Post-Graduation Planning: Optimizing Profit and Happiness

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I. Abstract

We present a linear programming model designed to assist Carnegie Mellon University students in choosing the optimal city for living and employment following graduation, which optimizes value according to monetary factors such as rent costs, transportation costs, and grocery expenses, and is adaptable to different preferences based on happiness variables such as proximity to family, recreational activities, climate, walkability, and safety. Extending this model into a 10-year plan using dynamic programming, we account for career growth through potential relocations, demonstrating a 48% increase in profit over a stationary plan. The model is further tested through selected user profiles, showcasing trade-offs between financial gain and happiness. Our research suggests San Francisco as the optimal city for maximizing discretionary income, while highlighting the significant role of personal preferences in determining the best post-graduation plan. Future enhancements could include broader variables, international opportunities, and evolving personal circumstances, reinforcing the model's utility in making informed, data-driven decisions for life after graduation.

II. Introduction

Deciding on post-graduation plans can be a daunting process, and there are countless factors to consider, from financial aspects to personal preferences and career goals. In the past 4 years, according to data published by the CMU Career and Professional Development Center, 62% of students graduating from Carnegie Mellon with a Bachelor's degree have been employed right after graduation, while 30% went on to pursue higher education. Clearly, a huge majority of CMU students are looking to join the workforce following their undergraduate years, especially in their last fall semester, and the authors of this paper are a few of them.

In the search for employment and the place to start the next chapter of our lives, a higher salary might be appealing. But in a city with a higher cost of living, we might not be optimizing our profit, which may be important for student loan payments, investments, and other priorities for spending after college. On the other hand, to many, other factors of living like access to public transportation or favorite hobbies or proximity to family is much more valuable. In an effort to help students make informed, data-driven choices for life after graduation, finding a balance between affordability, lifestyle preferences, and career opportunities, we built a linear program combining these factors to determine an individual's optimal city to live and work in post-grad, using CMU data, personal preferences, and state-specific costs. We extended this model for a 10-year plan using dynamic programming, accounting for moving cities for higher salary opportunities, to emphasize career growth as a priority as well.

III. Data

The first consideration was affordability: it is important to understand the financial landscape of living in different cities, how varying living costs such as housing, transportation, and utilities affect an overall budget. From the 2023 First Destination Outcomes Employment Infographic published by CMU's Career and Professional Development Center, we took the 8 cities with the highest number of CMU graduates; New York, San Francisco, Pittsburgh, Washington D.C., Seattle, Boston, and Chicago; to focus on in our model. We split Washington D.C. into two data points - those living in D.C. and those living in Virginia, then commuting to D.C. For each city, the CPDC infographic also provided an average salary for recently graduated students.

We identified four key factors that significantly impact living costs across U.S. cities: transportation, tax, food, and housing. For transportation, we account for two scenarios: using a car, and relying on public transportation. Every city in our dataset offers a monthly unlimited pass for public transit, so we included those costs. They are as follows:

New York:

30-day unlimited Metro Card valid for buses and subways ($132/month)

San Francisco:

Unlimited Muni-only monthly pass for buses, trolleys, and streetcars ($81/month)

Pittsburgh, Pennsylvania:

Monthly pass with unlimited rides ($97.50/month)

Washington, D.C.:

Washington Metropolitan Area Transit Authority (WMATA) monthly unlimited pass for the Metro System with both rail and bus services ($64/month)

Seattle, Washington:

Unlimited monthly PugetPass ($90/month)

Boston, Massachusetts:

Monthly Massachusetts Bay Transportation Authority (MBT) that provides unlimited rides across the network ($90/month)

Chicago, Illinois:

30-day unlimited Ventra pass, covering all Chicago Transit Authority buses and trains ($75/month)

If an individual has a car, we consider some additional variables: average gas price by state, sourced from AAA, average used car prices by state as reported by the World Population Review, and the average miles driven per state from the Federal Highway Administration. To estimate food expenses, we found the average monthly grocery cost per person by state, reported also by the World Population Review. The US Tax Foundation gave us data for income taxes by state, and finally, we collected average rental costs for one-bedroom apartments from Unbiased, an online investment advisor registered with the US Securities and Exchange Commission. The data collected can be seen in the table below.

