Peer Effects in the Hierarchy: Evidence from the Workplace

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This paper studies how coworkers' consumption affects one's own consumption and promotion chances in a hierarchical workplace. Using credit card data of employees, we show that one's consumption is influenced by coworkers at the same or higher levels, and that this peer effect is stronger for those who are more likely to be promoted. We also find that the peer effect rises before and falls after a promotion event for the promoted workers. This reveals how peer effects and hierarchy interact in the firm.

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1 Introduction

Social interactions play a significant role in economic decisions, including consumption behavior, as recognized both theoretically and empirically (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Bernheim, 1994; Kremer and Levy, 2008; Bailey, et al., 2018; De Giorgi, Frederiksen, and Pistaferri, 2020). Most studies on peer effects focus on homogenous groups, such as neighbors (Kuhn, et al., 2011; Kaustia and Knüpfer, 2012), consumers in a specific industry (Cai, Chen, and Fang, 2009; Moretti, 2011), or individuals with similar traits (Maurer and Meier, 2008). However, little is known about how hierarchies affect peer effects in consumption, despite the fact that individuals spend a third of their time in hierarchical structures like the workplace.

Our paper investigates the influence of coworkers' consumption on an individual's own consumption behavior in a hierarchical workplace. We use a unique dataset from a large Asian bank, which includes transaction-level credit card data and employer-employee information for 1,096 firms and 119,932 employees from July 2013 to June 2015. To our knowledge, this is the first study to explore how peer effects in consumption differ across different levels of the firm hierarchy. We estimate the effects of lagged average peer consumption at different layers on an individual's present consumption behavior, examining how the strength of the peer effect varies with promotion probability. Additionally, we explore the dynamic changes in peer effects around a promotion event for promoted and non-promoted workers.

We estimate peer effects in consumption among coworkers with and without considering hierarchy. We find that a 10 percent increase in peers' lagged weekly consumption is linked to a significant 0.55 percent rise in one’s own consumption. We then group coworkers by job positions (blue-collar workers, white-collar workers, and managers as the first, second, and third layers, respectively) or income clusters (with different clusters of similar income being considered as distinct layers) and compare peer effects across these hierarchical layers The results are similar for both grouping methods. Peer effects vary within and across layers in a rich pattern. For intermediate-layer workers, a 10 percent increase in average lagged consumption among same-layer coworkers is associated with a 0.41 percent increase in the individual's consumption. The effects of consumption by workers at higher and lower income layers are smaller in magnitude but still significant (0.25 and 0.17, respectively). Top-layer workers exhibit a similar pattern, except for the absence of higher-layer coworkers. In contrast, bottom-layer workers are more responsive to the lagged consumption of higher-layer peers compared to same-layer peers. ~~In contrast, bottom-layer workers are more responsive to higher-layer peers (0.13 percent) in comparison to same-layer peers (0.003 percent).~~

In the heterogeneity analysis, we find that the influence of higher-layer coworkers on an individual's consumption is particularly pronounced among young and highly-educated workers. Moreover, male workers display a significantly stronger response to the consumption of all types of coworkers relative to their female counterparts. Past research has shown that young, educated, and male workers tend to be more competitive (Landau, 1995; McWhirter, 1997; Ng. et al., 2005), particularly in settings of promotion and career advancement. These observations motivated us to investigate whether promotion incentives underlie the estimated consumption peer effects within a hierarchical framework.

To explore this possibility, we analyze how peer effects correspond to a worker's relatively permanent upward movement in income layer, which we use as a proxy for promotion. We start by assessing how peer effects relate to the ex-ante probability of promotion. To accomplish this, we use individual characteristics (such as income, wealth, age, gender, marital status, and education) to estimate each individual's promotion probability. Our results suggest that workers with a higher chance of promotion display stronger peer effects with coworkers at higher and same income layers, but not with those at lower income layers. These results provide initial support for the notion that promotion incentives underlie consumption peer effects in our context.

To have a more direct understanding of the relationship between peer effect and promotion, we use an event study approach to explore how peer effects change around a worker's promotion. For promoted workers, we observe a significant increase in peer effects with higher-layer coworkers starting10 weeks before and peaking 5 weeks after the promotion. Peer effects with the same-layer coworkers demonstrate similar but much weaker dynamic pattern and the peer effects with lower-layer coworkers do not have such dynamic pattern. For non-promoted workers with similar characteristics to the promoted ones, their peer effects with higher- and same-layer coworkers slightly increase before the promotion, but drop quickly when the promotion outcome is realized.

