# Understanding the Dynamics of Divorce Across Different Countries

## Modelling System Dynamics

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## ABSTRACT

Divorce remains a significant social phenomenon with far-reaching consequences for individuals, families, and society as a whole. Understanding the underlying dynamics of divorce is crucial for developing effective preventive methods and interventions. System dynamics models offer powerful tools for analyzing complex systems and identifying causal relationships that contribute to divorce. This paper presents a system dynamics model, that incorporates key education, economic, and societal factors, with a greater focus on the societal factors that contribute to divorce. The model is used to simulate various scenarios, and explore the potential impact of the above mentioned factors.

## 1 INTRODUCTION

Marriage, a cornerstone of human society, embodies the union of two individuals, promising lifelong companionship, shared experiences, and a foundation for family creation. However, despite its societal significance, marriage is not immune to challenges, and divorce remains a prevalent issue, impacting individuals, families, and society as a whole. Understanding the factors that contribute to divorce dynamics is crucial for informed decision-making, policy formulation, and interventions aimed at strengthening marital bonds.

System dynamics, a modeling approach that emphasizes the interconnectedness of cause-and-effect relationships, provides a powerful tool for analyzing complex social systems, such as marriage - divorce. This paper presents a system dynamics model developed to simulate divorce dynamics in the United States, capturing the intricate interplay of factors that influence marital stability.

The model's structure reflects our understanding of the key components that result in change in divorce rate. More specifically, we categorize the core factors that lead to divorce as Societal, Educational, and Economic. By doing so, we aim to simplify the structure of our model, in order to gain more intricate insights into the most prevalent factors that influence the divorce dynamics.

Our primary objective is to unravel the factors influencing changes in divorce rates and their variations across countries. A system dynamics model, incorporating differential equations, serves as our analytical tool. Data sourced from the OECD Family Database enriches the study, allowing for cross-country comparisons.

This research seeks to address the fundamental question: "What factors contribute to the change in divorce rates, and why does the divorce rate vary across different countries?" Through a systematic methodology, our findings aim to illuminate the intricate interplay of social, economic, and educational factors affecting marital stability. Additionally, we will explore policy interventions, which could minimize divorce across diverse countries.

## 2 BACKGROUND AND RELATED WORK

Several studies have explored the use of computational modeling to understand divorce dynamics. One notable example is a study by R. Duato et al[1], that proposed a social epidemiology model in which divorce is regarded as a social disorder propagated by divorced women through meetings with married women. The study found that divorce-related conversations often spread through word-of-mouth, and that this can have a significant impact on the likelihood of couples dissolving their marriages.

Another example of computational modeling of divorce is the work of Karagaac et al[2]. They developed a marriage and divorce model that incorporates societal factors such as gender inequality, educational attainment, and economic conditions. This model proved to be very useful and provided great inspiration in constructing our model.

These studies demonstrate the potential of computational modeling to provide insights into the complex factors that contribute to divorce. By simulating marriage and divorce dynamics, these models can help us understand how different educational, economic, and societal factors influence the likelihood of couples breaking up.

Societal factors, such as cultural norms, can influence the dynamics of relationships and the likelihood of marital dissolution[3]. Educational attainment has consistently emerged as a protective factor against divorce, with higher levels of education associated with lower divorce rates. This protective influence likely stems from the enhanced communication, conflict resolution skills, and critical thinking abilities fostered through education[3]. Economic factors, including unemployment, income inequality, and financial instability, can exacerbate stress, strain, and dissatisfaction within marriages, thereby increasing the risk of divorce[3]. Comprehending these intricate determinants of divorce, is important to derive data from and develop effective and accurate models.

## 3 DATA

The data used in this report is derived from multiple sources, but primarily from the Center of Disease Control and Prevention (CDC). More specifically, the data on divorce rates in the United States is obtained from the CDC. Pew Research Center provides detailed information on a range of demographic and economic characteristics, including marital status. The divorce rate is calculated as the number of divorces per 1,000 married individuals aged 18 and older. The divorce rate data covers the period from 2002 to 2018. The data is presented in a two-column table, with the first column indicating the year and the second column showing the divorce rate for that year.

Aside from the data mentioned above, we also made use of multiple sources, to procure data, to add to our variables, to have an accurate representation of our model. Such data was used for the following variables; Economic factor, Education, Delay for recovery, and Marriage rate. More specifically for the economic factor we used data referring to the GDP per capita, for the Educational factor we used data from multiple sources, same as for the societal factor.

Furthermore, we applied information from external sources to calculate the delays in our system as well as the initial values for our stocks that sum up to the 'Population' variable.

Lastly, it is important to note that through the data we procured, we created a CSV file to calibrate against with 2 columns; 'Year', and 'United States'.

## 4 SIMULATION MODEL

This section aims to cover all aspects regarding our simulation model, from its causal relationships to the inner workings of its equations and its dynamics.

