and 401 of the EpoR cytoplasmic domain that functions as a scaffold [\(Gobert](#page-93-7) *et al.*, [1996;](#page-93-7) [Barber](#page-93-8) *et al.*, [2001;](#page-93-8) Klingmüller et al., [1996\)](#page-93-9). Hence, phosphorylated JAK2 was considered in the model as the enzyme and the phosphorylated EpoR as an additional modifier. Both contribute as the  $p1(2)$  EpoR  $pJAK2$ complexes to phosphorylation of STAT5 by a second order term reflecting the activation by a dimer. As STAT5 phosphorylation by JAK2 is impaired in the absence of docking sites [\(Gobert](#page-93-7) *et al.*, [1996\)](#page-93-7), we included in the model that the activation of STAT5 by EpoR pJAK2 must always occur slower than the activation by the complexes  $p1(2)$  EpoR  $pJAK2$ . Dimerization of STAT5 is known to occur very rapidly after phosphorylation and could be neglected on the time-scale of our measurements. The phosphorylated STAT5 shuttles into the nucleus and binds to consensus sequences on the DNA activating gene transcription. After a certain sojourn time in the nucleus, dephosphorylated STAT5 translocates back into the cytoplasm to enter a new cycle of activation, which is an important feature of the system to continuously monitor receptor activation [\(Swameye](#page-95-7) *et al.*, [2003\)](#page-95-7). Hence, the different forms of STAT5 were integrated in the model by three distinct variables: unphosphorylated STAT5 in the cytosol (STAT5), phosphorylated STAT5 dimers in the cytosol (pSTAT5), and phosphorylated STAT5 dimers in the nucleus (npSTAT5). Three parameters describe the transitions between these variables: STAT5 activation, the import rate into the nucleus, and the export rate back into the cytosol that includes dissociation and dephosphorylation.

Phosphorylated STAT5 in the nucleus induces the expression of the negative feedback regulators CIS and SOCS3 based on our observations using gene expression profiling and immunoblotting analysis that revealed a rapid and strong upregulation of both SOCS members in Epo-induced CFU-E cells. Hence, CIS and SOCS3 were both included into the mathematical model as transcriptional feedbacks. Previously, SOCS3 has been proposed to bind via its SH2 domain to activated EpoR and JAK2 and to inhibit JAK2 activity by directly binding to the kinase activation loop via its KIR domain (Hörtner *et al.*, [2002;](#page-93-10) [Sasaki](#page-94-11) et al., [1999,](#page-94-11) [2000;](#page-94-12) [Babon](#page-93-11) et al., [2006\)](#page-93-11). CIS was identified as negative regulator of JAK/STAT signaling by binding to phosphotyrosine 401 of the EpoR, thereby competing for receptor binding with STAT5 [\(Ketteler](#page-93-5) et al., [2003;](#page-93-5) [Yoshimura](#page-95-8) et al., [1995\)](#page-95-8). Hence, SOCS3 and CIS were included in the model at different levels of signal transmission: CIS was considered as inhibitor of STAT5 activation only mediated by the p1EpoR pJAK2 complex. Additionally, CIS can inhibit phosphorylation of p2EpoRJAK2 due to unspecific binding (EpoR JAK2 CIS). In contrast, SOCS3 can inhibit JAK2 activation and the downstream events of STAT5 activation, i.e. phosphorylation of EpoR and recruitment of STAT5 to the specific pTyr binding sites on the EpoR. Therefore, SOCS3 in the model inhibits STAT5 phosphorylation mediated by both EpoR pJAK2 and p1(2) EpoR pJAK2.

The ODE model In the mathematical expressions that follow, the dynamical variables are indicated by square brackets and are given in nM. The model dynamics depends on an external treatment with erythropoietin, see in Eq. [2,](#page-12-2) given in units/cell:

<span id="page-17-0"></span>
$$
[Epo](t) = epo\_level
$$
\n
$$
(12)
$$

The rate equations corresponding to the reactions included in the model are give by:

<span id="page-17-1"></span>

Reactions  $v_{18}$  to  $v_{22}$  and  $v_{28}$  to  $v_{32}$  account for a delay that summarize the processing steps of the mRNA by a linear chain of reactions [\(MacDonald,](#page-94-13) [1976\)](#page-94-13) with common rate constant CISRNADelay and SOCS3RNADelay, respectively. The ODE system, see Eq. [2,](#page-12-2) determining the time evolution of the dynamical variables is composed out of the rate equations, see Eq. [4,](#page-12-3) by:

<span id="page-18-0"></span>

The volume factors vol cyt = 0.4 pl and vol nuc = 0.275 pl account for transitions between different compartments and are determined experimentally. The species npSTAT5, CISnRNA1–5 and SOCS3nRNA1–5 are located in the nuclear compartment, the remaining species in the cytoplasmatic compartment. For the species initial concentrations, see Eq. [3,](#page-12-2)

<span id="page-18-1"></span>

- $[SHP1](0) = \text{init\_SHP1}$  (75)  $[\text{STAT5}](0) = \text{init}\_\text{STAT5}$  (76)
	- (77)

was assumed. The initial concentrations of the remaining species was assumed to be zero.

**Parameter transformations** According to Eq. [8–](#page-13-2)[11,](#page-14-1) the ODE system of Eq. [13](#page-17-1) – [76](#page-18-1) is modified by the following parameter transformations:



Model calibration To generate the complete model output the ODE system has to be evaluated for 24 different experimental conditions that will be explained in the next sections in detail. The model parameters consist of 29 kinetic parameter involved in the rate equations; 3 non-zero initial concentrations for the species EpoR JAK2, SHP1 and STAT5; 86 offset and scaling parameters to account for measurement background and unknown scales of immunoblotting and qRT-PCR measurements respectively; 12 parameters representing the magnitude of the measurement noise for each measurement technique and, in case of immunoblotting, for each detection antibody utilized. The parameters were estimated by minimizing the objective function  $-2 \log(L)$ , see Eq. [6,](#page-13-3) by applying the MATLAB implementation (lsqnonlin) of the trust-region method [\(Coleman and Li,](#page-93-12) [1996\)](#page-93-12) with user supplied derivatives. For the calculation of the derivatives the sensitivity equations were simultaneously solved together with the original ODE system describing the dynamics by applying the CVODES solver [\(Hindmarsh](#page-93-13)  $et al., 2005$ ). To improve convergence of the estimation and due to the positive definite nature of the parameters such as rate constants, initial concentrations, concentration offsets and scales, and noise magnitudes, the parameters were estimated in logarithmic parameter space. In order to allow for normally distributed measurement noise the likelihood was evaluated in logarithmic concentration space [\(Kreutz](#page-94-6) et al., [2007\)](#page-94-6). The mainly multiplicative nature of the measurement noise transforms to an additive noise. To ensure for global parameter estimates, multiple optimization runs along the profile likelihood were performed. In total 115 free parameters are estimated from the experimental data, yielding a value of the objective function  $-2 \log(L) = -478.46$  for a total of 541 data points. The estimated parameter values are given in Section [2.4.](#page-49-0) For each parameter, with one exception, a flat prior distribution with hard bounds according to the values given in Sec. [2.4](#page-49-0) was assumed. For the initial concentration of the EpoR JAK2 complex, described by the parameter init EpoRJAK2, a prior distribution of  $N(0.6, 0.2^2)$  was assumed [\(Landschulz](#page-94-2) *et al.*, [1989\)](#page-94-2).