We discuss several possible mechanisms for the dynamic peer effects. The main one is promotion motive: workers may increase their consumption to match or impress their higher- and same-layer coworkers before and during the promotion, but lose the incentive after that. We focus on two channels of promotion motive: relationship-building and gift-exchange. We find that peer effects are stronger in restaurant and luxury goods consumption, which can enhance social ties or signal generosity to coworkers. These consumption patterns support both channels and the promotion motive mechanism. We also discuss and exclude several other mechanisms, such as social learning, social conformity, anticipation about future promotion, and unobserved worker characteristics that lead to higher promotion probability as well as stronger peer effects. Those mechanisms are unlikely to explain the dynamics patterns observed around promotion events, particularly the decline in peer effects after promotion.

Our study relates to two strands of literature. The first one is on consumption peer effects, which are mostly studied within homogenous groups, such as neighbors, consumers in a specific industry, individuals with similar characteristics, or exogenously assigned groups (see Duncan et al., 2005; Kremer and Levy, 2008; Maurer and Meier, 2008; Cai, Chen, and Fang, 2009; Kuhn et al., 2011; Moretti, 2011; Agarwal, Qian, and Zou, 2021). De Giorgi, Frederiksen, and Pistaferri (2020) estimate the consumption network effect in the workplace based on annual consumption measured from tax records. They construct peers' weighted average consumption based on distance in occupation and education, assuming that workers with similar occupation and education have stronger peer effect, an assumption that we explicitly test for in this study. Chen, Lu, and Zhang's (2017) field experiment on peer effects in driving behavior shows that drivers' traffic violations are significantly affected by the driving behavior of both similar-status and high-status car drivers, consistent with our findings in the workplace hierarchy. Our study contribute to this literature by examining peer effects in consumption across different layers of the workplace hierarchy for the first time to our knowledge.

The second strand of literature is on the explanations for peer effects, which mainly focus on two channels: social learning, which involves observational learning (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992) and word-of-mouth communication (Ellison and Fudenberg, 1995; Banerjee and Fudenberg, 2004), and social conformity and status-seeking (Asch, 1956; Akerlof, 1980; Bernheim, 1994). Empirical evidence supports both channels (Moretti, 2011; De Giorgi, Frederiksen, and Pistaferri, 2020). We add to this strand of literature by introducing the novel concept that promotion incentives may be an additional factor driving peer effects in the workplace hierarchy context that we investigate, and we provide preliminary evidence to support this idea.

The remainder of the paper proceeds as follows. Section 2 describes our data. Section 3 discusses the empirical strategy. Section 4 presents our main findings on peer effect. Section 5 presents the dynamic changes in peer effects and discusses the mechanism of promotion motive, as well as possible alternatives. Section 6 concludes.

2 Data

2.1 Data and Sample Restrictions

We use a unique dataset of transaction-level consumption and employer-employee information from a commercial bank in Asia (henceforth "Bank"). The Bank is the largest commercial bank in a high-income Asian economy.[2] It provides direct deposit services for a large number of firms, in which case all employees of those firms use the Bank to receive paychecks, as well as provides a wide range of financial services for those firms' employees. Our data cover the period from July 2013 to June 2015.

This dataset includes anonymized identifiers for individuals and firms, which allow us to identify peer groups of coworkers. For each worker, we observe the transaction-level credit card consumption information, including the amount, category, date, and merchant name of each transaction. We also observe the payroll, wealth information, and demographic characteristics of the workers, such as age, gender, education, marital status, and job position.[3] All monetary variables are inflation-adjusted.[4]

Our sample for estimation includes all full-time workers aged 18–65 years (140,792 individuals).

[2] The distribution of firm sizes in our dataset is similar to that in the official business census. The official business census in this economy provides a coarsened distribution of firm size, i.e., the number of firms in this economy with less than 5, 5 to 29, 30 to 49, 50 to 199, 200 to 499, and more than 500 employees. We accordingly coarsen the firm size distribution in our data and compare the resulting distribution to that from the census. Appendix Figure A1 shows the result: except for a lower density of the smallest firms with 5 employees or less, the distribution of firm size in our data closely corresponds to that in the official business census.

