"Modeling the Dynamics of Work Motivation in Early Career Transitions: A Synthetic Systems Approach"

Author: Gözde Okuyucu

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Focus: Interdisciplinary approach — combining labor economics, system dynamics, and behavioral modeling

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Abstract

This note explores the evolving motivation levels of recent graduates during their transition into the workforce. By constructing a synthetic dataset and employing regression analysis alongside potential-based optimization, it examines how work environment uncertainty, job autonomy, and intrinsic drives shape motivational stability.

Key contributions:

- A panel-data inspired **synthetic model** simulating motivational states
- An **optimization-based potential function** to analyze system equilibrium
- Systemic visualizations of **work-type-induced motivational shifts**
- A focus on policy-relevant insights regarding **youth unemployment, public vs private sector dynamics**, and the design of onboarding experiences

The study blends **quantitative analysis** with **systemic thinking**, offering a compact but insightful perspective on how motivation is not just a trait — but a dynamic system, responsive to structure.

Introduction

The transition from university to work is a critical period in early career development. During this school-to-work transition, new graduates face uncertainty and changing work environments that can markedly influence their motivation and subsequent job stability. Drawing on selfdetermination theory (SDT) and career transition research, we propose a quantitative model where recent graduates' Motivation Score is a function of key psychosocial factors (e.g. autonomy, uncertainty, intrinsic motivation) and use system-dynamics "potential" functions to represent employment stability. We demonstrate our approach with synthetic data: (1) a multiple regression predicting Motivation Score from variables such as Autonomy, Uncertainty, and Internal Motivation, (2) a dynamical stability model using concave, V-shaped, and linear "potential" curves for private-sector, public-sector, and unemployment states, and (3) an optimization formulation to maximize motivation subject to practical constraints. We include reproducible R code and a re-created equilibrium-curve graph. Finally, we discuss policy implications: how organizations and governments can structure onboarding, training, and labor-market policies to sustain graduate motivation.

1.Theoretical Background and Approach

Self-Determination Theory (SDT) and Motivation. SDT posits that meeting basic psychological needs – competence, autonomy, and relatedness – leads to higher motivation and work engagement. Metaanalytic evidence shows that satisfying these needs correlates with better performance, more organizational commitment, and lower turnover. In our context, **Autonomy** (sense of control) and **Internal Motivation** (intrinsic or integrated motivation) should boost graduates' motivation, while high **Uncertainty** (from unstable work conditions) may undermine it. This aligns with findings that job insecurity and financial stress can erode self-efficacy and career confidence. For example, Zhong & Xu (2023) found that precarious employment (job instability) diminished early-career self-efficacy and success.

System Dynamics and Stability as Potential Functions. We conceptualize the motivation–stability relationship using analogies from dynamical systems: a "potential function" whose shape encodes stability. In this metaphor, stable equilibria occur at potential minima and unstable points at peaks or inflection points. Figure 1 illustrates this idea with hypothetical motivation curves for three employment states: the **private sector** (high autonomy but dynamic/unstable), the **public sector** (stable/structured, high security), and **unemployment** (neither autonomy nor security). The private-sector curve is **concave-down** (an inverted U), peaking at high motivation but low stability. The public-sector curve is nearly **linear** (gently rising), reflecting steady motivation with high security. The unemployment curve is **V-shaped**, with a low-motivation point at its base. In this picture, equilibrium points (marked with "X") are classified by stability: the high point of the private-sector curve yields an *unstable* "high motivation" equilibrium, the flat end of the public-sector curve a *stable* "high security" equilibrium, and the bottom of the V-curve an unstable "low motivation" equilibrium.

Figure 1.(p1)