### <span id="page-20-0"></span>2.3 Mapping the model dynamics to the experimental data

In order to describe the quantities accessible by experiments, the dynamics of the species concentrations determined by the ODE system of Eq.  $49 - 73$  $49 - 73$  $49 - 73$  are mapped to model outputs. The model outputs can then be compared to the experimental data using the objective function of Eq. [6.](#page-13-3)

#### <span id="page-20-1"></span>2.3.1 Experiment: Long time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells (CFU-E Long)

Treatment: Epo 5 units/ml (1.25e-7 units/cell)

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-20-2"></span>
$$
pJAK2.au = log_{10}(offset-pJAK2-long ++ 2 \cdot scale-pJAK2-long \cdot ([EpoRpJAK2] + [p1EpoRpJAK2] + [p1EpoRpJAK2] + [p2EpoRpJAK2])initEpoRJAK2
$$
\n
$$
pEpoR.au = log_{10}(offset-pEpoR-long ++ 16 \cdot scale-pEpoR-long \cdot ([p12EpoRpJAK2] + [p1EpoRpJAK2] + [p2EpoRpJAK2])initEpoRJAK2
$$
\n
$$
CIS.au = log_{10}(offset\_CISLong + \frac{[CIS] \cdot scale\_CISLong}{CISEqc \cdot CISRNAEqc \cdot init\_STAT5})
$$
\n
$$
SOCS3.au = log_{10}(offset\_SOCS3Long + \frac{[SOCS3] \cdot scale\_SOCS3Long}{SOCS3Eqc \cdot SOCS3RNAEqc \cdot init\_STAT5})
$$
\n
$$
tSTAT5.au = log_{10}(select\_STTAT5Long \cdot ([STAT5] + [pSTAT5])pSTAT5.au = log_{10}(offset-pSTAT5Long + \frac{[pSTAT5] \cdot scale=pSTAT5Long}{init\_STAT5})
$$
\n(95)

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-20-3"></span>
$$
\sigma[\text{pJAK2.au}] = \text{sd.JAK2EpoR.au} \tag{97}
$$
\n
$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{98}
$$
\n
$$
\sigma[\text{CIS.au}] = \text{sd.CIS.au} \tag{99}
$$
\n
$$
\sigma[\text{SOCS3.au}] = \text{sd.SOCS3.au} \tag{100}
$$
\n
$$
\sigma[\text{tSTAT5.au}] = \text{sd.STAT5.au} \tag{101}
$$

$$
\sigma[\text{pSTAT5.au}] = \text{sd\_STAT5.au} \tag{102}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{103}
$$

$$
CISoe = 0 \tag{104}
$$

$$
SOCS3oe = 0
$$
\n
$$
SHP1oe = 0
$$
\n
$$
(105)
$$
\n
$$
(106)
$$

$$
epo\_level = 1.2 \cdot 10^{-07} \tag{107}
$$

The agreement of the model outputs and the experimental data, given in Tab. [S3,](#page-21-0) yields a value of the objective function  $-2\log(L) = -54.19$  for 73 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S11.](#page-21-1)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S52.](#page-83-1)

<span id="page-21-0"></span>

	pJAK2_au	$pEpoR_au$	$CIS_au$	SOCS3_au	$tSTAT5$ <sub>-au</sub>	pSTAT5_au
time [min]	conc. [au]	conc. [au]	conc.  au	conc. $ au $	conc.  au	conc. $ au $
0.000000	0.011066	0.004412	0.017007	NaN	0.580253	0.001090
5.000000	1.000000	0.700809	0.038819	NaN	1.000000	1.000000
10.000000	0.745856	1.000000	0.021344	0.109721	0.685016	0.907589
20.000000	0.745856	0.606469	0.037086	0.281462	0.564744	0.560146
40.000000	0.262055	0.190846	0.128730	NaN	NaN	NaN
60.000000	0.043105	0.100787	0.282493	0.568877	0.859841	0.390882
80.000000	0.163199	0.110949	0.820831	NaN	0.680306	0.168972
100.000000	0.092608	0.069846	0.922259	NaN	0.747586	0.163322
120.000000	0.025276	0.283019	NaN	1.000000	0.874022	0.193886
140.000000	0.134138	0.134038	0.773095	NaN	0.640665	0.121703
160.000000	0.135856	0.239555	0.751558	NaN	0.702241	0.126579
180.000000	0.056232	0.050682	0.951127	1.000000	0.841180	0.291617
220.000000	0.059243	0.040019	0.911415	NaN	0.574873	0.085725
240.000000	0.102116	0.085332	1.000000	0.969746	0.722746	0.275913

Table S3: Experimental data for the experiment CFU-E Long

<span id="page-21-1"></span>

Figure S11: Agreement of model outputs and experimental data for the experiment CFU-E Long The displayed model outputs (solid lines) are defined by Eq. [92](#page-20-2) – [96.](#page-20-2) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [97](#page-20-3) – [102.](#page-20-3)

## <span id="page-22-0"></span>2.3.2 Experiment: Absolute concentrations of proteins in CFU-E cells (CFU-E Concentrations)

Treatment: Epo 5 units/ml (1.25e-7 units/cell)

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-22-2"></span>
$$
STAT5_{-}abs = \log_{10}([STAT5]) \tag{108}
$$

$$
SHP1.abs = \log_{10}([SHP1] + [SHP1Act]) \tag{109}
$$

$$
CIS. abs = log10([CIS])
$$
\n(110)

$$
SOCS3\_abs = log_{10}([SOCS3])
$$
\n
$$
100 \cdot [SCTAT5]
$$
\n(111)

$$
pSTAT5B_{\text{.}rel} = \text{offset}_{\text{.}}pSTAT5_{\text{.}}\text{conc} + \frac{100 \cdot \text{pSTAT3}}{[STAT5] + [pSTAT5]} \tag{112}
$$

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-22-3"></span>
$$
\sigma[\text{STAT5}.\text{abs}] = \text{sd}.\text{STAT5}.\text{abs} \tag{113}
$$

$$
\sigma[\text{SHP1}_\text{abs}] = \text{sd}_\text{SHP1}_\text{abs} \tag{114}
$$

$$
\sigma[\text{CIS}.\text{abs}] = \text{sd}\text{CIS}.\text{abs} \tag{115}
$$
\n
$$
\sigma[\text{SOCS3}.\text{abs}] = \text{sd}\text{SOCS3}.\text{abs} \tag{116}
$$

$$
\sigma[\text{pSTAT5B-rel}] = \text{sd\_pSTAT5-rel} \tag{117}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\begin{array}{rcl}\n\text{ActD} & = & 0 \\
\text{CISoe} & = & 0\n\end{array}\n\tag{118}
$$

$$
SOCS3oe = 0
$$
\n
$$
(120)
$$

$$
\text{SHP1oe} = 0 \tag{121}
$$

$$
epo\_level = 1.2 \cdot 10^{-07} \tag{122}
$$

<span id="page-22-1"></span>The agreement of the model outputs and the experimental data, given in Tab. [S4,](#page-22-1) yields a value of the objective function  $-2 \log(L) = 13.22$  for 20 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S12.](#page-23-0)

