Emergent Inflation-Deflation Cycles from Minimalistic Wage Dynamics

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(Dated: May 19, 2025)

We introduce a minimal agent-based model to study the endogenous emergence of inflation-deflation cycles driven by micro-level wage dynamics. Companies in the model compete by adjusting wages based on short-term profitability, while workers probabilistically choose employers according to offered wages. Despite excluding typical macroeconomic phenomena such as debt and unemployment, the model generates cyclic but non-periodic dynamics characterized by inflationary expansions followed by deflationary downturns. These cycles arise from a simple feedback loop: wage increases enhance consumer purchasing power and demand, stimulating further wage growth until high wages and large company sizes increase systemic vulnerability. Stochastic fluctuations in transactions occasionally trigger sharp declines in aggregate demand, causing cascading wage cuts and bankruptcies. The resulting dynamics qualitatively match several empirical observations, including recession durations, inflation cycles, and asymmetric asset return distributions, though discrepancies remain in company-size distributions and company mortality rates. Our results illustrate how realistic macroeconomic instability can naturally arise from minimal, interaction-driven wage mechanisms alone.

I. INTRODUCTION

Understanding economic boom–bust cycles remains a central challenge in economics. Although business cycles have been recognised and studied extensively for centuries, their underlying mechanisms remain incompletely understood. Major economic recessions often spur new theoretical insights, exemplified by Fisher's debt-deflation theory after the Great Depression [1], and renewed criticisms of mainstream economic models, such as the dynamic stochastic general equilibrium (DSGE) framework, in the aftermath of the 2008 financial crisis [2]. A primary criticism directed at the more modern mainstream models is their high complexity, reliance on many adjustable parameters, and equilibrium assumptions that often fail to capture the dynamic instabilities of real-world markets.

Agent-based models provide a promising alternative that connects the micro-scale dynamics between agents with the macroscale behavior of a large system of numerous heterogeneous agents. Notable examples include the influential work of Lux and Marchesi [3], who showed how complex financial market dynamics emerge from simple trading rules and strategy shifts among traders.

In this paper, we extend the tradition of agent-based modeling by developing a deliberately simple framework that still captures core macroeconomic dynamics. The model consists of a simplified market with N companies generating revenue by selling consumer products and competing via wage adjustments. Economic activity is driven by W identical workers who choose employers probabilistically, favoring higher wages. At each discrete time step, workers spend their entire income on consumption, creating a direct and dynamic feedback loop between wage levels and consumer demand. As a result, the price of goods sold by companies is determined by the total wage payments made in the previous period.

To evaluate our simple model, we compare its emergent dynamics with several empirical benchmarks drawn from real-world data. Specifically, we examine macroeconomic indicators such as asset returns (benchmarked against S&P 500 companies [4]), company lifespans [5], the duration and frequency of recessions [6], the distribution of company sizes [7], and inflation trends [8]. Despite its minimal design, which omits unemployment and debt, the model qualitatively reproduces key empirical patterns, including recession dynamics and the inflation-deflation cycles.

II. MODEL

Our system consists of N companies and a fixed workforce of W workers. Each company k is characterized by three state variables: the number of workers w_k, the wage paid s_k, and the capital C_k. The system evolves in discrete time steps. At each step, a randomly selected set of companies performs transactions and updates their wage, and subsequently, workers relocate to new companies based on the wages offered. Companies whose capital falls below zero are declared bankrupt and replaced by new entrants. The transaction and worker relocation phases are illustrated in Fig. 1.

Companies and Transactions

At each time step, $N - N_{w=0}$ companies are selected uniformly at random with replacement to perform a transaction, where $N_{w=0}$ is the number of companies with zero workers. In a transaction, workers each produce one unit of output, which is sold to increase capital. Assuming workers spend everything they earned in