### 4.1 Causal Loop Diagram

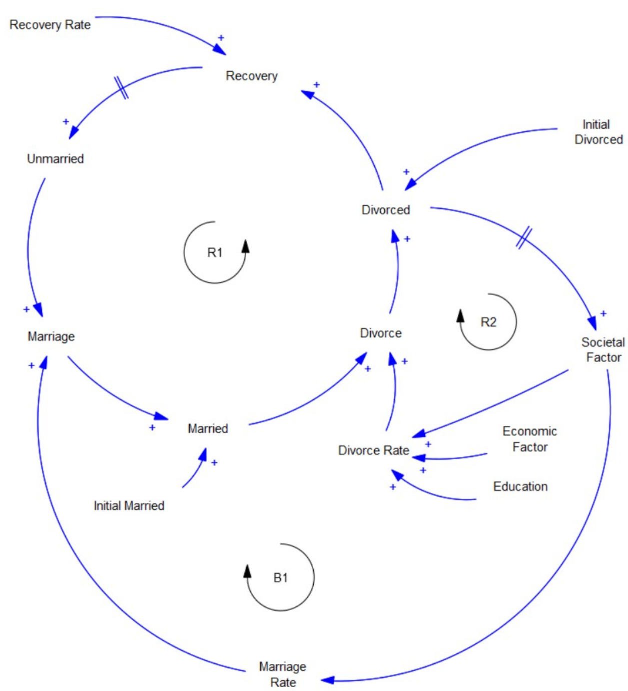


**Figure 1:** Causal Loop Diagram

### 4.2 Identifying the Feedback Loops

In the present system, we observe three feedback loops (Figure 1).

Firstly, the reinforcing feedback loop R1 ('Unmarried', 'Marriage', 'Married', 'Divorce', 'Divorced', 'Recovery'), illustrates the main mechanics of our model, which is the cycle of marriage, divorce, and potential sequential marriage. The more 'Unmarried', the higher the 'Marriage', and by extension the more 'Married'. Similarly, the more 'Married', the higher the amount of 'Divorce', which by extension increases the amount of 'Divorced'. The more 'Divorced', the higher the 'Recovery' variable, resulting in a reinforcing feedback loop. This feedback loop would cause uncontrolled growth in our system, but the growth is halted due to the variables ('Recovery', 'Marriage', and 'Divorce') being multiplied by variables that represent fractions.

Secondly, the reinforcing feedback loop R2 ('Divorced', 'Societal Factor', 'Divorce rate', 'Divorce'), refers to the ability of divorced individuals to impact the social perception of divorce. The more 'Divorced People', the bigger the 'Societal Factor' (accounting for a delay for word of mouth mechanism to take effect), the higher the 'Divorce rate', and by extension the 'Divorce' variable, which of course increases the number of the 'Divorced'.

Lastly, the balancing feedback loop B1 ('Divorced', 'Societal Factor', Marriage Rate', 'Marriage), refers to the ability of divorced individuals to negatively impact the marriage rate. More specifically, when 'Divorced' increases, 'Societal Factor' increases, which causes 'Marriage Rate' to decrease, and subsequently the 'Marriage' variable. The lower the value of 'Marriage', the lower the values of 'Married', 'Divorce', and 'Divorced', resulting in an overall balancing effect.

### 4.3 Dynamics Hypothesis

Originally in our system a 'warmup' period is expected, as we have initial values in our variables that will require a certain amount of time to represent real-world scenarios.

The divorce rate in the United States is likely to oscillate around a stable equilibrium, where periods of increasing divorce rates are interspersed by periods of decreasing divorce rates. This oscillation will be caused by a complex interplay of factors, including societal, educational, and economic factors. The delays present in the system will be the root cause of the oscillations. More specifically, the delay from 'Divorced' to 'Societal Factor', which represents the time it takes for society to adapt to the cultural perception/acceptance of divorce, will be a driving force in causing the divorce rate to oscillate.

The feedback loops will act as a self-reinforcing mechanism, such that changes in one variable will lead to changes in other variables, which will then lead to changes in the original variable. This can lead to periods of exponential growth or decay in the divorce rate. The strength of the feedback loops will depend on the specific values of the variables. For example, if societal norms are strong, they will tend to dampen the oscillation of the Divorce rate. Conversely, if Economic factors are weak, they will tend to amplify the oscillation of the Divorce rate.

It is important to note that the dynamic hypothesis for our system at this stage is based entirely on the CLD provided in Figure 1, and it constitutes a simplified representation of our system, where in reality the actual dynamics might be much more complex.

### 4.4 Stock and Flow Diagram

In order to turn our model into an SFD it is important to understand the components that drive change in the divorce rate. The divorce rate is influenced by a combination of societal, economic, and educational factors. It is calculated as a weighted sum of three factors, where the weights represent the relative importance of each factor, which is different between any two countries. The weights are initially equal, indicating that all three factors are equally important, serving as a starting point to perform the calibration based on the real data. These weights could vary between different societies or countries, leading to different divorce rates. It is important to note, that the societal factor (social acceptance of divorce) is calculated using a sigmoid function, which is an essential part of our system.