	STAT5_abs	SHP1_abs	CIS <sub>abs</sub>	SOCS3 <sub>-abs</sub>	pSTAT5B_rel
time [min]	conc. $[nM]$	conc. $[nM]$	[nM] conc.	conc. $[nM]$	conc.  rel
0.000000	62.683305	28.434776	$\rm NaN$	NaN	0.508000
0.000000	117.228683	30.863729	NaN	NaN	0.684588
0.000000	69.034077	21.750069	NaN	NaN	1.147136
0.000000	NaN	NaN	NaN	NaN	1.160932
10.000000	NaN	NaN	NaN	NaN	78.020000
10.000000	NaN	NaN	NaN	NaN	68.447433
10.000000	NaN	NaN	NaN	NaN	74.054191
10.000000	NaN	NaN	NaN	NaN	71.551395
120,000000	NaN	NaN	29.061795	12.354824	NaN
120,000000	NaN	NaN	26.097567	7.255641	NaN
120.000000	$\rm NaN$	NaN	19.652393	11.542239	NaN

Table S4: Experimental data for the experiment CFU-E Concentrations

<span id="page-23-0"></span>

Figure S12: Agreement of model outputs and experimental data for the experiment CFU-E Concentrations The displayed model outputs (solid lines) are defined by Eq.  $108 - 112$  $108 - 112$ . The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [113](#page-22-3) – [117.](#page-22-3)

#### <span id="page-24-0"></span>2.3.3 Experiment: Time-course of CIS and SOCS3 mRNA expression (CFU-E RNA)

Treatment: Epo 5 units/ml (1.25e-7 units/cell)

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

$$
SOCSSRNA_foldA = log_{10}(\frac{[SOCSSRNA] \cdot scale\_SOCSSRNA_foldA}{SOCSSRNAEqc \cdot init\_STAT5} + 1)
$$
\n(123)

<span id="page-24-1"></span>
$$
SOCS3RNA_{1}foldB = \log_{10}(\frac{[SOCS3RNA] \cdot scale_{2}OCS3RNA_{1}foldB}{SOCS3RNAEqc \cdot init_{2}TAT5} + 1)
$$
\n(124)

$$
SOCS3RNA_foldC = log_{10}(\frac{[SOCS3RNA] \cdot scale\_SOCS3RNA_foldC}{SOCS3RNAEqc \cdot init\_STAT5} + 1)
$$
\n(125)

CISRNA\_foldA = 
$$
\log_{10}(\frac{[CISRNA] \cdot scale_CISRNA_foldA}{CISRNAEqc \cdot init_STAT5} + 1)
$$
 (126)

CISRNA-foldB = 
$$
log_{10}(\frac{[CISRNA] \cdot scale\_CISRNA-foldB}{CISRNAEqc \cdot init\_STAT5} + 1)
$$
 (127)

$$
CISRNA_foldC = log_{10}(\frac{[CISRNA] \cdot scale_CISRNA_foldC}{CISRNAEqc \cdot init_STAT5} + 1)
$$
\n(128)

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-24-2"></span>

$\sigma$ [SOCS3RNA-fold]	= sd.RNA-fold	(129)
$\sigma$ [SOCS3RNA-fold]	= sd.RNA-fold	(130)
$\sigma$ [SOCS3RNA-fold]	= sd.RNA-fold	(131)
$\sigma$ [CISRNA-fold]	= sd.RNA-fold	(132)
$\sigma$ [CISRNA-fold]	= sd.RNA-fold	(133)
$\sigma$ [CISRNA-fold]	= sd.RNA-fold	(134)

$$
(\mathcal{M}_\mathcal{A},\mathcal
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{135}
$$

$$
CISoe = 0 \t(136)
$$

$$
SOCS3oe = 0
$$
\n
$$
SHP1oe = 0
$$
\n
$$
(137)
$$
\n
$$
(138)
$$

$$
epo\_level = 1.2 \cdot 10^{-07}
$$
 (139)

The agreement of the model outputs and the experimental data, given in Tab. [S5,](#page-25-0) yields a value of the objective function  $-2\log(L) = -58.03$  for 34 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S13.](#page-26-0)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S52.](#page-83-1)

<span id="page-25-0"></span>



<span id="page-26-0"></span>

Figure S13: Agreement of model outputs and experimental data for the experiment CFU-E RNA The time course experiments of mature CIS and SOCS3 mRNA expression was performed independently three time and the different replicates are shown. The displayed model outputs (solid lines) are defined by Eq. [123](#page-24-1) – [128.](#page-24-1) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [129](#page-24-2) – [134.](#page-24-2)

#### <span id="page-27-0"></span>2.3.4 Experiment: Time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells with Actinomycin D treatment (CFU-E ActD)

Treatment: Epo 5 units/ml  $(1.25e-7 \text{ units/cell}) + \text{Act}D 1 \text{ mug/ml}$ 

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-27-1"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-27-2"></span>
$$
\sigma[\text{pJAK2.au}] = \text{sd.JAK2EpoR.au} \tag{145}
$$

$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{146}
$$
\n
$$
\sigma[\text{tSTAT5.au}] = \text{sd.STAT5.au} \tag{147}
$$

$$
\sigma[\text{pSTAT5.au}] = \text{sd\_STAT5.au} \tag{148}
$$

 $\sigma$ [CIS\_au] = sd\_CIS\_au (149)

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0,1 \tag{150}
$$

$$
CISoe = 0 \tag{151}
$$

$$
SOCS3oe = 0
$$
\n
$$
SHP1oe = 0
$$
\n
$$
(152)
$$
\n
$$
(153)
$$

$$
epo\_level = 1.2 \cdot 10^{-07}
$$
 (154)

The agreement of the model outputs and the experimental data, given in Tab. [S6,](#page-28-0) yields a value of the objective function  $-2\log(L) = -92.61$  for 90 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S14.](#page-29-0)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S53.](#page-84-0)

<span id="page-28-0"></span>

	ActD	pJAK2_au	$pEpoR_au$	$tSTAT5$ <sub>-au</sub>	pSTAT5_au	$CIS_au$
time   min		conc. $ {\rm au} $	$ {\rm au} $ conc.	au  conc.	$ {\rm au} $ conc.	$ {\rm au} $ conc.
0.000000	$\overline{0}$	0.018583	0.033087	0.832432	0.001913	0.013228
5.000000	$\overline{0}$	1.000000	0.864151	0.897297	0.860465	0.009361
10.000000	0	0.749594	0.841509	0.859459	0.944186	0.008917
30.000000	$\Omega$	0.234697	0.126962	0.670270	0.479070	0.027977
60.000000	$\Omega$	0.081389	0.125487	0.735135	0.170543	0.307400
90.000000	$\overline{0}$	0.045459	0.053000	0.583784	0.081384	0.557875
120.000000	$\overline{0}$	0.036175	0.158660	0.886486	0.184496	0.836812
150.000000	0	0.068541	0.099906	0.681081	0.131005	0.859583
180.000000	0	0.074649	0.079128	0.471351	0.115660	1.000000
0.000000		0.022248	0.011298	0.902703	0.001822	0.013949
5.000000	1	0.594490	1.000000	1.000000	0.959690	0.007951
10.000000	1	0.888415	0.788679	0.924324	1.000000	0.010046
30.000000	1	0.212550	0.328313	0.583784	0.438760	0.020216
60.000000	1	0.124319	0.123555	0.794595	0.322481	0.006040
90.000000		0.175585	0.177253	0.772973	0.331783	0.007545
120.000000		0.098708	0.192845	0.756757	0.421705	0.004163
150.000000		0.163742	0.170830	0.745946	0.462016	0.012579
180.000000		0.141824	0.135834	0.514595	0.336434	0.007964