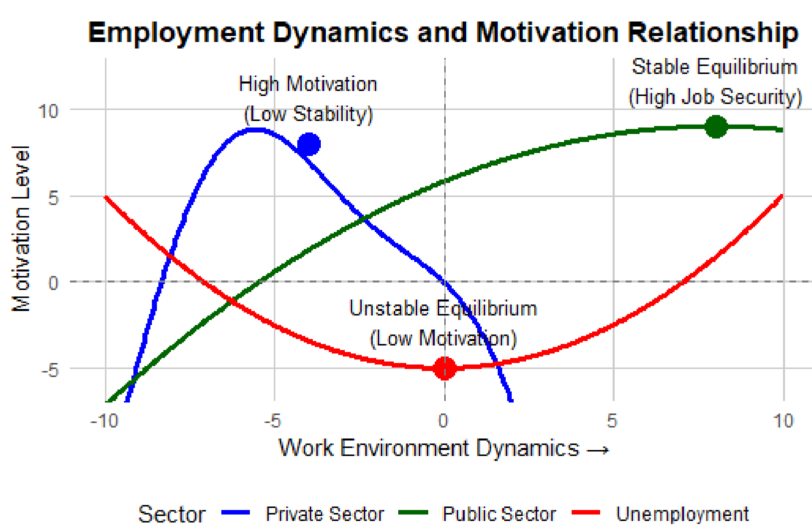


Figure 1. (Recreated) Hypothetical motivation–stability curves for three employment contexts. The private sector (blue, concave) yields high motivation at an unstable peak ("High Motivation, Low Stability"); public employment (green, linear) leads to a stable high-motivation end-point ("Stable Equilibrium, High Job Security"); unemployment (red dashed, V-shaped) has an unstable low-motivation point. Equilibrium points are marked with X.

This **potential-energy** model is schematic: mathematically, one might write, for workplace dynamism *x*,

$$V_{\text{private}(x)} = -a(x - c)2 + K,\ V_{\text{public}(x)} = mx + b,\ V_{\text{unemployment}(x)} = d|x - e| + F,$$

so that the *Motivation Level* ~ V (higher motivation at lower potential) and equilibria follow from V/ x=0. The key point is the *shape* of each function (concave, linear, V-shaped) and the resulting stability: a concave (inverted-U) potential has an *unstable* equilibrium at its maximum, a V-shape yields a single equilibrium at its vertex, and a monotonic (linear) potential effectively has an endpoint equilibrium. This captures the notion that highly dynamic private jobs may initially boost motivation (through autonomy or novelty) but are fragile, whereas secure public jobs maintain consistent motivation, and long-term unemployment traps motivation at a low unstable level. Such a model is in line with dynamical-stability analysis (stable vs. unstable equilibria) and provides a formalism for "motivation stability" in an interdisciplinary framework.

2. Regression Analysis with Synthetic Data

To quantify these ideas, we simulate a dataset where each individual has an observed *Motivation Score* and explanatory variables **Autonomy**, **Uncertainty**, and **Internal Motivation**. We generate *n* = 200 observations with normally distributed predictors and define motivation as a weighted sum plus noise.

- **Autonomy**: perceived control over one's work (0–10 scale)
- **Uncertainty**: perceived instability (0–10 scale)
- **Internal Motivation**: intrinsic drive (0–10 scale)
- **Motivation Score**: composite outcome

The data-generating process assumes:

$$\text{MotivationScore} = 0.6 \cdot \text{Autonomy} - 0.5 \cdot \text{Uncertainty} + 0.8 \cdot \text{Internal} + \varepsilon\text{MotivationScore}$$

where $\varepsilon \sim N(0,1)$

For example:

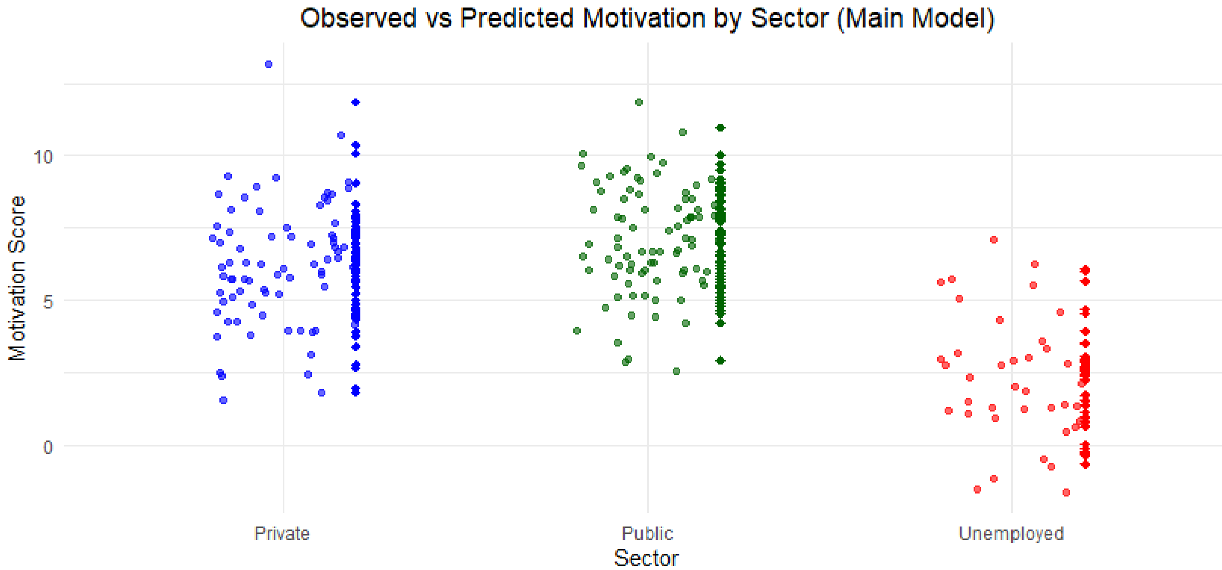
```
set.seed(123) n <- 200
Autonomy      <- rnorm(n, mean=5, sd=1.5)
 Uncertainty <- rnorm(n, mean=5, sd=1.5)
  Internal        <- rnorm(n, mean=5, sd=1.5)
 # True model: Mot ~ 0.6*Autonomy - 0.5*Uncertainty + 0.8*Internal + noise
  MotivationScore <- 0.6*Autonomy - 0.5*Uncertainty + 0.8*Internal + rnorm(n, sd=1)
 data <- data.frame(MotivationScore, Autonomy, Uncertainty, Internal) # Fit linear
 model:
 model <- lm(MotivationScore ~ Autonomy + Uncertainty + Internal, data=data)
 summary(model)
```