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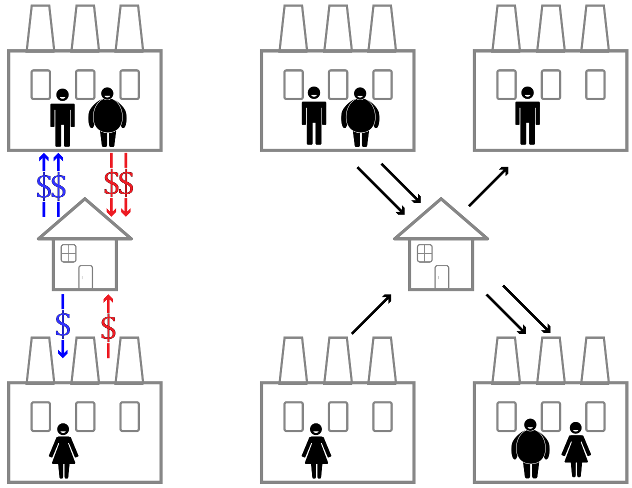

FIG. 1: Model with its two central phases. At any time, a company has a wage and an accumulated capital. The left panel shows that each company sells and pays wages proportionally to the number of workers. The right panel illustrates worker relocation , where each worker independently selects a new company. The choice depends on the company wage s_i to an exponent α that quantifies competition. The model includes rules for how wages and company capital change.

the previous time step, the average consumer will pay $\mu(t-1)/W$ per unit of output, where $\mu(t)$ is the sum of wages paid by all companies at time t. Simultaneously, the company pays each worker a wage of s_k. Thus, the net change in the company's capital is

$$\Delta C_k = w_k \frac{\mu(t-1)}{W} - w_k s_k(t-1), \tag{1}$$

where

$$\mu(t) = \sum_{\text{selected } i} w_i(t) s_i(t), \tag{2}$$

is the sum of wages paid by the companies selected to transact. From Eq. 1, we get that a company makes a profit $\Delta C_k > 0$ if $s_k < \mu/W$. Since μ is the weighted sum of wages, and high-wage companies attract more workers, μ/W is typically greater than the average wage.

Wage Update

Companies that made a profit ($\Delta C_k > 0$) or had zero workers ($w_k = 0$) now increase their wage by a fixed percentage $\Delta s/s$ of their current wage, and companies that lost capital ($\Delta C_k < 0$) reduced their wage by the same percentage but adjusted for the asymmetry between percentage gains and losses.

$$s_k \leftarrow \begin{cases} s_k\,(1 + \Delta s/s), & \text{if } \Delta C_k > 0 \text{ or } w_k = 0, \\ s_k \left(1 - \frac{\Delta s/s}{1+\Delta s/s}\right), & \text{if } \Delta C_k < 0. \end{cases} \tag{3}$$

Companies with no capital change and non-zero workers do not update their wage.

Worker Reallocation

After the wage updates, all W workers reselect their employer. The probability that a worker chooses company k is given by

$$P(\text{worker chooses } k) = \frac{s_k^\alpha}{\sum_{i=1}^{N} s_i^\alpha}, \tag{4}$$

where α is a parameter describing workers' sensitivity to wage differences.

Bankruptcies and Startups

A company is declared bankrupt if its capital falls below zero. Upon bankruptcy, the company is replaced by a startup company with $w_k = 0$ and $C_k = 0$. The startup chooses its initial wage by sampling from the set of companies that made a profit in the current time step, with an added small random perturbation in the range $[-m, m]$, after which a minimal wage $s_{\min}$ is enforced. If no companies made a profit, the new wage is instead chosen randomly among the top 50% companies that lost the least.

Summary of the Model Dynamics

For T time steps:

1. A set of $N - N_{w=0}$ companies is randomly selected to make transactions.

2. In each transaction, companies sell and pay wages proportionally to the number of workers.

3. Companies update their wage based on whether they have made a profit or loss.

4. All workers are redistributed among companies, with selection probabilities determined by wages.

5. Companies with negative capital are declared bankrupt and replaced by startups whose initial wage is chosen from the profitable companies, with a small noise perturbation.

In total, this gives us the following parameters: The system size parameters N and W are the number of companies and total workers, respectively; the time scale parameter $\Delta s/s$ which determines the magnitude of wage updates; the workers' sensitivity to wage differences α, the mutation magnitude m added to startup's chosen wage, and finally the minimum wage $s_{\min}$.