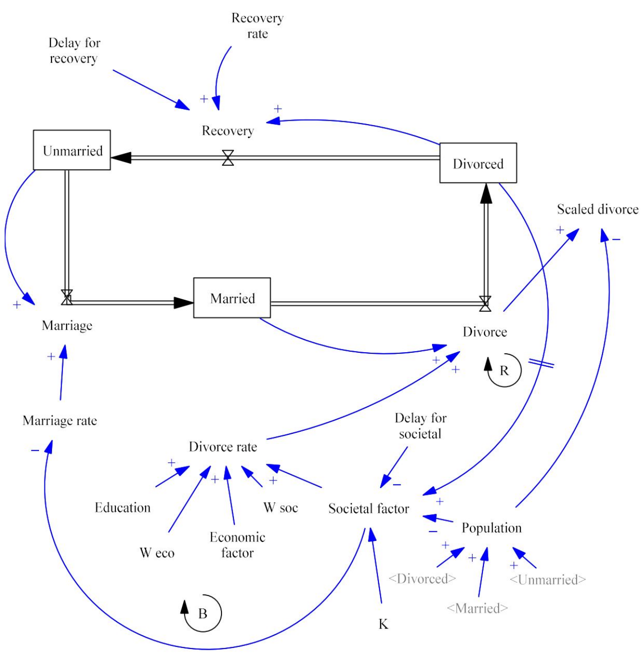


**Figure 2:** Stock and Flow Diagram

## 4.5 Components of our model

See Table 5 in appendix

# 5 CALIBRATION

To perform calibration on our model based on the United States data, it is essential to identify the unknown parameters. Some of them are unknown due to lack of reliable data, like the *Recovery rate* and the *Delay for societal*, while others represent and capture the information needed to answer our research question. The first is the $K$ parameter used in the sigmoid function of the *Societal factor*. The exact shape of the curve is determined by $K$, which controls its steepness. A higher value of $K$ will result in a steeper curve, meaning that societal acceptance will be more sensitive to changes in the number of divorced people.

The other values to calibrate, are the three weights that are used to calculate the *Divorce rate*. As mentioned in Section 4.5, the effects of the education level in a country, its GDP per capita, and the acceptance of divorces in the society, are weighty averaged to create the final rate. The sum of these three weights is equal to 1, so only two of them are implemented and calibrated in our model.

Thus, we perform calibration using Python and the pysd library, as suggested during this course, by following the minimisation of the mean squared error methodology in the pysd cookbook [1]. However, due to the dynamic nature of the model, we only consider

[1]https://pysd-cookbook.readthedocs.io/en/latest/analyses/fitting/Fitting_with_Optimization.html

| Variable Name | Value |
|---|---|
| $K$ | 2.9930 |
| W soc | 0.3634 |
| W eco | $1.1234 * 10^{-17}$ |
| Recovery rate | $2.0410 * 10^{-3}$ |
| Delay for societal | 0.4660 |

**Table 1:** Calibration results

data after a warm-up period of 10 years. Therefore, instead of starting in 1992, we start in 2002 and finish in 2018. This warm-up period allows the system to settle into its equilibrium state before we start collecting data for calibration. In other words, we want to ensure that the data we use for calibration reflects the steady-state behaviour of the model rather than the transient behaviour during the initial adjustment period.

Finally, in order to apply the constraint that the two weight's sum has to be equal or less than 1, we used the Sequential Least Squares Programming (SLSQP) method of the optimize.minize() function of the pysd library. The ranges of each parameter are identical to the one shown in Table 5, except for *Delay for societal*, which has a range of $[0, 10]$.

The resulting values, with MSE = 0.2128, can be seen in Table 1 and the comparison of the historical and simulated data after calibration in Figure 3.

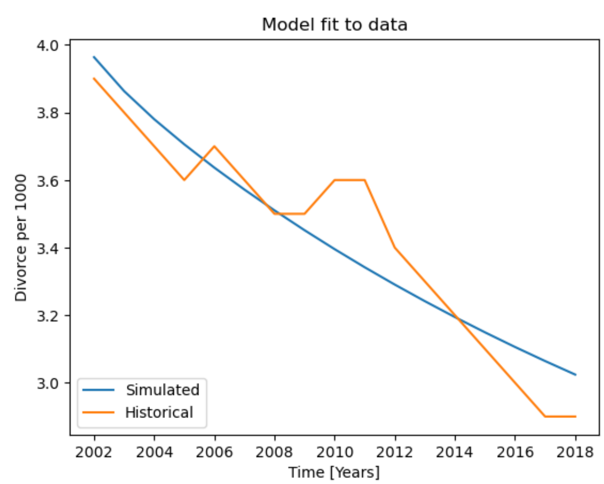


**Figure 3:** Comparison of historical and simulated data with calibration

# 6 SENSITIVITY ANALYSIS

## 6.1 Sensitivity Indices

In addition to the calibration of our model, we also conducted a sensitivity analysis to assess the impact of changes in the variables used in the calibration. This analysis provides insights into the robustness of our model and its sensitivity to variations in these parameters.

The first-order sensitivity results are presented in Table 3, and the total order results are in Table 2. A visual representation of these results can be found in Figure 4.