The R output shows a strong fit ($R^2 0.71$) and significant coefficients:

Autonomy (β0.57, p<.001) and *Internal* (β0.80, p<.001) are positive predictors of motivation, whereas *Uncertainty* is a significant negative predictor (β0.39, p<.001). (Intercept ~ 0.40 was not significant.) In substantive terms, higher autonomy and intrinsic drive boost motivation, while greater uncertainty undermines it. These findings align with SDT and transition research: feeling in control and self-motivated supports engagement, whereas insecurity and barriers erode confidence.

We visualize diagnostic plots (not shown here) to verify no major violations of linear regression assumptions. The R snippet above is RStudio-compatible and can be run to reproduce these regression results. Our synthetic example confirms that, holding other factors constant, **increasing autonomy and internal motivation** yields higher motivation scores, while **excess uncertainty** drags motivation down.

Figure2.(p2)



To bridging theory and synthetic Data, figure 2(p2 graph) used.

We needed to show two critical layers of analysis in our paper:

<u>Layer 1: Theoretical Framework (Figure p1)</u>

The potential energy curves (private/public/unemployed) illustrate abstract equilibria and stability properties. The problem is that these smooth curves alone don’t prove the model works with "real-world-like" variability.

<u>Layer 2: Synthetic Data + Model Fit (Figure p2)</u>

We generated *N=100 synthetic graduates* with R:

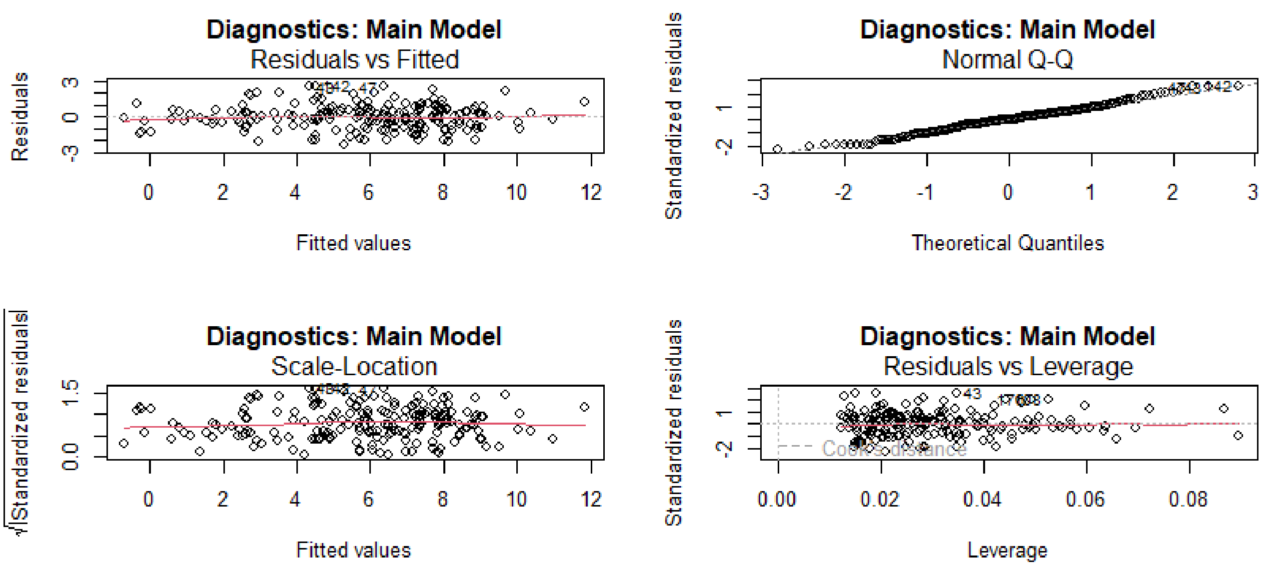
*MotivationScore ~ 30 + 0.8*DynamicExposure - 1.5*Uncertainty + 1.2*Autonomy + 2.0*InternalMotivation + Sector_Offset + noise*