III. RESULTS

Our standard parameters are $W = 20N$ (motivated by [7]), $\Delta s/s = 0.1$, $s_{\min} = 0.1m$ and $m = 0.1$ (for $s_{\min}$'s dependence on m, see supplement **??**). We investigate two system sizes, $N = 100$ and $N = 1000$, and two worker wage sensitivities, $\alpha = 2$ and $\alpha = 4$. The more extreme $\alpha = 6$ and $\alpha = 8$ are investigated in the supplement **??**.

Predicted Market Dynamics

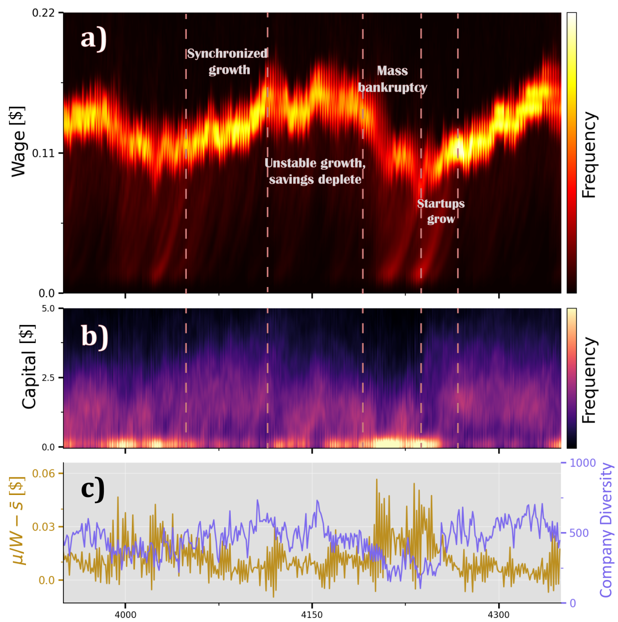

FIG. 2: a) illustrates the wages in the system over time, for standard parameters. The colour shows the number of companies with the corresponding wage. One sees a cyclic pattern, with relatively sharp declines where some companies have low wages and others still maintain high wages. The different epochs are marked with text explaining the main characteristics. b) shows the company capital of the different companies, highlighting the short period with very low capital concurrent with wage collapse (for visual clarity, we have not differentiated between the top 0.5% of values). c) shows the average company profit and company size diversity defined in Eq. (5).

The model economy exhibits robust cyclic but non-periodic dynamics, similar to the traditional business cycle (expansion, peak, recession, trough) [9, 10] and the recent publication [11]. Fig. 2 measures the market by the distribution of wages over time in a), the distribution of capital over time in b), and c) shows the average profit per worker, and the company diversity D defined as the reciprocal Simpson index [12]:

$$D = \frac{\left(\sum_j^N w_j\right)^2}{\sum_j^N w_j^2} \tag{5}$$

So, if one company employs all workers, $D = 1$. If workers are equally distributed among all companies, then $D = N$.

In Fig. 2, I have identified four epochs that the system goes through in a cycle:

- Starting just after a trough, companies exhibit coherent growth, with relatively high D and wages that are relatively narrowly distributed around a mean. The average profit per worker (estimated as $\mu/W - \bar{s}$, where $\bar{s} = \sum_k^N s_k/N$ is the mean company wage) is positive but declining.

- At its peak, wage growth is no longer sustainable, and companies suffer capital losses until a mass bankruptcy is triggered.

- Bankruptcies create space for startup companies with low wages and, as a result, the surviving companies attract a large fraction of the workers, reflected in few large and many small companies and thus a low D.

- With their low wages, startup companies are highly likely to make a profit and continue to grow their wage until they meet the surviving companies' declining wages. After the convergence of wages, the economy again enters the epoch of coherent growth.

This cyclic dynamic resembles inflation-deflation cycles, where periods of synchronized growth and rising wages correspond to periods of inflation, driven by increasing consumer purchasing power (captured by μ/W). The high wages leave larger companies vulnerable due to higher capital volatility, such that occasional shocks (reduced number of transacting workers) can cause periods with wage reductions and bankruptcies, reflecting deflationary spirals where reduced purchasing power and capital losses feed back negatively on wages and consumer spending.

The overall interplay between cyclic and stochastic dynamics depends on parameters: A smaller system causes more irregularity, while a lower wage sensitivity α has the opposite effect.