In the sensitivity analysis of our model, we observed that the parameters K and Recovery rate are the most influential when varied

| Parameter | ST | ST Range |
|---|---|---|
| W eco | 0.003195 | [0.001625, 0.004765] |
| W soc | 0.013437 | [0.006104, 0.020770] |
| K | 0.282145 | [0.205999, 0.358291] |
| Recovery rate | 0.697511 | [0.528082, 0.866940] |
| Delay for societal | 0.017451 | [0.005770, 0.029132] |

**Table 2:** Total-order sensitivity indices and their ranges

| Parameter | S1 | S1 Range |
|---|---|---|
| W eco | 0.002683 | [0.001113, 0.004253] |
| W soc | 0.030359 | [-0.005452, 0.066170] |
| K | 0.304157 | [0.182868, 0.425446] |
| Recovery rate | 0.588671 | [0.348373, 0.828969] |
| Delay for societal | -0.002908 | [-0.042671, 0.036855] |

**Table 3:** First-order Sensitivity Indices and their ranges

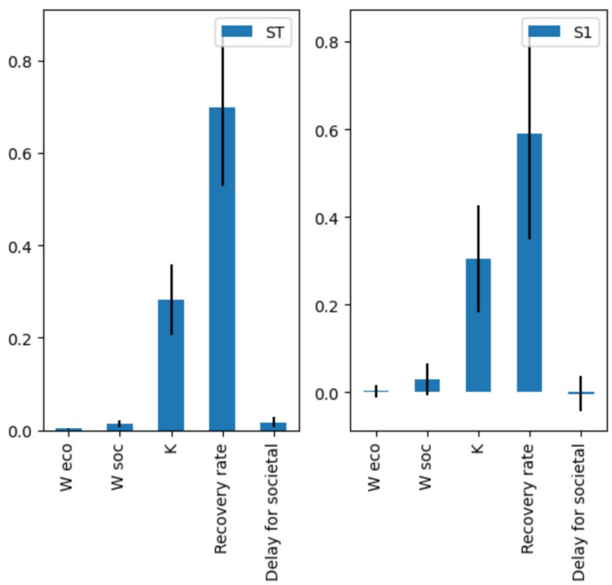


**Figure 4:** Tornado diagram for year 2018

independently, as indicated by their high first-order sensitivity indices (S1). This suggests that our model's output is highly sensitive to changes in these parameters.

Interestingly, the Recovery rate also has a high total-order sensitivity index (ST), indicating its significant contribution to the output variance when considering both its first-order effects and any higher-order interactions. This underscores the importance of the Recovery rate parameter in our model.

On the other hand, the parameters W eco and W soc have relatively low ST values, implying that they contribute less to the output variance. This suggests that our model is less sensitive to changes in these parameters.

The Delay for societal parameter presents an intriguing case with its negative S1 value, hinting at a potential inverse relationship with the output. However, the statistical significance of this result is questionable as the confidence interval includes zero.

Given these findings, it would be beneficial to perform another round of calibration focusing on the most sensitive parameters, namely K and Recovery rate. This targeted recalibration, detailed in Section 6.3, aims to enhance the model's precision by prioritizing adjustments to parameters with the highest sensitivities.

## 6.2 Understanding the most sensitive parameters influence on divorce

Our analysis of the model parameters revealed that 'K' and 'Recovery rate' are the most sensitive variables. A deeper investigation into the effects of changes in these high-sensitivity variables provided further insights into their impact on our model.

**The 'Recovery rate' Parameter**

The 'Recovery rate' parameter appears to have a significant impact on the 'Divorce'. The relationship between these two variables can be broken down into three distinct stages based on the 'Recovery rate': low (e.g., 0.05), moderate (e.g., 0.50), and high (e.g., 0.95).

(1) **Low Recovery Rate (e.g., 0.05):** At the beginning, the 'Divorce' is relatively low. However, a small increase in the 'Recovery rate' results in a significant jump in the 'Divorce'. This steep initial impact suggests that at lower 'Recovery rates', even minor improvements can lead to substantial changes in the 'Divorce'.
(2) **Moderate Recovery Rate (e.g., 0.50):** As the 'Recovery rate' continues to increase, the 'Divorce' also increases, but at a slower pace, reaching 4.13e+07 at a 'Recovery rate' of 0.50. The relationship between 'Recovery rate' and 'Divorce' appears to be less sensitive at this stage compared to lower 'Recovery rates'. This could be due to the fact that as recovery progresses, it becomes more challenging to make significant improvements, leading to a slower decrease in the 'Divorce'.
(3) **High Recovery Rate (e.g., 0.95):** At high 'Recovery rates', the 'Divorce' reaches its highest value. Further increases in the 'Recovery rate' show a diminishing impact on reducing 'Divorce', suggesting saturation or diminishing returns at higher 'Recovery rates'. This could be due to the fact that at advanced stages of recovery, most of the significant improvements have already been made, and further efforts result in only minor improvements in the 'Divorce'.

This suggests a positive correlation between 'Recovery rate' and 'Divorce', indicating that as the 'Recovery rate' increases, the 'Divorce' also increases. However, the rate of increase in 'Divorce' would depend on the current 'Recovery rate'. At lower 'Recovery rates', the 'Divorce' would increase more rapidly, while at higher 'Recovery rates', the 'Divorce' would increase more slowly.