Table S6: Experimental data for the experiment CFU-E ActD

<span id="page-29-0"></span>

Figure S14: Agreement of model outputs and experimental data for the experiment CFU-E ActD The displayed model outputs (solid lines) are defined by Eq.  $141 - 144$  $141 - 144$ . The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq.  $145 - 149$  $145 - 149$ .

### <span id="page-30-0"></span>2.3.5 Experiment: Time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells densely sampled (CFU-E Fine)

Treatment: Epo 50 units/ml (1.25e-6 units/cell)

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-30-1"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-30-2"></span> $\sigma$ [pJAK2\_au] = sd\_JAK2EpoR\_au (157)

$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{158}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:



The agreement of the model outputs and the experimental data, given in Tab. [S7,](#page-31-0) yields a value of the objective function  $-2 \log(L) = -6.72$  for 60 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S15.](#page-32-0)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S54.](#page-85-0)

<span id="page-31-0"></span>

	$pEpoR_au$
au	conc.  au
0.021170	0.309735
0.026163	0.026991
0.196809	0.210914
0.379053	0.423965
0.413121	0.911504
0.368683	0.683624
0.491135	0.998525
0.906730	0.768711
1.000000	1.000000
0.799582	0.523721
0.760638	0.417404
0.653261	0.906609
0.828014	0.199115
0.603720	0.513451
0.478723	0.339233
0.240796	0.776046
0.400709	0.951327
0.752344	0.283131
0.352837	0.166667
0.228122	0.217117
0.186170	0.120501
0.388270	0.143482
0.172816	0.084532
0.077106	0.080112
0.163934	0.097754
0.237340	0.121588
0.126846	0.069500
0.063812	0.148168
0.113429	0.157817
0.222362	0.104460
	pJAK2_au conc.

Table S7: Experimental data for the experiment CFU-E Fine

<span id="page-32-0"></span>

Figure S15: Agreement of model outputs and experimental data for the experiment CFU-E Fine The displayed model outputs (solid lines) are defined by Eq. [156](#page-30-1) – [156.](#page-30-1) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [157](#page-30-2) – [158.](#page-30-2)

#### <span id="page-33-0"></span>2.3.6 Experiment: Time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells over-expressing CIS (CFU-E CISoe)

Treatment: Epo 5 units/ml  $(1.25e-7 \text{ units/cell}) + \text{CIS over-expression}$ 

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-33-1"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

<span id="page-33-2"></span>
$$
\sigma[\text{pJAK2.au}] = \text{sd.JAK2EpoR.au} \tag{169}
$$
\n
$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{170}
$$
\n
$$
\sigma[\text{CIS.au}] = \text{sd.CIS.au} \tag{171}
$$
\n
$$
\tag{172}
$$

$$
\sigma[\text{SOCS3.au}] = \text{sd\_SOCS3.au} \tag{172}
$$
\n
$$
\sigma[\text{d} \text{DSTAT5} \text{aul}] = \text{sd\_STAT5} \text{ au} \tag{173}
$$

$$
o[p_{\text{D1110-au}}] = 3a_{\text{D1110-au}}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{174}
$$

$$
\text{CI} = 0,1 \tag{175}
$$
\n
$$
\text{SOC} = 0 \tag{176}
$$

$$
SUCS 30e = 0
$$
\n
$$
SHP10e = 0
$$
\n
$$
(177)
$$

$$
epo\_level = 1.2 \cdot 10^{-07} \tag{178}
$$

The agreement of the model outputs and the experimental data, given in Tab. [S8,](#page-34-0) yields a value of the objective function  $-2 \log(L) = -49.42$  for 40 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S16.](#page-34-1)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S55.](#page-86-0)

<span id="page-34-0"></span>

	CISoe	pJAK2_au	$pEpoR_au$	$CIS_{-}au$	SOCS3 <sub>-au</sub>	pSTAT5_au
time [min]		laul conc.	$ {\rm au} $ conc.			
0.000000	$\Omega$	0.026772	0.023098	0.028805	0.275751	0.070604
10.000000	$\Omega$	1.000000	1.000000	0.026064	0.351145	1.000000
60.000000	$\Omega$	0.248910	0.226178	0.101835	0.921120	0.711207
120,000000	0	0.224042	0.240681	0.075319	1.000000	0.633621
0.000000		0.017810	0.032018	1.000000	0.325700	0.062931
10.000000		0.835979	0.227847	0.702752	0.192880	0.352586
60.000000		0.307672	0.186534	0.744954	0.554707	0.411207
120.000000		0.268365	0.205215	0.660550	0.516478	0.534483

Table S8: Experimental data for the experiment CFU-E CISoe

<span id="page-34-1"></span>

Figure S16: Agreement of model outputs and experimental data for the experiment CFU-E CISoe The displayed model outputs (solid lines) are defined by Eq. [165](#page-33-1) – [168.](#page-33-1) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [169](#page-33-2) – [173.](#page-33-2)

### <span id="page-35-0"></span>2.3.7 Experiment: Time-course of EpoR phosphorylation dynamics in CFU-E cells overexpressing CIS (CFU-E CISoe)

Treatment: Epo 5 units/ml  $(1.25e-7 \text{ units/cell}) + \text{CIS over-expression}$ 

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

pEpoR.au = 
$$
log_{10}
$$
(offset\_pEpoR.cisoe\_pepor +  
+  $\frac{16 \cdot scale_pEpoR.cisoe_pepor \cdot ([p12EpoRpJAK2] + [p1EpoRpJAK2] + [p2EpoRpJAK2])}{init_EpoRJAK2}$ ) (179)

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-4) is given by:

$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{180}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{181}
$$

$$
CISoe = 0,1 \tag{182}
$$

$$
SOCS3oe = 0
$$
\n
$$
SHP1oe = 0
$$
\n
$$
(183)
$$
\n
$$
(184)
$$

$$
= 1.2 \cdot 10^{-07}
$$
 (185)  
(185)

The agreement of the model outputs and the experimental data, given in Tab. [S9,](#page-35-1) yields a value of the objective function  $-2\log(L) = -10.12$  for 10 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S17.](#page-36-0)

<span id="page-35-1"></span>The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S55.](#page-86-0)