Monetary Factors:

	Graduates	Average Salary	Income Tax	Average Monthly Rental Cost	Avg Monthly Cost of Groceries	Avg Used Car Monthly Payment	Avg Gas Price (per gallon)	Monthly Public Transportation Fare	Average Miles Driven per Month
N		S	T	R	G	C	F	P	M
New York, New York	193	$129,404	6.00%	$2,552.00	$482.87	$338.00	$3.20	$132.00	7748.7966
San Francisco, California	105	$131,695	9.30%	$1,145.00	$370.96	$358.00	$4.60	$81.00	9458.6233
Pittsburgh, Pennsylvania	93	$80,971	3.07%	$1,692.00	$401.02	$328.00	$3.35	$97.50	4654.5633
Washington, D.C.	54	$91,807	8.50%	$2,235.00	$298.01	$320.00	$3.31	$64.00	5117.5733

Washington, D.C. (located in Virginia)	54	$91,807	5.75%	$1,455.00	$298.01	$320.00	$3.06	$64.00	5897.5733
Seattle, Washington	49	$119,447	7.00%	$2,255.00	$402.08	$336.00	$4.05	$90.00	7296.8366
Boston, Massachusetts	47	$86,116	5.00%	$1,336.00	$406.21	$328.00	$3.06	$90.00	5434.1233
Chicago, Illinois	27	$133,568	4.95%	$1,840.00	$327.21	$343.00	$3.31	$75.00	8963.4566

Finally, we value decision making; choosing cities that align not only with personal financial goals but also with career aspirations and personal preferences that may affect mental health. The happiness factors, as we are referring to them, include proximity to family, access to recreational activities, the local climate, walkability, and safety. Identifying these factors came down to deciding what was important for us, as representative students: what we may consider while applying for or accepting jobs in different cities. Proximity to family might be important, especially for those with close relationships with home. For some, this may be a non-factor, if those relationships can stand the distance or don't exist at all. Access to hobbies, anywhere from nearby skiing and hiking to music venues and theaters to beaches and surf, would enhance quality of life and provide opportunities for relaxation and enjoyment. Climate is also an important factor, as some people prefer warmer or cooler weather depending on their lifestyle. Walkability refers to the ease of getting around on foot, which may be ideal for individuals who don't drive. And of course, safety might be critical for anyone with a preference for cities with low crime rates.

In order to assign values for each city in each of these categories, we employed prompt engineering to generate the rankings with an assumed preference for temperate climate, assuming also that family is in Pittsburgh. Note that, as a model for applied use, these factors are adjustable depending on individual hobbies, family location, and climate preference, which may require new rankings.

Happiness Factors:

	Distance to	Climate	Proximity to	Safety	Walkability

	family		hobbies		
New York, New York	7	5	8	6	9
San Francisco, California	2	8	9	4	5
Pittsburgh, Pennsylvania	10	6	6	7	6
Washington, D.C.	7	6	8	5	9
Washington, D.C. (located in Virginia)	7	6	7	6	4
Seattle, Washington	3	7	8	5	7
Boston, Massachusetts	5	5	8	7	9
Chicago, Illinois	7	6	7	5	8

IV. Variable Declaration

Having collected coefficient data for each of our monetary and our happiness factors, we now define these factors as variables for our linear program. Note that a lowercase variable indicates that it's a happiness variable, measured by some integer between 0 and 10.

Let $x_i = 1$ if city i is selected as the location, and $x_i = 0$ otherwise.
Let $y = 1$, if the individual prefers to use a car for transportation, and $y = 0$ if they prefer to use public transportation.