**The 'K' Parameter**

The 'Divorce' value increases as 'K' increases from -4 to 1, suggesting a positive correlation between 'K' and 'Divorce'. This relationship can be described as an upward curve or positive slope. However, after 'K' reaches 1, the 'Divorce' value starts to decrease as 'K' continues to increase, indicating a negative correlation between 'K' and 'Divorce' or a downward curve.

Before K reaches 1, there is a significant increase in the 'Divorce', which could indicate a critical point or bifurcification where the system undergoes a qualitative change in behavior. Similarly, above 'K = 1', there is a significant decrease in the 'Divorce', mirroring the trend observed for negative values and suggesting symmetry

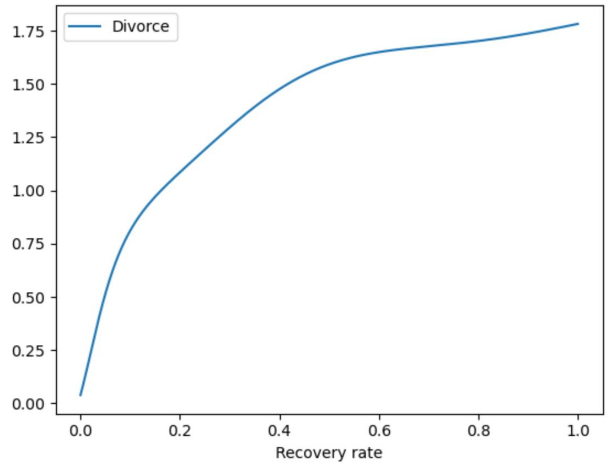


**Figure 5:** Recovery rate's Influence on Divorce

around 1. This symmetry could be indicative of a bifurcation point where the system transitions between different qualitative states, with the emergence of a new equilibrium point. After 'K=1', the 'Divorce' starts approaching 0 in the long run.

The minimum 'Divorce' occurs at the maximum 'K' value, and the maximum 'Divorce' is at 'K=1'. This suggests that the relationship between 'K' and 'Divorce' is non-linear, but rather, it appears to be more of a curve that reaches a peak at 'K=1'.

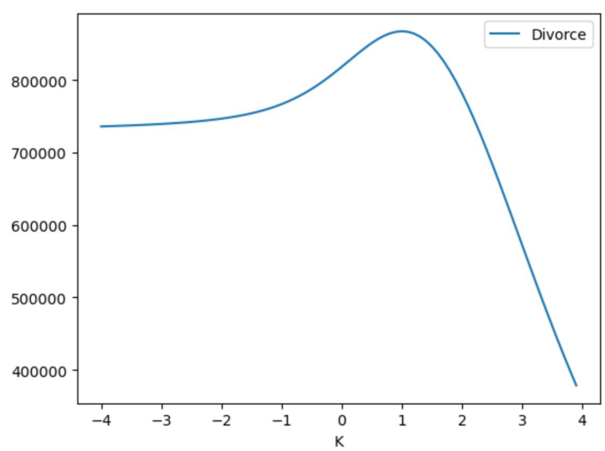


**Figure 6:** K's Impact on Divorce

## 6.3 Removing less sensitive parameters

As stated in Section 6.1, it could be beneficial to simplify the model by removing some parameters with low sensitivity. As the 'Economic factor' with each weight 'W eco' and 'Delay for societal' are the two least sensitive ones, they are removed from the model and calibration with the same methodology is performed once more. The results with RMSE = 0.2187 can be seen in Table 4, with the comparison of the historical and simulated Divorces per 1000 per year in Figure 7.

| Variable Name | Value |
|---|---|
| $K$ | 3.1090 |
| W soc | 0.5892 |
| Recovery rate | $2.021 * 10^{-3}$ |