	CISoe	$pEpoR_au$
time [min]		conc. [au]
0.000000	0	0.128892
5.000000	$\mathbf{\Omega}$	1.000000
10.000000	0	0.884430
60.000000	0	0.314607
120.000000	0	0.211878
0.000000	1	0.115088
5.000000	1	0.329053
10.000000	1	0.266453
60.000000	1	0.231140
120.000000		0.176565

Table S9: Experimental data for the experiment CFUE CISoe pEpoR


Figure S17: Agreement of model outputs and experimental data for the experiment CFU-E pEpoR CISoe The displayed model outputs (solid lines) are defined by Eq. [180.](#page-35-0) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [180.](#page-35-1)

# 2.3.8 Experiment: Time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells over-expressing SOCS3 (CFU-E SOCS3oe)

Treatment: Epo 5 units/ml  $(1.25e-7 \text{ units/cell}) + \text{SOCS3 over-expression}$ 

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-37-0"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

<span id="page-37-1"></span>

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:



$$
\text{CISoe} = 0 \tag{197}
$$
\n
$$
\text{SOCS3oe} = 0.1 \tag{198}
$$

$$
SHP1oe = 0
$$
\n
$$
(199)
$$
\n
$$
(199)
$$

$$
epo\_level = 1.2 \cdot 10^{-07}
$$
 (200)

The agreement of the model outputs and the experimental data, given in Tab. [S10,](#page-38-0) yields a value of the objective function  $-2 \log(L) = -21.39$  for 40 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S18.](#page-38-1)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S56.](#page-87-0)

<span id="page-38-0"></span>

	SOCS <sub>3</sub> oe	$pJAK2$ -au	$pEpoR_au$	$CIS_{-}au$	SOCS3_au	pSTAT5 <sub>-au</sub>
time [min]		$ {\rm au} $ conc.				
0.000000	0	0.074825	0.046290	0.179174	0.027811	0.005504
10.000000	0	1.000000	1.000000	0.136152	0.023494	1.000000
60.000000	0	0.237762	0.363958	1.000000	0.083936	0.342302
120,000000	$\Omega$	0.265734	0.367491	0.969697	0.101606	0.333333
0.000000		0.086247	0.063251	0.069424	1.000000	0.014742
10.000000		0.447552	0.897527	0.078250	0.886546	0.028251
60.000000		0.060606	0.137809	0.078962	0.802209	0.007425
120.000000		0.044056	0.124382	0.056576	0.678715	0.001610

Table S10: Experimental data for the experiment CFU-E SOCS3oe

<span id="page-38-1"></span>

Figure S18: Agreement of model outputs and experimental data for the experiment CFU-E SOCS3oe The displayed model outputs (solid lines) are defined by Eq. [187](#page-37-0) – [190.](#page-37-0) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [191](#page-37-1) – [195.](#page-37-1)

# 2.3.9 Experiment: Time-course of JAK2-STAT5 phosphorylation dynamics in CFU-E cells over-expressing SHP1 (CFU-E SHP1oe)

Treatment: Epo 5 units/ml (1.25e-7 units/cell) + SHP1 3.5-fold over-expression

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-39-0"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

<span id="page-39-1"></span>

 $\sigma$ [CIS\_au] = sd\_CIS\_au (209)  $\sigma$ [tSTAT5 au] = sd STAT5 au (210)

$$
\sigma[\text{ts}|\text{A15}.\text{au}] = \text{sd}.\text{st1415}.\text{au}
$$
\n
$$
\sigma[\text{bs}|\text{A15}.\text{au}] = \text{sd}.\text{st1415}.\text{au}
$$
\n
$$
\sigma[\text{cs}|\text{A15}].\text{au}
$$
\n
$$
(211)
$$

$$
\sigma
$$
[EHP1 au] = sd SHPI au (212)

$$
U[\text{with } \text{L} \text{ and } \text{in } \text{S} \text{ and } \text{in } \text{L} \text{ and } \text{in } \text{
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{213}
$$

$$
\text{CISoe} = 0 \tag{214}
$$
\n
$$
\text{SOCS3oe} = 0 \tag{215}
$$

$$
SUCS 30e = 0
$$
\n
$$
SHP1oe = 0,1
$$
\n(216)

$$
epo\_level = 1.2 \cdot 10^{-07} \tag{217}
$$

The agreement of the model outputs and the experimental data, given in Tab. [S11,](#page-40-0) yields a value of the objective function  $-2 \log(L) = -99.69$  for 60 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S19.](#page-40-1)

The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S57.](#page-88-0)

<span id="page-40-0"></span>

	SHP <sub>1</sub> oe	pJAK2_au	$pEpoR_au$	$CIS_au$	$tSTAT5$ <sub>-au</sub>	pSTAT5_au	$t$ SHP1_au
time [min]		$ {\rm au} $ conc.	$ {\rm au} $ conc.	$ {\rm au} $ conc.	conc.  au	$ {\rm au} $ conc.	au conc.
0.000000	$\Omega$	0.019283	0.035222	0.071794	0.495370	0.061201	0.166346
5.000000	0	1.000000	1.000000	0.062287	0.583333	0.760736	0.183654
10.000000	0	0.991870	0.517241	0.072862	0.595370	1.000000	0.285577
30,000000	$\Omega$	0.513008	0.317734	0.134231	0.576852	0.474847	0.300962
60.000000	$\Omega$	0.306504	0.144089	1.000000	0.425926	0.342331	0.201923
0.000000		0.037398	0.024631	0.051126	1.000000	0.050071	0.812500
5.000000		0.983740	0.423645	0.043077	0.688889	0.473006	0.870192
10.000000		0.926829	0.435961	0.046109	0.753704	0.580982	1.000000
30,000000		0.337398	0.160837	0.157737	0.781481	0.420245	0.913462
60.000000		0.121138	0.075369	0.748988	0.623148	0.236196	0.815385

Table S11: Experimental data for the experiment CFU-E SHP1oe

<span id="page-40-1"></span>

Figure S19: Agreement of model outputs and experimental data for the experiment CFU-E SHP1oe The displayed model outputs (solid lines) are defined by Eq. [202](#page-39-0) – [206.](#page-39-0) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [207](#page-39-1) – [212.](#page-39-1)

# 2.3.10 Experiment: Dose response of JAK2 and EpoR phosphorylation in CFU-E cells 7 minutes after Epo stimulation (CFU-E DoseResp 7min)

Treatment: Epo dose response at 7 minutes

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-41-1"></span>
$$
pJAK2.au = log10(offset-pJAK2-dr7 ++ 2 \cdot scale-pJAK2-dr7 \cdot ([EpoRpJAK2] + [p1EpoRpJAK2] + [p1EpoRpJAK2] + [p2EpoRpJAK2])initEpoRJAK2
$$
  
\n
$$
pEpoR.au = log10(offset-pEpoR-dr7 ++ 16 \cdot scale-pEpoR-dr7 \cdot ([p12EpoRpJAK2] + [p1EpoRpJAK2] + [p2EpoRpJAK2])init-EpoRJAK2
$$
 (219)