Let R_i = monthly rental cost
Let U_i = monthly utility costs
Let T_i = income tax in city i
Let G_i = average monthly groceries cost
Let C = monthly car payment for a used car
Let F_i = monthly gas price for city i
Let P_i = monthly public transportation cost in city i

Let S_i = monthly average salary in city i after applying income tax
Let M_i = monthly average miles driven per month in city i

Let d_i = distance to family (0 = far, 10 = close)
Let c_i = climate ranking (0 bad, 10 good)
Let p_i = proximity to hobbies (0 bad, 10 good)
Let s_i = safety/crime rates (0 bad, 10 good)
Let w_i = city walkability (0 bad, 10 good)

Let z_x = user ranking of importance
→ user rank importance 0-10, which is normalized so that $0 <= z_x <= 1$

V. Assumptions

To formulate the integer program, we made the following assumptions about individual financial planning and happiness preferences: Our constraints are based on the widely used 50/30/20 budgeting rule, which allocates income into three categories: 50% for needs, 30% for wants, and 20% for savings. Here, we defined "needs" to include rent, utilities, and food. We also assume a minimum yearly savings of $2,000, though this value is adjustable to align with user preferences. For happiness, we incorporate user preferences alongside each city's individual scores across the different happiness categories. The model ensures that the weighted happiness sum exceeds 20 points, a threshold that can be adjusted for individuals seeking more or less happiness. Additional assumptions were made for the dynamic programming implementation, which will be discussed later.

VI. Formulation:

Monetary Only Model:
Maximize $\Sigma x_i((1-T_i)S_i - (R_i + G_i + y(C + F_iM_i) + (1 - y)P_i))$

Subject to:

$0.5 * S_i >= R_i + U_i + G_i$

$0.2*S_i >= 2000$

$\Sigma x_i = 1$

$i \in$ {New York, San Francisco, Pittsburgh, Washington D.C., Virginia, Seattle, Boston, Chicago}

Happiness Model:

Maximize $\Sigma x_i((1-T_i)S_i - (R_i + G_i + y(C + F_iM_i) + (1 - y)P_i) + z_d d_i + z_c c_i + z_p p_i + z_s s_i + z_w w_i)$

Subject to:

$0.5 * S_i >= R_i + U_i + G_i$

$z_d*d_i+z_c*c_i+z_p*p_i+z_s*s_i >= 20$

$0.2*S_i >= 2000$

$\Sigma x_i = 1$

$i \in$ {New York, San Francisco, Pittsburgh, Washington D.C., Virginia, Seattle, Boston, Chicago}

VII. Dynamic Programming Adaptation

The integer programming model served as the foundation for the dynamic programming approach. This model extends the optimization of profit and happiness over a 10-year plan, outputting a list of cities and allowing users to consider moving each year. To model future decisions and predict salary changes, several additional assumptions were made. In particular, the model assumes a fixed 5% annual salary increase for staying at the same job (not relocating) from year i to year i+1, whereas moving to a new city and switching jobs results in a 15% salary increase. These figures are based on national averages: annual raises of 3–5% versus a 10–20% increase when switching jobs. It is important to note that these increases are city-specific and not cumulative based on the current salary. For example, if someone earns $100,000 in D.C., but moves to Seattle where the salary is $80,000, the following year's salaries will be $103,000 (D.C.) versus $92,000 (Seattle), not $115,000. This reflects the reality that companies in a new city are unlikely to match salaries from a different market solely due to relocation. Additionally, moving incurs a happiness penalty and a $5,000 cost.

To implement this, we initially constructed a tableau where rows represent current cities, and columns represent years. Each subsequent column was computed by taking the maximum value from the previous year and adding the current objective function value. While this approach worked, the model was slower than expected, so to improve efficiency, we replaced it with a greedy algorithm. The revised algorithm optimizes computation time by solving the integer program sequentially at each time step with updated salaries. Since it only considers the optimal city each year, it avoids the need to backtrack through the tableau, reducing both runtime and storage requirements.

VIII. Results

Before incorporating the happiness component, we ran the integer program considering only monetary factors. The results identified San Francisco as the optimal city for maximizing profit, with a discretionary income of $100,678 after one year. For a stationary 10-year plan, the total discretionary income amounts to $1,315,730. Using our dynamic programming approach, the optimal sequence of cities is: San Francisco → Chicago → Chicago → San Francisco → New York → Seattle → New York → Chicago → San Francisco → Seattle. This strategy results in a total profit of $1,942,132, representing a 48% increase over the stationary plan. These results demonstrate that our model is effective and that moving, while potentially cumbersome in practice, can significantly enhance profitability. The next step is to analyze how incorporating the happiness component affects these outcomes.