**Table 4:** Calibration results after sensitivity analysis

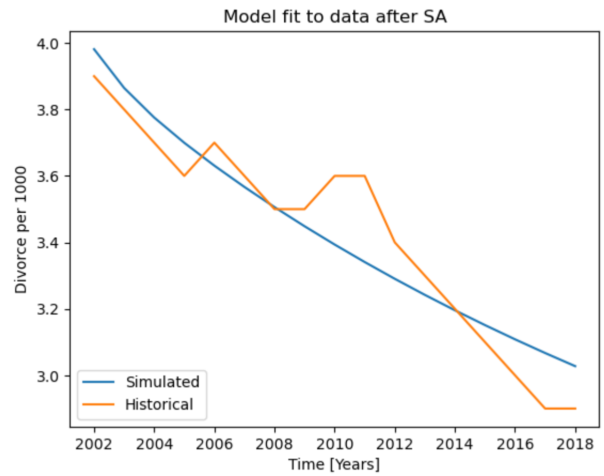


**Figure 7:** Comparison of historical and simulated data with calibration after SA

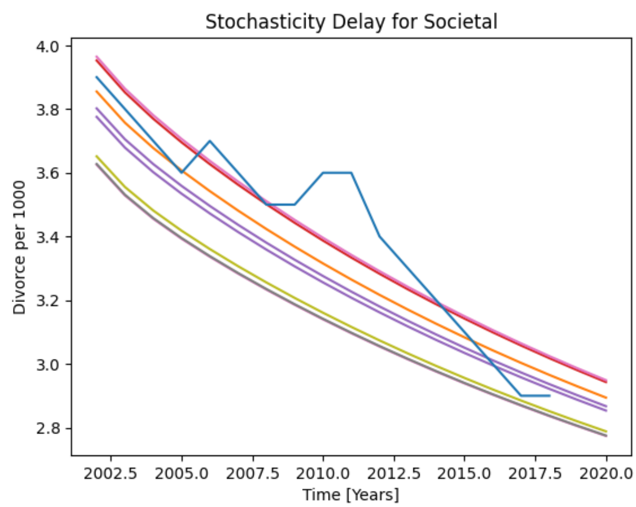


**Figure 8:** Stochasticity to a variable with low sensitivity

## 7 STOCHASTICITY

Our model introduces stochasticity in order to capture how robust it is with respect to the factors influencing divorce rates in the US from year 2002 to 2018. To observe the effect of stochasticity on a variable of low sensitivity in the model, the code runs the model multiple times by using different seed values for randomness. It then plots these runs alongside the historical data. The variable in question is 'Delay for societal', which was identified in the sensitivity analysis.

From Figure. 8, it can be observed that introducing stochasticity to "Delay for societal" results in minor variations in the projected divorce rates per 1000 people. Each coloured line represents a different seed value, showing slight deviations but generally following a similar trend. This suggests that even with the introduction of stochasticity, the variable does not significantly alter the overall trend of the model's output.

In other words, the model's predictions remain relatively stable despite the introduction of randomness, indicating that the factors with high sensitivity are likely the primary drivers of the divorce rate in the model. This aligns with the aim of the model, which is to identify the factors that influence the divorce rates in the US.

In order to plot the distribution of final outcomes, the code runs the model 100 times with different seed values for randomness and collects the final divorce rate for each run. These final outcomes are then plotted as a histogram to observe the distribution.

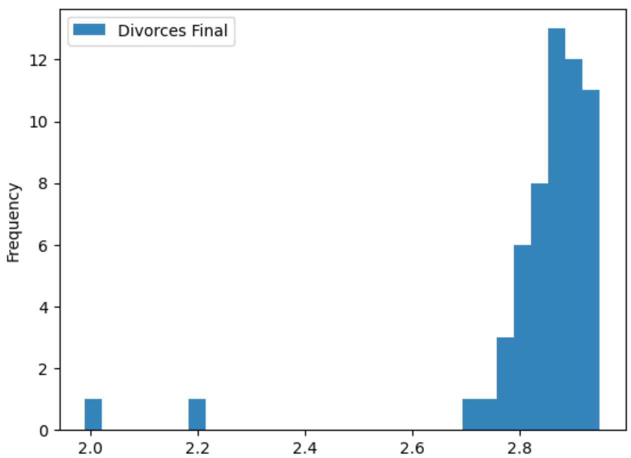


**Figure 9:** Histogram of distribution for divorces

From the histogram (Figure. 9), it can be observed that the distribution of final divorce outcomes is skewed towards higher values. The x-axis represents “Divorces Final” per 1000 people, ranging from around 2.0 to just below 3.0. The y-axis represents frequency, indicating how often each outcome occurs.

Most bars are concentrated towards higher “Divorces Final” values, indicating a skewness in that direction. The highest frequency of cases occurs when the number of divorces per 1000 people in the population is between approximately 2.6 and 2.8.

This suggests that, despite the introduction of stochasticity, the model more frequently predicts a higher divorce rate. However, the presence of the gap and the spread of the bars also indicate that there is a degree of variability in the outcomes, which is expected given the stochastic nature of the model.

## 8 POLICY INTERVENTION

Based on our sensitivity analysis, the most sensitive variables are the 'Recovery rate' and 'K'.

### 8.1 Introduction of Therapy to Recovery Rate

Policymakers can influence the rate at which couples recover from marital problems by making therapy more accessible. This can be done by offering free or low-cost therapy through community programs or by promoting public awareness campaigns about the benefits of therapy for marriages.

To implement this, we can add a multiplier effect that depends on the level of therapy in the real world. For example, if there is a lot of therapy available, the multiplier effect will be higher. We can call this new variable 'Therapy Effect'. It will range from 0 to 2, with an initial value of 1. A value of 1.1 means that there is a 10% increase in the rate at which couples recover from marital problems.

As shown in Figure 10, if the 'Therapy Effect' is 100%, the number of divorced people will decrease. However, this will only mean that there are more people who are not married, but the divorce rate will stay the same.