[3] Workers collect paychecks with income tax deducted via a salary checking account at the Bank. We observe all incoming payroll transactions for each worker. We measure monthly net financial wealth by adding the monthly account balance of all types of accounts and subtracting the balance of loans.

[4] The data on the CPI for this economy is from the World Bank. All variables are converted into real values in June, 2013.

We restrict our sample to workers who remained at the same firm during the entire sample period (93.65% of the sample workers remain). Additionally, we only consider firms with 20 or more employees to ensure the feasibility of the clustering method for income layers (90.96% of the sample workers remain). This selection procedure yields a sample of 119,932 employees in 1,096 firms. To avoid the consumption correlation driven by periodic expenditures, we exclude periodic consumption, such as gasoline, home utilities, phone bills, traffic tickets, etc. We then aggregate the consumption at the individual-week level.

We use credit card spending data to study consumption peer effect because it is accurate and high-frequency. This is a common approach in the literature of high-frequency consumption (e.g., Gan, 2010; Agarwal and Qian, 2014, 2017). Credit card spending may not capture all consumption, but this is less relevant for our purpose. We compare one's own consumption with different coworker groups' consumption, which should not depend much on the share of credit card spending in total spending.

2.2 Descriptive Statistics

Table 1 provides the summary statistics of our sample. The workers in our sample have an average monthly income of about 3,600 USD and spend about 1,000 USD on their credit cards, which is 29.98% of their income. Most of them are male (54.9%) and have an associate's or a higher degree (86.2%). Their average age is 37.8 years and their marital status is mostly single (62.1%). They work in firms with a median size of 50 employees and an average size of 182 employees.

Table 1: Summary Statistics

	Count	Mean	S.D.	p25	p50	p75
Consumption (monthly)	2158853	1093.6	7810.0	104.1	287.4	790.7
Income (monthly)	2158853	3648.2	13887.3	1486.6	2199.3	3530.6
Wealth	2158853	31378.2	106714	1001.8	4904.8	22615.2

Age	2158853	37.8	7.9	32	37	43
Firm size	1096	182.0	736.9	28	50	123

Gender	Female	Male	
	0.451	0.549	
Marital status	Married	Not married	
	0.379	0.621	
Education	Graduate degree	Bachelor's degree	Associate's degree
	0.244	0.439	0.179
	High school	Mid school and below	
	0.132	0.006	
Job position	Blue-collar	White-collar	Managerial
	0.487	0.145	0.208

2.3 Definition of the Peer Group

In our baseline analysis, we define a worker's peer group as all coworkers in the same firm. This is a natural and credible reference group because workers spend substantial amounts of time in their firms—possibly the largest amount of time outside of their family units—and interact intensively with their coworkers, which may affect their bebavior (Dahl, Loken, and Mogstad, 2014; Hvide and Ostberg, 2015; Cornelissen, Dustmann, and Schönberg, 2017; Dimmock, Gerken, and Graham, 2018; De Giorgi, Frederiksen, and Pistaferri, 2020).

Our unique contribution is to analyze peer effects within a hierarchical coworker structure. We divide the employees of each firm into layers. First, we divide employees according to their job positions: blue-collar workers, white-collar workers, and managers. The data limitation is that the job position information is self-reported, not regularly updated and the classification is relatively broad. In order to have a more accurate measure and identify employees' dynamic changes across layers, we also use monthly income information to construct the income hierarchy and identify employees' movements across income layers.[5]

The construction of an income hierarchy has several advantages. First, employees collect paychecks, with income tax deducted, via a checking account at the Bank, allowing us to observe the actual monthly income for each employee, avoiding the measurement error issues in self-reported survey data. Second, the income flows also allow us to observe the dynamic changes at a monthly frequency, which we exploit in our subsequent analysis. Third, past studies suggest that income is a good measure of marketable knowledge and skills (Garicano and Rossi-Hansberg, 2015; Caliendo, Monte, and Rossi-Hansberg, 2015), which determine how the firm organizes and groups employees. Within the firm, income levels and job levels are significantly related (Baker, Gibbs, and Holmstrom, 1994), and large income variation exists even among same-level management jobs (Baker and Holmstrom; 1995; Caliendo, Monte, and Rossi-Hansberg, 2015).