The introduction of happiness preferences prompts the requirement for user rankings, i.e. a ranking z_x for each happiness variable x, from 0 to 10, of how important to the user that happiness variable being satisfactory is to them. For example, someone may be comfortable in any kind of climate, or might have no desire to be in proximity to family. We decided to invent six representative individuals to help model out how our program responds to different user rankings. There are 4 different "Person A's" to distinguish between preferences for monetary profit versus profit in happiness value. Note the last row represents one's importance coefficient for profit where 0.1 represents a high importance of profit in relation to happiness, while a score of 0.0001 represents a prioritization of happiness over money.

	personA1	personA2	personA3	personA4	personB	personC
family	10	10	10	0	9	2
climate	10	10	10	10	3	4
hobbies	10	10	10	10	2	6
safety	10	10	10	10	7	2
walkability	10	10	10	10	1	9
money prioritization	0.1	0.01	0.001	0.0001	0.0001	0.001

The results after running our dynamic programming algorithm on each of the subjects above were as follows:

Person A1:

Chicago - Chicago - New York - San Francisco - San Francisco - San Francisco - Seattle - Seattle - Chicago

Discretionary Income over 10 years: $1,909,802

Happiness over 10 years: 62.6

Person A2:

San Francisco - San Francisco - Chicago - Chicago - New York - New York - Seattle - Seattle - Chicago - Chicago

Discretionary Income over 10 years: $1,881,630

Happiness over 10 years: 63.6

Person A3:

Chicago - Chicago - San Francisco - San Francisco - New York - New York - Seattle - Seattle - Chicago - Chicago

Discretionary Income over 10 years: $1,877,017

Happiness over 10 years: 63.6

Person A4:

New York - New York - New York - New York - Chicago - Chicago - Chicago - Chicago - Washington D.C. - Washington D.C.

Discretionary Income over 10 years: $1,634,201

Happiness over 10 years: 68.4

Person B:

Pittsburgh - Pittsburgh - Pittsburgh - Pittsburgh - Pittsburgh - Pittsburgh - Pittsburgh - Pittsburgh - New York - New York

Discretionary Income over 10 years: $1,167,486

Happiness over 10 years: 77.57

Person C:

New York - New York - New York - New York - Chicago - Chicago - Chicago - Chicago - Washington D.C. - Washington D.C.

Discretionary Income over 10 years: $1,634,201

Happiness over 10 years: 72.97

From this data, we see that person A1 achieves the highest income, but sacrifices overall happiness slightly in comparison to the other profiles. A2 and A3 have similar incomes and the same happiness, yet slightly different city lists, indicating some flexibility in choosing an optimal plan. Person A4 prioritizes happiness significantly over profit, achieving the highest happiness score in the "Person A" group, but earning substantially less (~$300,000 lower income). As we focus on individuals with more tailored preferences (B and C), we see the model selects and remains in cities that align more closely with their goals. In particular, person B, remaining in Pittsburgh for most of the 10 years, achieves the highest happiness score among all profiles but earns significantly less income. This suggests that stability and consistent happiness can come at the cost of financial growth.

Overall, the results demonstrate a clear trade-off between maximizing income and prioritizing happiness, with individuals like Person A1 favoring financial growth at the expense of happiness, while Person B achieves higher happiness through stability with reduced earnings. Notably, Person C strikes an effective balance, maintaining both income and happiness by transitioning strategically between major cities. These findings highlight the model's adaptability in accommodating diverse user priorities and suggest that optimal strategies ultimately depend on an individual's unique preferences.