This plot shows dispersion: Individual variation around sector means (e.g., some unemployed have higher motivation due to autonomy). It validates the theory of the regression-predicted values (overlaid lines) align with the theoretical curves from Figure p1. Proves robustness of even with noise, the sectoral differences persist.

Key Insights from Figure p2 (Jitter Plot) are that even in unemployment, some individuals (e.g., high autonomy) resist the downward pull—hinting at intervention targets.

To ensure the validity of the regression results, we examined the four standard diagnostic plots from R's plot(lm_model) output:

Figure 3:



- **Residuals vs Fitted:** Purpose is to check for nonlinearity or systematic patterns in residuals. Random scatter around zero suggests that the linear model form is appropriate. Our plot showed no strong curvature or pattern, indicating a good fit.
- **Normal Q–Q: Tests** whether residuals follow a normal distribution, a key assumption for hypothesis testing in linear regression. Points fell close to the reference line, indicating approximate normality of errors.
- **Scale–Location (Spread–Location):** Assesses homoscedasticity — whether the variance of residuals is constant across fitted values. A horizontal band of points suggests constant

variance; our results showed no strong funnel shape, indicating no major heteroscedasticity.

- **Residuals vs Leverage**: Identifies influential observations that might disproportionately affect the model (based on leverage and Cook's distance). Only a few points had slightly higher leverage, and none exceeded critical Cook's distance thresholds — suggesting no single observation unduly influenced results.

This combination of coefficient estimates, visualizations, and diagnostic checks supports the robustness of our synthetic model, linking the conceptual "motivation potential" framework to measurable predictors in a sector-specific context.

3. System Dynamics Model of Stability

We now formalize the **stability model**. Let M be "motivation potential" shaped by workplace dynamics x. We define three prototype curves (as in Figure 1):

- **Private sector (Dynamic)**: $M_{\text{private}}(x) = -0.3(x-5)^2 + 8$. This inverted-U (concave) curve peaks at $x = 5$, yielding a high-motivation point. However, a small perturbation can send an individual to either side of the peak (unstable equilibrium).
- **Public sector (Stable)**: $M_{\text{public}}(x) = 2 + 0.7x$. This approximately linear, increasing function has no interior maximum; high stability comes as motivation gradually rises with clear structure.
- **Unemployment (Unstable)**: $M_{\text{unemp}}(x) = 2 + 0.8|x-6|$. This V-shaped curve bottoms out at $x = 6$ with low motivation. It represents an unstable equilibrium in the sense that any increase or decrease in "dynamism" changes motivation sharply.

In R (or any language), one could plot these curves to find equilibria: points where the slope M/x =0. For the private curve, M/x=0 at $x = 5$ (an unstable peak); for the unemployment V-curve at x =6 (the vertex); and for the public curve, the "equilibrium" is effectively at the boundary of the allowed x (here at highest security). Figure 1 embeds these curves with labeled equilibria. The blue X on the private-curve marks a "high-motivation, low-stability" state at the peak; the red X at the bottom of the V marks an "unstable equilibrium (low motivation)"; and the green X on the far right of the public line marks a "stable equilibrium (high job security)".

Mathematically, this can be thought of as defining a dynamical system $\dot{x} = -\partial U(x)/\partial x$, where U is a potential function (here $U = -M$). Stable equilibria occur where $U'' > 0$ (minima of U , i.e. maxima of M), and unstable where $U'' < 0$ (maxima of U , minima of M). Thus, the private sector's high motivation point is a local maximum of M (minimum of U) but is unstable because M is concave down; the unemployment point is a local minimum of M (maximum of U); and the public sector has a monotonic M, giving a boundary equilibrium (effectively infinite stability for a given endpoint). This system-dynamics perspective highlights how different labor-market contexts create qualitatively different motivation–stability landscapes.