To identify income layers within the firm, we use income data and apply an optimal k-means clustering method.[6] This method consists of the following steps: For each firm, if the number of total layers k is given, we can classify incomes into layers using the clustering method and calculate the within-cluster sum of squares WWS_k,

$$WWS_k = \sum_{g=1}^{k}\sum_{i=1}^{n}(income_{ig} - \overline{income}_g)^2 \tag{1}$$

where $income_{ig}$ denotes each income in layer g, and $\overline{income}_g$ is the average income in that layer. Thus, for each k (k =1, …, 10), there is a WWS_k, and the optimal number of layers k^* can be estimated by maximizing the second-order difference of $\log(WWS_k)$. This optimal k^* is also the

[5] Our baseline defines peers as working at the same firm. To show robustness to more stringent definition of peer group, we alternatively define peers as employees working at the same firm and living in the same municipality (inferred by the billing address), and the results remain unchanged (Online Appendix Table A.1). We do not use this more stringent definition because the geographical size of the economy we study is small, and workers at the same office may live and commute from multiple regions.

[6] See Makles's (2012) optimal k-means clustering algorithm.

kink in the curve generated from $\log(WWS_k)$ among all candidate values of k:

$$k^* = \arg\max[\log(WWS_{k-1}) - \log(WWS_k)] - [\log(WWS_k) - \log(WWS_{k+1})] \tag{2}$$

We estimate the optimal number of income layers for each firm and classify workers' monthly income into layers using the above method. The median number of layers for each firm in our dataset is 3. Online Appendix Figure A2 reports the distribution of the number of layers, showing that 96.26% of the firms have 2 to 4 layers.

3 Empirical Strategy

First, we explore the effect of all coworkers in the firm on an individual's consumption by estimating the following linear-in-mean Equation (3),

$$\ln c_{ijt} = \alpha + \beta \ln c_{-i,j,t-1} + X_{ijt}\gamma + \lambda_i + \eta_{jq} + \varepsilon_{ijt} \tag{3}$$

where i indexes workers, j indexes firms, and t indexes week. $\ln c_{ijt}$ is individual i's log consumption in firm j at time t. $\ln c_{-i,j,t-1}$ is the lagged log average peer consumption. X_{ijt} is a vector of time-varying characteristics, including log income, log wealth, age, squared age, marital status, education, number of workers in the firm, and the lagged log own consumption of worker i. λ_i denotes worker fixed effects, and η_{jq} denotes firm–quarter effects. Standard errors are clustered at the individual level. The parameter of interest is the coefficient β, which measures the peer effects within the firm.

Second, to study the peer effects from the point of view of hierarchy, we also investigate how the consumption of coworkers at different layers within the same firm affect an individual's consumption differently, using specification (4):

$$\begin{aligned} \ln c_{iljt} = \alpha + \beta_U \ln c_{l+1,j,t-1} + \beta_S \ln c_{-i,l,j,t-1} + \beta_L \ln c_{l-1,j,t-1} \\ + X_{iljt}\gamma + \lambda_i + \eta_{ljq} + \varepsilon_{iljt} \end{aligned} \tag{4}$$

where l indexes layers. $\ln c_{l+1,j,t-1}$, $\ln c_{-i,l,j,t-1}$, and $\ln c_{l-1,j,t-1}$ are the lagged log average consumption of peers at higher, the same, and lower layers, respectively. The parameters of interest are the coefficients β_U, β_S, and β_L, which measure peer effects with coworkers at higher, the same, and lower layers, respectively. η_{ljq} denotes firm-layer-quarter effects. Other specifications are the same as in Equation (3).

To estimate peer effects, we address the potential challenges of reflection, sorting, and common shocks (Manski, 1993), using the following approaches.[7]

First, we avoid the reflection problem by exploring the effect of peers' lagged consumption on individuals' current consumption, following the literature (Clark and Loheac, 2007; Kaustia and Knüpfer, 2012). This way, we isolate the one-way effect of peers on an individual: an individual's current consumption may be affected by peers' consumption in the past, while peers' past consumption cannot depend on this individual's current consumption.

Second, we address the sorting problem by controlling for individual fixed effects, which account for time-invariant unobserved characteristics that may affect both peer group selection and individuals' behavior (Cornelissen, Dustmann, and Schönberg, 2017). This strategy extends the peer group fixed effects model used by most previous studies (i.e., Kaustia and Knüpfer, 2012).