IX. Conclusion and Next Steps

Our results show that the best outcome for an individual to maximize value, whether monetary or related to personal well-being and contentment, after graduation is highly variable based on personal preferences. However, on a basic level focused on maximizing money-in-pocket, San Francisco is the optimal location. Nonetheless, several additional factors could complicate this model, including proximity to a partner, vacation days, stock options, dietary preferences (such as high protein or vegan and gluten-free diets), and extra costs or fees like health emergency expenses and vacation costs. Health insurance costs are another consideration. Furthermore, international job opportunities and the rise of remote and hybrid work models have made travel more accessible. In a few years, many of us may start families, making a one-bedroom apartment or an old car insufficient. At that point, we may look into buying property or moving to areas with better school districts.

As evident in our results, the best outcome for an individual to maximize value (whether monetary value or personal well-being and contentment) in their lives after graduation is extremely variable based on preferences when we introduce those variables, but on a base level of most money-in-pocket, San Francisco is the place to go. Of course, there are more factors to consider, with different costs, that would widen and complexify our model: proximity to a partner, vacation days, stock options, dietary preferences (such as high protein or vegan and gluten-free diets), and extra costs or fees like health emergency expenses and vacation costs could all be incorporated. Furthermore, international job opportunities which also offer potential optimal living situations, but more and more jobs are now following remote or hybrid models, making travel easier. In a few years, many of us may start families, making a one-bedroom apartment or an old car insufficient. At that point, we may look into buying property or moving to areas with better school districts.

We can make this model more and more complex, with more cities to consider, more variables to consider, better approximations for individual preferences and spending habits, as well as adapting to growth and change in preferences as years go on. But the further we get, we can get caught up in attempting to model reality, which is not mathematically reasonable, so estimating reality with averages and generalizations is the best we can do. It’s compelling nonetheless that a model like ours can help us make data-driven decisions about what’s in our best interest for the future.

X. Implementation:

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
@author: groupA
```

```
"""

import pandas as pd
from gurobipy import *

# Initialize model
model = Model('bestCity')
cityList=[]

# Read and clean data
df = pd.read_csv("OptDataClean.csv")
df['S'] = df['S'].str.replace(',', '')
S = pd.to_numeric(df['S'], errors='coerce') / 12  # Monthly salary
df['R'] = df['R'].str.replace(',', '')
R = pd.to_numeric(df['R'], errors='coerce')      # Monthly rent
G = pd.to_numeric(df['G'], errors='coerce')      # Cost of groceries
C = pd.to_numeric(df['C'], errors='coerce')      # Monthly car payment
F = pd.to_numeric(df['F'], errors='coerce')      # Gas price
P = pd.to_numeric(df['P'], errors='coerce')      # Public transportation
T = pd.to_numeric(df['T'], errors='coerce')      # State income tax
df['M'] = df['M'].str.replace(',', '')
M = pd.to_numeric(df['M'], errors='coerce')      # Average Yearly Miles Driven

# Add lowercase variables
d = pd.to_numeric(df['d'], errors='coerce')      # Distance to family
c = pd.to_numeric(df['c'], errors='coerce')      # Climate ranking
p = pd.to_numeric(df['p'], errors='coerce')      # Proximity to hobbies
s = pd.to_numeric(df['s'], errors='coerce')      # Safety/crime rates
w = pd.to_numeric(df['w'], errors='coerce')      # Walkability

#z = pd.to_numeric(df['personA'], errors='coerce')
z = pd.to_numeric(df['personB'], errors='coerce')
#z = pd.to_numeric(df['personC'], errors='coerce')


# normalizing z
z[0] = 10
z_sum = z[0]+z[1]+z[2]+z[3]+z[4]
if z_sum == 0:
   z[:5] = [0] * 5
```

```
else:
    z = [z_i / z_sum for z_i in z]
z[5] = 0.0001



# Variables
x = model.addVars(8, vtype=GRB.BINARY, name='choose_city')
y = 0  # Use personal vehicle: 1 or public transportation: 0
model.update()

# Original objective
original_obj = quicksum(x[i] * ((1 - T[i]) * S[i]
                        - (R[i] + G[i] + y * (C[i] + F[i] * M[i]) + (1 - y) * P[i]))
                  for i in range(8))

def money_obj(i, T, S, R, G, C, F, P, M):
    return ((1 - T[i]) * S[i] - (R[i] + G[i] + y * (C[i] + F[i] * M[i]) + (1 - y) * P[i]))

def happy_obj(i, d, c, p, s, w):
    return z[0] * d[i] + z[1] * c[i] + z[2] * p[i] + z[3] * s[i] + z[4] * w[i]