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

<span id="page-41-2"></span>
$$
\sigma[\text{pJAK2.au}] = \text{sd.JAK2EpoR.au} \tag{220}
$$

$$
\sigma[\text{pEpoR.au}] = \text{sd.JAK2EpoR.au} \tag{221}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:



The agreement of the model outputs and the experimental data, given in Tab. [S12,](#page-41-0) yields a value of the objective function  $-2 \log(L) = -31.22$  for 30 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S20.](#page-42-0)

<span id="page-41-0"></span>The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S58.](#page-89-0)

	epo <sub>-level</sub>	pJAK2_au	$pEpoR_au$
time [min]		conc. [au]	conc. [au]
7.000000	0.1	0.040590	0.052184
7.000000	0.1	0.045387	0.040024
7.000000	0.1	0.080443	0.036836
7.000000	1	0.154244	0.131051
7.000000	1	0.165314	0.270366
7.000000	1	0.225461	0.179457
7.000000	10	0.453875	0.599764
7.000000	10	0.590406	0.806375
7.000000	10	0.730627	0.335301
7.000000	100	0.564576	0.659976
7.000000	100	0.797048	0.785124
7.000000	100	1.000000	0.695396
7.000000	1000	0.501845	1.000000
7.000000	1000	0.760148	0.671783
7.000000	1000	0.826568	0.916175

Table S12: Experimental data for the experiment CFU-E DoseResp 7min

<span id="page-42-0"></span>

Figure S20: Agreement of model outputs and experimental data for the experiment CFU-E DoseResp 7min The displayed model outputs (solid lines) are defined by Eq. [219](#page-41-1) – [219.](#page-41-1) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [220](#page-41-2) – [221.](#page-41-2)

# 2.3.11 Experiment: Dose response of JAK2 and EpoR phosphorylation in CFU-E cells 30 minutes after Epo stimulation (CFU-E DoseResp 30min)

Treatment: Epo dose response at 30 minutes

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-43-1"></span>

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

$$
\sigma[\text{pJAK2.au}] = \text{sd.JAK2EpoR.au}
$$
\n(229)

<span id="page-43-2"></span> $\sigma[\text{pEpoR.au}] = \text{sd} \text{JAK2EpoR.au}$  (230)

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:



The agreement of the model outputs and the experimental data, given in Tab. [S13,](#page-43-0) yields a value of the objective function  $-2 \log(L) = 22.26$  for 36 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S21.](#page-44-0)

<span id="page-43-0"></span>The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S59.](#page-90-0)

	epo_level	pJAK2_au	$pEpoR_au$
time  min		conc.  au	conc.  au
30.000000	0.1	0.090671	0.121262
30.000000	0.1	0.069679	0.103322
30.000000	0.1	0.108746	0.246512
30.000000	1	0.381924	0.342193
30.000000	1	0.235277	0.481728
30.000000	1	0.228280	0.634551
30.000000	5	0.769679	0.657807
30.000000	5	0.667638	0.697674
30.000000	5	0.673469	0.740864
30.000000	10	0.725948	0.607973
30.000000	10	0.650146	0.657807
30.000000	10	0.626822	1.000000
30.000000	50	0.827988	0.744186
30.000000	50	0.758017	0.471761
30.000000	50	0.548105	0.787375
30.000000	100	1.000000	0.717608
30.000000	100	0.787172	0.687708
30.000000	100	0.755102	0.717608

Table S13: Experimental data for the experiment CFU-E DoseResp 30min

<span id="page-44-0"></span>



The displayed model outputs (solid lines) are defined by Eq.  $228 - 228$  $228 - 228$ . The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [229](#page-43-2) – [230.](#page-43-2)

# 2.3.12 Experiment: Dose response of STAT5 phosphorylation in CFU-E cells 10 minutes after Epo stimulation (CFU-E DoseResp pSTAT5 10min)

Treatment: Epo dose response at 10 minutes

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

<span id="page-45-1"></span>
$$
pSTAT5_a u = \frac{[pSTAT5] \cdot scale_pSTAT5_a dr10}{init_sTTAT5}
$$
 (236)

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

<span id="page-45-2"></span>
$$
\sigma[\text{pSTAT5.au}] = \text{sd\_STAT5.au} \tag{237}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\text{ActD} = 0 \tag{238}
$$

$$
\text{CI} \text{Soe} = 0 \tag{239}
$$
\n
$$
\text{SOCS} \text{Soe} = 0 \tag{240}
$$

$$
SHP1oe = 0 \tag{241}
$$

$$
epo\_level = 2.5 \cdot 10^{-09}, 1.2 \cdot 10^{-08}, 2.5 \cdot 10^{-08}, 1.2 \cdot 10^{-07}, 2.5 \cdot 10^{-07}, 2.5 \cdot 10^{-06}
$$
\n(242)

The agreement of the model outputs and the experimental data, given in Tab. [S14,](#page-45-0) yields a value of the objective function  $-2 \log(L) = -9.46$  for 18 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S22.](#page-46-0)

<span id="page-45-0"></span>The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S60.](#page-91-0)

	epo_level	pSTAT5_au
time  min		conc.  au
10.000000	0.1	0.009338
10.000000	0.1	0.004178
10.000000	0.1	0.009596
10.000000	0.3162	NaN
10.000000	0.5	0.204456
10.000000	0.5	0.063670
10.000000	0.5	0.130130
10.000000	0.7	NaN
10.000000	1	0.393185
10.000000	1	0.193971
10.000000	1	0.275229
10.000000	1.58	NaN
10.000000	3.16	NaN
10.000000	5	0.647444
10.000000	5	0.596330
10.000000	5	0.711664
10.000000	7.07	NaN
10.000000	10	0.824377
10.000000	10	0.726081
10.000000	10	1.000000
10.000000	31.62	NaN
10.000000	100	0.845347
10.000000	100	0.699869
10.000000	100	0.968545

Table S14: Experimental data for the experiment CFU-E DoseResp pSTAT5 10min

<span id="page-46-0"></span>

Figure S22: Agreement of model outputs and experimental data for the experiment CFU-E DoseResp pSTAT5 10min

The displayed model outputs (solid lines) are defined by Eq. [236](#page-45-1) – [236.](#page-45-1) The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [237](#page-45-2) – [237.](#page-45-2)

# 2.3.13 Experiment: Dose response of CIS expression in CFU-E cells 90 minutes after Epo stimulation (CFU-E DoseResp CIS 90min)

Treatment: Epo dose response at 90 minutes

The model outputs, see Eq. [5,](#page-13-0) available in this data set are given by:

$$
CIS_au1 = \frac{[CIS] \cdot scale1.CIS_dr90}{CISEqc} \tag{243}
$$

<span id="page-47-1"></span>
$$
CIS_au2 = \frac{[CIS] \cdot scale2_CIS_dr90}{CISEqc} \tag{244}
$$

The error model that describes the measurement noise for each model output, see Eq. [7,](#page-13-1) is given by:

<span id="page-47-2"></span>
$$
\sigma[\text{CIS}_\text{a} \text{au1}] = \text{sd}_\text{c} \text{CIS}_\text{a} \text{au} \tag{245}
$$

$$
\sigma[\text{CIS}_- \text{au2}] = \text{sd}_-\text{CIS}_- \text{au} \tag{246}
$$