Fig. 3 examines four systems, the first column with a small α, and the second column with a larger α. Comparing the systems $N = 100$ to $N = 1000$ between the top and bottom panels, we see that the smaller systems are more irregular. The diversity of company sizes is similarly less predictable, with more erratic collapses into a state with few companies.

For $\alpha = 2$, wages are tightly clustered around the mean, average profits per worker are close to zero, and diversity remains consistently high. The larger system

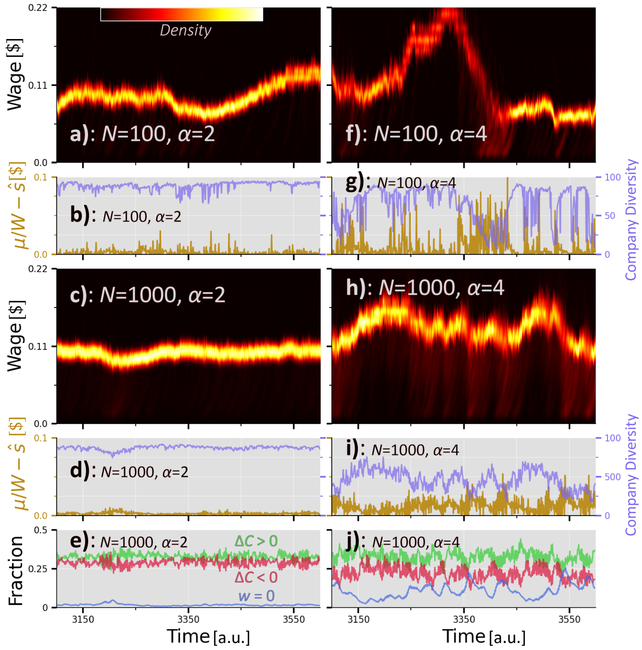

FIG. 3: Parameter influence on system behaviour. In the first column $\alpha = 2$, while second column use $\alpha = 4$. In the upper four panels, $N = 100$, while the lower six consider $N = 1000$. a), c), f), and h) illustrate the wages and their probability distribution as a function of time. Panels b), d), g), and i) show the average profit per worker and company size diversity D; e) and j) show the fraction of companies with a profit (green), with capital loss (red), and with zero workers (blue).

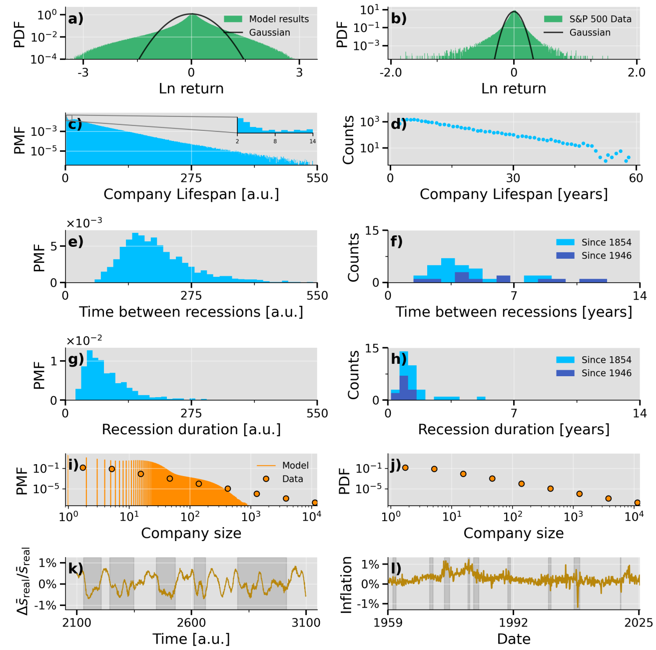

FIG. 4: Comparing the model to empirical data. The first column shows results from the model, and the second empirical data. Qualitatively, the model roughly agrees with the chosen benchmarks, except for the distribution of company sizes. Standard parameters used with $T = 250.000$. Asset return data is from Yahoo Finance [4], fetched using the Python library Yfinance [13]. Company lifespan data is read from Fig. 2c in [5], both recession datasets are from NBER [6], and the company size data is from [7]. Inflation is calculated from PCEPI data produced by BEA [8].

remains nearly unchanged over time. In contrast, for $\alpha = 4$, small waves of bankruptcies occur in addition to the larger ones, visible as "trails" of subpar wages converging toward the mean. Although similar trails exist in the $\alpha = 2$ case, they are rarer and involve fewer companies, making them less noticeable. These dynamics are also reflected in panels e) and j), which show the fractions of profitable and passive companies. At most time steps, more companies raise wages than reduce them. This wage-increasing tendency (seen in the green and blue curves vs. the red) represents an over-optimistic behavior tempered by bankruptcies. Since a larger α leads to larger companies, and large companies are more vulnerable to shock in the model, bankruptcies are less synchronized in $\alpha = 4$ compared to $\alpha = 2$.