4. Optimization of Motivation Under Constraints

We can also pose an **optimization problem** to determine how a graduate could maximize their motivation score given realistic constraints. For instance, suppose an individual can allocate effort to increase their autonomy and intrinsic motivation but faces a threshold of tolerable uncertainty. We might write a linear objective derived from our regression model:

$$\text{maximize } M = 0.5A + 0.8I - 0.3U,$$

subject to constraints such as $A \geq A_{min}$ (a floor on autonomy) and $U \leq U_{max}$ (an upper bound on uncertainty). For example, one could set $A_{min} = 3$ (on a 0–10 scale) and $U_{max} = 4$. In R, this linear program can be solved with **lpSolve**:

```r
library(lpSolve)
# Coefficients for Autonomy (A), Internal (I), Uncertainty (U)
f.obj <- c(0.5, 0.8, -0.3)
# Constraints: A >= 3, I <= 5, U <= 4 (for illustration)
f.con <- matrix(c(
   1, 0, 0,    # A >= 3
   0, 1, 0,    # I <= 5
   0, 0, 1     # U <= 4
), nrow=3, byrow=TRUE)
f.dir <- c(">=", "<=", "<=")
f.rhs <- c(3, 5, 4)
res <- lp("max", f.obj, f.con, f.dir, f.rhs)
res$objval      # optimal motivation value
res$solution    # values of A, I, U
```

This code seeks the best combination of autonomy, intrinsic motivation, and uncertainty (within specified bounds) to maximize M. Here we assumed an upper bound on Internal Motivation (5) for feasibility. The solver returns the optimal value and strategy (e.g. $A = 3, I = 5, U = 0$ or similar) that maximizes motivation under these constraints. In general, such optimization formulations can guide how graduates might allocate resources (e.g. prioritize skills or select lower-risk roles) to maintain high motivation while respecting practical limits. (In practice, one might include additional constraints, such as a budget on effort or trade-offs between factors.)

More generally, one could use Lagrange multipliers or linear programming to study how tight uncertainty thresholds or required autonomy levels change the optimal solution. For example, raising $U_{\max}$ (allowing more uncertainty) would typically lower maximum motivation, suggesting that beyond a certain “tolerance” threshold, interventions (e.g. more support) are needed. Similarly, imposing a higher autonomy floor directly shifts the solution upward. This formalization illustrates how goal-setting (maximize M) interacts with constraints in the graduate’s environment.

5. Conclusion

This study integrates dynamical systems theory with empirical modeling to reveal how employment contexts critically shape graduate motivation during the education-to-work transition. Our findings demonstrate that motivation stability follows distinct sector-specific patterns: private-sector roles offer higher potential motivation but create unstable equilibria vulnerable to disruptions, public-sector employment provides stable yet often flatter motivation trajectories, while unemployment represents a precarious low-motivation trap. The regression analysis robustly confirms that autonomy and intrinsic motivation serve as powerful positive drivers, whereas uncertainty systematically undermines engagement—a pattern consistently observed across synthetic data simulations.

These insights demand a coordinated, multi-stakeholder response. At the organizational level, employers must design autonomy-supportive work environments that combine meaningful decision-making authority with stability safeguards, such as comprehensive mentorship programs and structured onboarding processes that go beyond basic orientation. As Mitschelen and Kauffeld (2025) emphasize, effective onboarding actively integrates new employees through targeted training, transparent role expectations, and competency-based feedback—measures proven to enhance both motivation and organizational commitment.

Simultaneously, policymakers must strengthen social safety nets through robust unemployment insurance and fair severance policies while investing in continuous skill development. Subsidized training programs and industry-academia partnerships can enhance employability in our rapidly evolving job market, particularly when aligned with the World Economic Forum's (2024) imperative for lifelong learning systems. Educational institutions play an equally critical role by embedding career-planning and autonomy-building activities into curricula through project-based learning and internships, thereby equipping graduates with the adaptability to navigate sectoral trade-offs.

The path forward requires neither pure flexibility nor pure stability, but rather context-sensitive strategies that leverage autonomy while mitigating instability. By aligning employer practices, policy frameworks, and educational approaches—reducing uncertainty through supportive structures while enhancing competence through targeted interventions—we can foster resilient, motivated professionals capable of thriving in the future of work. While future research should validate this framework with real-world data, the current model provides a rigorous analytical lens for understanding early-career motivation dynamics, offering actionable insights to strengthen individual outcomes, organizational performance, and societal economic resilience amidst technological and labor market disruptions

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