To evaluate the ODE system of Eq.  $49 - 76$  $49 - 76$  $49 - 76$  for the conditions in this experiment, the following parameters are set to:

$$
\begin{array}{rcl}\n\text{ActD} & = & 0 \\
\text{CISoe} & = & 0\n\end{array}\n\tag{247}
$$

$$
\text{CIsoe} = 0 \tag{248}
$$
\n
$$
\text{SOCS3oe} = 0 \tag{249}
$$

$$
SHP1oe = 0 \t(250)
$$

$$
epo\_level = 2.5 \cdot 10^{-09}, 2.5 \cdot 10^{-08}, 1.2 \cdot 10^{-07}, 2.5 \cdot 10^{-07}, 2.5 \cdot 10^{-06}
$$
\n(251)

The agreement of the model outputs and the experimental data, given in Tab. [S15,](#page-47-0) yields a value of the objective function  $-2 \log(L) = -38.39$  for 30 data points in this data set. The agreement of model outputs and experimental data is shown in Fig. [S23.](#page-48-0)

<span id="page-47-0"></span>The trajectories of the dynamical variables and external inputs that correspond to the experimental conditions in this experiment are shown, together with their prediction confidence intervals, later in Fig. [S61.](#page-92-0)

	epo_level	$CIS$ -au1	$CIS$ au $2$
time $ \text{min} $		conc. [au]	au  conc.
90.000000	0.1	0.041597	0.036280
90.000000	0.1	0.037763	0.045195
90.000000	0.1	0.038971	0.041019
90.000000	1	0.513332	0.557756
90.000000	1	0.472805	0.403881
90.000000	1	0.452635	0.541982
90.000000	5	0.792155	0.713065
90.000000	5	0.970147	0.604428
90.000000	5	0.906889	0.519957
90.000000	10	0.970911	0.949133
90.000000	10	0.999971	0.586600
90.000000	10	0.853607	0.873716
90.000000	100	0.729914	1.000000
90.000000	100	0.886000	0.850285
90.000000	100	1.000000	0.912522

Table S15: Experimental data for the experiment CFU-E DoseResp CIS 90min

<span id="page-48-0"></span>



The displayed model outputs (solid lines) are defined by Eq.  $243 - 244$  $243 - 244$ . The error model that describes the measurement noise for each model output is indicated by shades around the model outputs and is given by Eq. [245](#page-47-2) – [246.](#page-47-2)

# 2.4 Estimated model parameters

The model parameters were estimated by maximum likelihood estimation applying the MATLAB lsqnonlin algorithm in logarithmic parameter space. In Tab.  $S16 - S19$  $S16 - S19$  $S16 - S19$  the estimated parameter values are given. The parameter name prefix init\_ indicates the initial value of a dynamic variable. The parameter name prefix offset indicates an offset of the experimental data. The parameter name prefix scale indicates a scaling factor of the experimental data. The parameter name prefix sd indicates the magnitude of the measurement noise for a specific measurement. Parameters highlighted in red color indicate that their estimated value is close to its bounds, see in Sec. [2.5](#page-53-0) for reasons.

<span id="page-49-0"></span>

### Table S16: Estimated values of the dynamic parameters

 $\hat{\theta}$  indicates the estimated value of the parameter.  $\theta_{min}$  and  $\theta_{max}$  indicated the allowed upper and lower bounds for the parameter.  $10^{\hat{\theta}}$  indicates the value of the parameter in normal space.



Table S17: Estimated values of the offset parameters<br> $\hat{\theta}$  indicates the estimated value of the parameter.  $\theta_{min}$  and  $\theta_{max}$  indicated the allowed upper and lower bounds for the parameter.  $10^{\hat{\theta}}$  indicates the value of the parameter in normal space.



Table S18: Estimated values of the scaling parameters<br> $\hat{\theta}$  indicates the estimated value of the parameter.  $\theta_{min}$  and  $\theta_{max}$  indicated the allowed upper and lower bounds for the parameter.  $10^{\hat{\theta}}$  indicates the value of the parameter in normal space.

<span id="page-52-0"></span>

	name	$\theta_{min}$	Â	$\theta_{max}$	$10^{\theta}$	unit
104	sd_CIS_abs	$-3$	$-1.1447$	$+3$	$+7.17 \cdot 10^{-02}$	nM
105	sd_CIS_au	$-3$	$-0.8728$	$+3$	$+1.34 \cdot 10^{-01}$	a.u.
106	sd_JAK2EpoR_au	$-3$	$-0.7171$	$+3$	$+1.92 \cdot 10^{-01}$	a.u.
107	sd_RNA_fold	-3	$-0.9868$	$+3$	$+1.03 \cdot 10^{-01}$	
108	sd_SHP1_abs	$-3$	$-1.1877$	$+3$	$+6.49 \cdot 10^{-02}$	nM
109	sd_SHP1_au	-3	$-1.1110$	$+3$	$+7.74 \cdot 10^{-02}$	a.u.
110	sd_SOCS3_abs	$-3$	$-0.9884$	$+3$	$+1.03 \cdot 10^{-01}$	nM
111	sd_SOCS3_au	$-3$	$-1.1172$	$+3$	$+7.63 \cdot 10^{-02}$	a.u.
112	sd_STAT5 <sub>-abs</sub>	$-3$	$-0.9226$	$+3$	$+1.20\cdot10^{-01}$	nM
113	sd_STAT5_au	$-3$	$-0.9083$	$+3$	$+1.24 \cdot 10^{-01}$	a.u.
114	sd_pSTAT5_rel	-3	$+0.4094$	$+3$	$+2.57 \cdot 10^{+00}$	
115	sd_pSTAT5_socs3oe	$-3$	$-0.2412$	$+3$	$+5.74 \cdot 10^{-01}$	a.u.

Table S19: Estimated values of the measurement noise parameters<br> $\hat{\theta}$  indicates the estimated value of the parameter.  $\theta_{min}$  and  $\theta_{max}$  indicated the allowed upper and lower bounds for the parameter.  $10^{\hat{\theta}}$  indicates the value of the parameter in normal space.

# <span id="page-53-0"></span>2.5 Identifiability and confidence intervals of the estimated model parameters

In order to evaluate the identifiability of the model parameters and to assess confidence intervals the profile likelihood was evaluated. Instructions how to interpret the result are given in [Raue](#page-94-0) *et al.* [\(2009\)](#page-94-0). We restrict the further analysis to the parameters that influence the model dynamics and hence are relevant for the biological questions that are addressed. The remaining parameters such as offset and scaling parameters necessary to describe the experimental setup do not influence the dynamics directly and can be treated as nuisance parameters. Please note that using the profile likelihood the indirect influence of the nuisance parameters on the estimation uncertainty of the dynamical parameters is still considered.

The mean calculation time of the profile likelihood per parameter was  $9.1 \pm 6.6$  minutes on a standard desktop computer (2.66 GHz Intel Core i5 with 8 GB RAM). An overview of the profile likelihood is displayed in Fig. [S24.](#page-53-1) In Fig. [S25](#page-55-0) – [S51](#page-81-0) the profile likelihood of each parameter is shown in more detail. Also the functional relations to the other parameters are displayed. Finally, in Tab. [S20,](#page-82-0) 95% point-wise confidence intervals for the estimated parameter values derived by the profile likelihood are given.