Model versus Financial data

Fig. 4 examines six empirical data sets from the perspective of the model. These are asset return, company lifespan, time between recessions, duration of recessions, company size distribution, and inflation. The first column is the model, and the second is the data. The results only reproduce the historical financial data qualitatively, but allow for quantitative comparisons.

The first row shows the asset return $r(t;\tau)$. In the model, the closest to such a profit measure is the relative change in capital:

$$r_k(t;\tau) = \frac{C_k(t+\tau) - C_k(t)}{C_k(t)} \tag{6}$$

$$\approx \ln(C_k(t+\tau)) - \ln(C_k(t)). \tag{7}$$

The plot only includes $C_k \geq m$ values to prevent divergence near $C_k = 0$. I compare the model for $\tau = 1$ time step with the 503 companies currently on the S&P 500 index (data from [4]). The earliest possible date used was 2020-01-01, and the latest was 2025-04-01. The asset return is measured over a time interval of two working weeks $r(t, \tau = 10 \text{ days})$ (inspired by Fig. 1 and 2 in [14]). Note that the S&P 500 has an inherent survivorship bias, as delisted (dead) companies are not included. Despite this, the two distributions share three important characteristics: the peak is slightly positive, the tails are fat, and the left tail declines more slowly than the right tail.

The second row displays the lifespan of individual companies k, measured from their birth to $C_k < 0$. The data is read from Fig. 2c in [5]. The data show an exponential decline, except for very low values, where startups with zero capital are particularly likely to go bankrupt the first time they transact, especially if they choose a too high wage. The data also shows exponential decay, with a half-life of about 8 years, where the model has a half-life of 30 time steps. It seems that there are two timescales for the lifespan, one fast for companies dying almost instantaneously, and the slow, exponential decay. The short time scale can be seen in the insert in Fig. 4 c). Notably, the only way for companies to die in the model is due to bankruptcy, a fate that occurs only in 4.5% of real company terminations [5]. Thus, one cannot easily translate the timescale between models and financial data, the model has *more* deaths than expected.

Fig. 4 e) and f), compare the time between recessions for the model and data collected by the National Bureau of Economic Research (NBER) [6]. NBER defines recessions as starting "in the month after a peak in the business cycle and ending in the month of the trough". The "peak" and "trough" are found over multiple variables like GDP and unemployment, while I identify extrema solely from μ in the model. The NBER data start at 1854, and recessions since 1946 are in a darker color to highlight how the modern economy may differ. The spread in durations is roughly 25% larger in the data than the model.

Panels g) and h) show the duration of each recession, with a median recession length being about 1/3 of the interval between recessions. In comparison, the recessions in the model are only about 1/2 of the interval between recessions.

Panels i) and j) compare the distribution of company sizes (number of workers) to that of US company sizes in 2021 [15]. The data have been retabulated following [7], which also shows that company sizes are distributed by power law $p(w) \propto\approx 1/w^2$. The predicted distribution for the model is not scale invariant but peaks around the mean number of people allocated per company, $W/N = 20$. This distribution reflects the total relocation of workers at each time step, which only allows big companies to emerge when their wages are unusually large. The model company sizes between 50 and 500 are more broadly distributed and less in contrast to the reported power law. Noticeably, the distribution becomes more power-law-like for higher α. However, in any case, the power law of real company sizes likely reflects the large diversity in types of production lines in analogy to the toolbox scenario for biological networks [16].