# New objective
model.setObjective(quicksum(x[i] * (z[5]*((1 - T[i]) * S[i]
                        - (R[i] + G[i] + y * (C[i] + F[i] * M[i]) + (1 - y) * P[i])) + z[0]*d[i] +
z[1]*c[i] + z[2]*p[i] + z[3]*s[i] + z[4]*w[i]) for i in range(8)), GRB.MAXIMIZE)


# Constraints
model.addConstr(quicksum(x[i] for i in range(8)) == 1, name='only_one_city')
model.addConstr(quicksum(.5 * x[i] * (S[i] - (R[i] + G[i])) for i in range(8)) >= 0,
name='income_necessities')
model.addConstr(original_obj * 12 >= 10000, name='original_obj_minimum')

# Solve and display results
model.optimize()
model.printAttr('X')
index = model.getAttr("X").index(1.0)
profit = 12 * money_obj(index, T, S, R, G, C, F, P, M)
happy = happy_obj(index, d, c, p, s, w)
```

```
currCity = df['N'][index]
cityList.append(currCity)

# print soln
print("The best location to move to is " + currCity + ".")
print("Your profit after 1 year is $" + str(int(profit)))
print("Current happiness level: " + str(happy))
#if model.Status == GRB.OPTIMAL:
 #  profits = 12 * model.getObjective().getValue()
 #   index = [i for i in range(8) if x[i].X > 0.5][0]
#    currCity = df['N'][index]
 #   print(f"The best location to move to is {currCity}.")
 #   print(f"Your adjusted profit score is ${int(profits)}.")
#else:
#    print("No optimal solution found.")

# Next year function
def next_year(profit, index, currS, happy, nextS=0):
    nextS = [val * 1.05 if i == index else val * 1.15 for i, val in enumerate(currS)]
    m = [0 if i == index else 1 for i in range(8)] # moving boolean array

    model = Model('nextBestCity')
    x = model.addVars(8, vtype=GRB.BINARY, name='choose_city')
    model.update()

    # Original objective
    original_obj = quicksum(x[i] * ((1 - T[i]) * nextS[i]
                                - (R[i] + G[i] + y * (C[i] + F[i] * M[i]) + (1 - y) * P[i]))
                        for i in range(8))

    #happiness_obj = (z[0]*d[i] + z[1]*c[i] + z[2]*p[i] + z[3]*s[i] + z[4]*w[i] for i in range(8))

    # Objective
    model.setObjective(quicksum(x[i] * (z[5]*((1 - T[i]) * S[i]
                                - (R[i] + G[i] + y * (C[i] + F[i] * M[i] + m[i] * 5000) + (1 - y) * P[i])) -
0.1*m[i] + z[0]*d[i] + z[1]*c[i] + z[2]*p[i] + z[3]*s[i] + z[4]*w[i]) for i in range(8)),
GRB.MAXIMIZE)

    # Constraints
    model.addConstr(quicksum(x[i] for i in range(8)) == 1, name='only_one_city')
```

```
    model.addConstr(quicksum(.5 * x[i] * (nextS[i] - (R[i] + G[i])) for i in range(8)) >= 0,
name='income_necessities')
    #model.addConstr(original_obj >= 10000, name='original_obj_minimum')

    # Solve
    model.optimize()
    model.printAttr('X')
    index = model.getAttr("X").index(1.0)
    profit += 12 * money_obj(index, T, nextS, R, G, C, F, P, M)
    happy += happy_obj(index, d, c, p, s, w)
    currCity = df['N'][index]
    cityList.append(currCity)

    # print soln
    print("The best location to move to is " + currCity + ".")
    print("Your profit is now $" + str(int(profit)))
    return profit, index, nextS, happy

for n in range(1,10):
    profit, index, S, happy = next_year(profit, index, S, happy)

print(cityList)
print(profit)
print(happy)
```