<span id="page-53-1"></span>

Figure S24: Overview of the profile likelihood of the model parameters

The solide lines indicate the profile likelihood. The broken line indicates the threshold to assess point-wise 95% confidence intervals. The asterisk indicate the optimal parameter values.

The profile likelihood for parameters CISInh, CISRNATurn, SOCS3RNADelay and SOCS3RNATurn reveal two local optima in the likelihood landscape with larger value of the objective function. With respect to the 95% confidence level these local optima are compliant with the experimental data as well and are considered for the calculation of the uncertainty of the model predictions.

Given the experimental data available the parameters CISRNATurn, EpoCISInh, JAK2EpoRDea-SHP1, SHP1ActEpoR, SOCS3RNADelay and SOCS3Turn are practically non-identifiable. For each of these parameters only a lower respectively upper confidence bound is finite. This means that the model is undetermined in the sense that:

- The turnover of CIS RNA described by the parameter CISRNATurn can be arbitrarily fast, see more detailed in Fig. [S29.](#page-59-0) This is a consequence of the limited experimental resolution of the processes at the RNA level.
- The inhibition strength of receptor phosphorylation by the EpoRJAK2 CIS complex described by the parameter EpoCISInh can be arbitrarily large, see more detailed in Fig. [S32.](#page-62-0) Please note that this parameter only effects the CIS overexpression setting.
- Increased deactivation of JAK2EpoR by SHP1 can be compensated by decreased activation of SHP1 by JAK2EpoR. Parameters JAK2EpoRDeaSHP1 and SHP1ActEpoR are anti-correlated, see the functional relations both in Fig. [S35](#page-65-0) and Fig. [S36](#page-66-0) and remember the logarithmic parameter scale. This is a consequence of missing information about the relative level of SHP1 activation.
- The delay utilized in SOCS3 RNA transcription described by the parameter SOCS3RNADelay can be arbitrarily small, see more detailed in Fig. [S42.](#page-72-0) This is a consequence of the limited experimental resolution of the processes at the RNA level.
- The turnover of SOCS3 protein described by the parameter SOCS3Turn can be arbitrarily fast, see more detailed in Fig. [S44.](#page-74-0) This is a consequence of the limited experimental resolution of the processes at the RNA level.

These observations are all consequences of uncertainties in the estimation of the parameters and are due to incomplete experimental data. They are not to be confused with biological robustness against perturbations. The remaining uncertainties in the parameter estimates were translated to the predicted model dynamics, see in Sec. [2.6.](#page-83-0) This allows to assess the precision of the model predictions realistically.

<span id="page-55-0"></span>











Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of CISInh are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:09:38.83.





<span id="page-59-0"></span>











<span id="page-62-0"></span>











<span id="page-65-0"></span>

Figure S35: Profile likelihood of parameter JAK2EpoRDeaSHP1

Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of JAK2EpoRDeaSHP1 are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:07:00.61.

<span id="page-66-0"></span>



Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of SHP1ActEpoR are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:15:15.65.





Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of SHP1Dea are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:03:53.24.









Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of SOCS3Eqc are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:07:16.20.














## Figure S43: Profile likelihood of parameter SOCS3RNATurn

Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of SOCS3RNATurn are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:28:01.92.













Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of STAT5ActJAK2 are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:04:01.25.





Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of STAT5Exp are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:09:36.78.





Upper panel: The solide line indicates the profile likelihood. The broken line indicates the threshold to assess confidence intervals. The asterisk indicate the optimal parameter values. Lower panel: The functional relations to the other parameters along the profile likelihood of STAT5Imp are displayed. In the legend the top five parameters showing the strongest variations are given. The calculation time was 00:02:31.67.















Table S20: Confidence intervals for the estimated parameter values derived by the profile likelihood  $\hat{\theta}$  indicates the estimated optimal parameter value.  $\sigma^-$  and  $\sigma^+$  indicate 95% point-wise confidence intervals.

## 2.6 Confidence intervals of the predicted model dynamics

The remaining uncertainties in the parameter estimates are translated to confidence intervals of the model trajectories, see in Raue *[et al.](#page-94-0)* [\(2010\)](#page-94-0) for details. Therefore, the trajectories corresponding to all acceptable parameter values according to the profile likelihood are evaluated. The resulting upper and lower time point-wise confidence bands for each experimental setting are displayed in Fig. [S52](#page-83-0) – [S61](#page-92-0) for a 95% confidence level.

The dynamics of active SHP1 shows large confidence bands indicating that the relative amount of active and inactive SHP1 can not be determined well. This is a result of the corresponding practically nonidentifiable parameters JAK2EpoRDeaSHP1 and SHP1ActEpoR, see in Fig. [S35](#page-65-0) and Fig. [S36.](#page-66-0) Similarly, the absolute concentration amounts of npSTAT5 and the RNA species of CIS and SOCS3 show large variations. This due to the lack of absolute concentration measurements in the nuclear compartment or of a measurement of the ratio of cytoplasmatic to nuclear STAT5. Please not that the model predictions shown in Fig. 5 and Fig. 6 of the main text display the relative changes of npSTAT5 between different conditions. The relative changes of npSTAT5 is less affected by uncertainty and therefore allows for a reasonable biological interpretation.

<span id="page-83-0"></span>

Figure S52: Trajectories of the dynamical variables and external inputs for the experiment CFU-E Long The dynamical behaviour is determined by the ODE system, see Eq.  $49 - 73$  $49 - 73$ .



Figure S53: Trajectories of the dynamical variables and external inputs for the experiment CFU-E ActD The dynamical behaviour is determined by the ODE system, see Eq.  $49 - 73$  $49 - 73$ .



Figure S54: Trajectories of the dynamical variables and external inputs for the experiment CFU-E Fine The dynamical behaviour is determined by the ODE system, see Eq. [49](#page-18-0) – [73.](#page-18-0)



Figure S55: Trajectories of the dynamical variables and external inputs for the experiment CFU-E CISoe The dynamical behaviour is determined by the ODE system, see Eq.  $49 - 73$  $49 - 73$ .



Figure S56: Trajectories of the dynamical variables and external inputs for the experiment CFU-E SOCS3oe The dynamical behaviour is determined by the ODE system, see Eq.  $49 - 73$  $49 - 73$ .



Figure S57: Trajectories of the dynamical variables and external inputs for the experiment CFU-E SHP1oe The dynamical behaviour is determined by the ODE system, see Eq.  $49 - 73$  $49 - 73$ .



Figure S58: Trajectories of the dynamical variables and external inputs for the experiment CFU-E DoseResp 7min



Figure S59: Trajectories of the dynamical variables and external inputs for the experiment CFU-E DoseResp 30min



Figure S60: Trajectories of the dynamical variables and external inputs for the experiment CFU-E DoseResp pSTAT5 10min

<span id="page-92-0"></span>

Figure S61: Trajectories of the dynamical variables and external inputs for the experiment CFU-E DoseResp CIS 90min

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