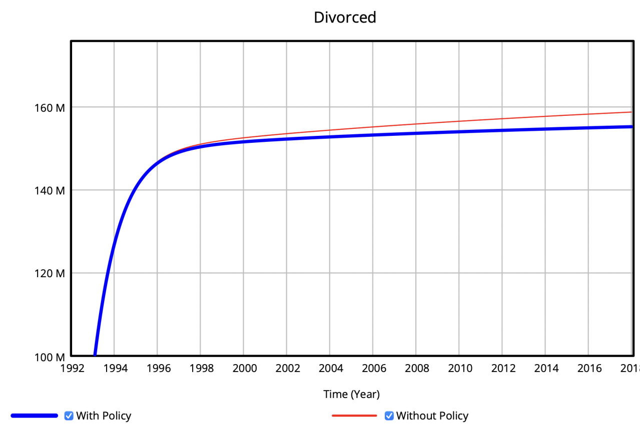


**Figure 10:** Introduction of Therapy to Recovery Rate

### 8.2 Introduction of Societal "Unacceptance" to Divorces

In order to decrease the divorce rate, policymakers or the government could discourage people from viewing divorce as a positive outcome and work to make it less socially acceptable.

To do that, they can introduce something that decreases the social acceptance towards divorces - K. In our model, we didn't frame an external variable. However, we noticed that by decreasing the K value from 2.993 (initial) to 2.6937 (10% decrease), the divorce rate will decrease in the long run.

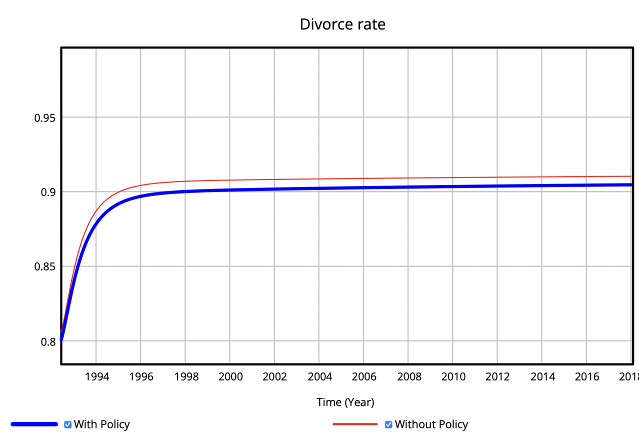


**Figure 11:** Effect of Negative Societal "Unacceptance" towards Divorce on Divorce Rates

As a positive side effect, lowering the acceptance of divorce also decreases the number of unmarried people. (Figure. 12)

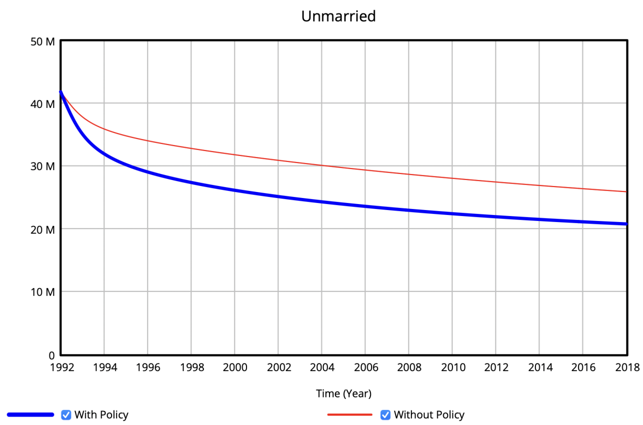


**Figure 12:** Effect of Negative Societal "Unacceptance" towards Divorce on Unmarried People

## 9 SYSTEM TRAPS

System traps are self-perpetuating patterns that can lead to undesirable outcomes, even when interventions are implemented. In the context of divorce, system traps can hinder efforts to promote marital stability and reduce the divorce rate.

Drift to low performance remains a prevalent trap in the system. While the policy interventions aimed at increasing the recovery rate and discouraging divorce have had some temporary positive effects, the overall divorce rate has not significantly decreased. This highlights the persistence of the reinforcing feedback loop that drives divorce rates, where the higher divorce rate normalizes divorce and encourages more people to get divorced.

The policy interventions have also inadvertently demonstrated the presence of policy resistance. While they have led to a decrease in the number of individuals remaining in the Divorced stock, they have not translated into a substantial increase in the number of married individuals. This suggests that the underlying societal norms and attitudes that normalize divorce remain firmly entrenched, making it difficult to effectively address its root causes through solely model parameter adjustments.

Furthermore, the policy interventions have introduced a new system trap: burden shifting. By making therapy more accessible and discouraging divorce, the interventions have shifted the burden of promoting marital stability onto individuals and organizations. This can lead to dependency on external incentives and moral hazard, where individuals may prioritize short-term gains over long-term relationship stability.

In the end, addressing system traps requires a comprehensive approach that goes beyond model parameter adjustments and focuses on addressing the root causes of divorce. This includes promoting healthy relationships through education and support, addressing socioeconomic factors that contribute to divorce, challenging negative societal attitudes, identifying and addressing the factors that contribute to the normalization of divorce, fostering consensus among stakeholders, ensuring effective implementation, engaging in ongoing monitoring and evaluation, shifting the focus from external incentives to intrinsic motivations for marriage, and promoting a culture that values and supports marriage.

## 10 CONCLUSION AND FUTURE WORK

This paper presents an innovative system dynamics model for simulating divorce dynamics in the United States. The model successfully captures the intricate interplay of factors that influence divorce, specifically; societal, educational, and economic factors.