The final row of Fig. 4 compares inflation. Inflation is measured as the change in the real average wage paid $\Delta\bar{s}_{\mathrm{real}}/\bar{s}_{\mathrm{real}}(t-1)$ per time step. This is compared to the monthly inflation using Personal Consumption Expenditures Price Index (PCEPI) [8], shown from 1959 to 2025. I compare my model against the monthly inflation, as opposed to the more commonly used year-over-year inflation, as the monthly inflation more closely resembles my time-step inflation. The areas shaded in gray are recessions, in the case of the model found in μ, and the recessions in the data are from NBER [6]. The model does not include productivity growth, so its inflation fluctuates around 0%, whereas the empirical data exhibits a small positive trend, roughly equal to 0.1% (in year-to-year inflation it fluctuates around the 2% that many federal banks aim for [17]). Despite this offset, the two series display similar qualitative features. Both series show irregular but recurring inflation-deflation cycles, with visual similarities in the burstiness and jagged structure of the time series. The model also captures the mean-reverting nature of inflation, and from the shaded recession areas, it is seen how generally the recessions occur during disinflation/deflation and vice versa, just like in the data. However, the model inflation changes rapidly and reaches extreme values much more often than the empirical data.

IV. DISCUSSION

This paper has demonstrated that a minimal agent-based model, absent of debt, unemployment, and price-setting behaviour, can still exhibit inflation-deflation cycles, recessionary dynamics, and clustered bankruptcies. These macroeconomic patterns emerge endogenously from simple micro-level rules: companies adjust wages based on short-term profits, and workers probabilistically choose employers based on wage competitiveness.

The core instability arises from the wage-feedback loop: wage increases raise consumer demand, which boosts company profits and spurs further wage growth. However, high wages also make companies fragile, as capital changes scale with company size. Shocks occur when, by chance, large companies are not chosen to transact, causing aggregate demand to collapse, precipitating wage cuts and bankruptcies. This feedback mechanism produces boom–bust dynamics without any need for exogenous shocks.

Despite its simplicity, the model reproduces several qualitative features observed in economic data. These include:

- Inflation clustering and cyclicality, similar to empirical inflation series.
- Exponential decay in company lifespans, though with unrealistic short timescales.
- Fat-tailed and asymmetric asset return distributions, albeit without autocorrelation.
- Recession durations and frequencies that qualitatively resemble real-world business cycles.

However, two major discrepancies stand out:

1. Timescale mismatch: The model fails to simultaneously reproduce observed company lifespans and

recession durations. Companies are significantly more short-lived than recessions, pointing to excessive company fragility.

2. Company size distribution: Real-world companies follow a power-law distribution, whereas the model's company sizes are peaked around the mean. Only for large α does the size distribution begin to approximate a power-law.

These mismatches highlight that while simple micro-rules can generate realistic cycles, some structural elements, such as sectoral segmentation, hiring constraints, or debt, may be essential for reproducing real-world scaling laws and persistence.

The model's high explanatory power comes at the cost of unrealistic micro-level assumptions. Notably:

- Wage rigidity and unemployment are absent, exaggerating volatility.
- Companies lack buffers such as savings or credit, leading to frequent bankruptcies.
- Worker reallocation is instantaneous and frictionless, distorting labour mobility.

These simplifications are defensible in light of the model's minimalism, but they rule out its applicability for policy inference or quantitative forecasting. Importantly, the wage sensitivity α strongly influences macro volatility, while others (e.g., minimum wage or startup noise) mainly affect system scale or prevent degeneracies.

Future extensions could address these issues by introducing more realistic labour dynamics (e.g., unemployment, matching frictions, or the shirking-worker model in [18]), company-level decision rules beyond short-term profit maximisation, or capital investment constraints. Even modest additions, such as staggered worker updates, might reduce fragility while preserving cyclic behaviour.

Ultimately, this work supports a central thesis in econophysics: that complex macroeconomic patterns may arise from simple, interaction-driven rules without assuming equilibrium or full rationality. The model demonstrates that non-periodic yet structured economic cycles can emerge from companies merely responding to short-term profitability, mediated by worker mobility.

While it is far from comprehensive, the model highlights how boom-bust cycles can emerge endogenously from competitive dynamics alone. Its contribution lies not in precision forecasting, but in showing that macroeconomic structure can arise from rules that are minimal and thus easily interpretable. This provides a useful base for further exploration into economic instability using agent-based methods.

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