The developed system dynamics model offers a valuable tool for understanding and analyzing divorce dynamics in the United States. Its capabilities for simulating various scenarios and evaluating the impact of different interventions make it a powerful tool for informing policy decisions and developing evidence-based strategies to strengthen marital bonds and reduce divorce rates.

The present model was conceptualized with the US in mind, but it can be expanded to other countries, or different domains. The model could be enriched by incorporating more granular sociodemographic factors, such as race, ethnicity, socioeconomic status, educational attainment, and religious background. This would allow for a more nuanced understanding of how these factors influence divorce rates and the effectiveness of interventions.

Furthermore, the model could be further developed into interactive decision support tools that enable policymakers and practitioners to simulate potential interventions and evaluate their likely impact on divorce rates. This would facilitate informed decision-making and the development of evidence-based strategies.

## REFERENCES


[1] R. Duato and Lucas Jódar. 2013. Mathematical modeling of the spread of divorce in Spain. *Mathematical and Computer Modelling* 57 (04 2013), 1732–1737. https://doi.org/10.1016/j.mcm.2011.11.020

[2] Berat Karaagac and Kolade Owolabi. 2023. A numerical investigation of marriage divorce model: Fractal fractional perspective. *Scientific African* 21 (08 2023), e01874. https://doi.org/10.1016/j.sciaf.2023.e01874

[3] Liyun Su, Changhai Liang, Xiaohe Yang, and Yang Liu. 2018. Influence Factors Analysis of Provincial Divorce Rate Spatial Distribution in China. *Discrete Dynamics in Nature and Society* 2018 (07 2018), 1–11. https://doi.org/10.1155/2018/6903845

# A APPENDIX

| Name | Type | Description | Unit | Equation | Range | Initial Values |
|---|---|---|---|---|---|---|
| Married | Stock | Number of individuals currently in a marital relationship. | People | $\frac{d\text{Married}}{dt} = \text{Recovery} - \text{Marriage}$ | $[0, \infty]$ | US: 113,295,000 |
| Divorced | Stock | Number of individuals who have undergone divorce. | People | $\frac{d\text{Divorced}}{dt} = \text{Divorce} - \text{Recovery}$ | $[0, \infty]$ | US: 30,170,000 |
| Unmarried | Stock | Number of individuals who are ready for remarriage post-divorce and those who have never been married. | People | $\frac{d\text{Unmarried}}{dt} = \text{Recovery} - \text{Marriage}$ | $[0, \infty]$ | US: 71,966,000 |
| Marriage | Flow | Number of marriages occurring per year. | People/year | $Marriage = \text{Marriage rate} \times Unmarried$ | $[0, \infty]$ | — |
| Marriage rate | Rate | The annual rate at which marriages occur. | — | $Marriagerate = 0.3 \times (1 - \text{Societal factor})$ | $[0, 1]$ | US: 0.3 |
| Recovery | Flow | Part of the divorced population ready for remarriage. | People/year | $Recovery = \text{DELAY1}(Divorced \times \text{Recovery rate}, \text{Delay for recovery})$ | $[0, \infty]$ | — |
| Delay for recovery | Time | Time it takes for the divorced population to become ready for another marriage. | Years | | $[0, \infty]$ | US: 3 |
| Recovery rate | Rate | The rate at which recovery (readiness for remarriage) occurs annually. | — | | $[0, 1]$ | US: 0.3 |
| Divorce | Flow | Number of divorces occurring per year. | People/year | $Divorce = \text{Divorce rate} \times Married$ | $[0, \infty]$ | — |
| Divorce rate | Rate | The annual rate at which divorces occur. | — | $Divorcerate = (1 - W_{\text{eco}} - W_{\text{soc}}) \times \text{Education} + W_{\text{eco}} \times \text{Economic factor} + W_{\text{soc}} \times \text{Societal factor}$ | $[0, 1]$ | US: 4.8 |
| Education | Constant | The education index of a country, measured by combining average adult years of schooling with expected years of schooling for individuals under the age of 25. | — | | $[0, 1]$ | US: 0.9 |
| $W_{\text{eco}}$ | Constant | Weight of the economic factor representing its importance for the divorce rate. | — | | $[0, 1]$ | US: 0.33 |
| Economic factor | Constant | Normalized Gross Domestic Product per capita. | GDP/person | | $[0, 1]$ | US: 0.53333 |
| $W_{\text{soc}}$ | Constant | Weight of the societal factor representing its importance for the divorce rate. | — | | $[0, 1]$ | US: 0.33 |
| Societal Factor | | Represents the societal acceptance of divorce in the country. | — | $\text{SMOOTH3}\left(\frac{1}{1+\exp(-K \times (\frac{\text{Divorced}}{\text{Population}}))}, \text{Delay for societal}\right)$ | $[0, 1]$ | — |
| $K$ | Constant | Determines the curve's steepness in the Sigmoid function, reflecting societal sensitivity to changes in the number of divorced individuals. | — | | $[-\infty, \infty]$ | US: 1 |
| Delay for societal | Constant | The average time it takes for societal acceptance of divorce in a country. | Years | | $[0, \infty]$ | US: 0.5 |

**Table 5:** Description of Variables in the Model