Third, we alleviate the concern of common shock by controlling for firm-layer-quarter fixed effects to capture time-varying peer-group-specific shocks. This approach follows some past studies that control for multiple fixed effects to account for common shocks at different levels (Kaustia and Knüpfer, 2012; Hvide and Östberg, 2015). These studies also assess the possibility of finer-level shocks by analyzing subsamples and comparing effects across groups, providing evidence for the

[7] Reflection refers to the situation where the behaviors of an individual and his/her peer group influence each other. The issue of sorting may emerge if individuals sort into peer groups based on similar time-invariant unobserved characteristics and then have similar consumption behavior. The common shock problem may arise if individuals within a peer group are affected by a common time-varying shock that leads to similar behavior.

social interaction mechanism rather than the common shock explanation. Specifically, Kaustia and Knüpfer (2012) analyze how past stock returns of neighbors in the same zip code area affect investors' stock market entry decision in the current month. They include province-month fixed effects to remove the effects of provincial-level shocks, a level higher than the zip code used for defining peer group. Hvide and Östberg (2015) examine the effects of coworkers' stock market investment decisions on one's own using monthly level data. They control for plant-year fixed effects to account for time-varying plant-specific shocks. Adopting similar method and control at a more delicate level, we control for firm-layer-quarter fixed effects to capture common shocks. These approaches also potentially account for unobserved shared background characteristics within peer groups and time trends in consumption, respectively. Additionally, we also control for an individual's lagged own consumption to address the possibility of serial correlation in consumption.

A remaining concern is that firm-layer-specific time-varying shock within quarter may lead to positive consumption correlations among workers. However, firm-layer-week effect cannot be added in the regression because lagged higher/lower-layer peers' average consumption is the same for each individual in the same firm-layer and in a given week, thus there is no variations to identify the coefficient of peer effects. Hvide and Östberg (2015) deal with the possibility of plant-level shocks within-year by comparing effects between small and large plants, and they find larger effects in small plants compared to large plants, supporting the social interaction mechanism rather than the alternative explanation of common shocks within-year. Similarly, Kaustia and Knüpfer (2012) assess the possible concern of zip-code-month level shocks by analyzing subsamples, proving the concern is unlikely. Following their reasoning, if firm-layer-week shocks drive the results, we would expect the similar correlations within layers across different layers (i.e., bottom, intermediate and top). But we find significant differences in the correlations, which do not support this alternative.

4 Estimating Peer Effects in Hierarchical Structure

4.1 The Overall Peer Effects

We begin by estimating how an individual's consumption is related to the lagged consumption of all coworkers in the firm. Table 2 reports the estimates of regression in Equation (3). Column (1) includes only control variables in X_{ijt}, while columns (2) and (3) additionally control for individual fixed effects and firm–quarter fixed effects, respectively. The estimated relationship between peers' lagged log average consumption and individuals' own consumption is robust across the columns. For example, in column (3), a 10 percent increase in peers' lagged average consumption is related to a 0.55 percent increase in individual's consumption, holding other factors constant.

Finding 1. The individual worker's consumption is significantly related to the lagged consumption of coworkers within the firm.

Table 2: Peer Effects

	(1)	(2)	(3)
Dependent variable:		*Log consumption*	
Lagged log average peer consumption	0.062***	0.083***	0.055***
	(0.003)	(0.002)	(0.003)
Controls	Yes	Yes	Yes
Individual fixed effects		Yes	Yes
Firm-quarter fixed effects			Yes
Observations	2,158,853	2,158,853	2,158,853
R^2	0.084	0.164	0.288
Number of individuals	119,932	119,932	119,932

Notes: This table shows the effect of lagged log average peer consumption on the individual's current log consumption. The peer group is defined as workers in the same firm. The dependent variable is the logarithm of consumption. The main independent variable is lagged log average peer consumption. Control variables include lagged log own consumption, log income, log wealth, age, squared age, marital status, five education indicators, number of workers in the firm. Standard errors are clustered at the individual level and reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, 10% level, respectively.

4.2 Peer Effects in the Hierarchy

We then move on to our test of peer effects from the point of view of hierarchy using Equation (4). We redefine peer groups based on managerial and income layers in each firm and explore how individual consumption is related to the consumption of coworkers at different layers.

Table 3 presents the estimation results. Panel A and Panel B show results in managerial and income layers, respectively. Columns (1) to (3) report the estimates for bottom-, intermediate-, and top-layer worker-weeks, respectively.[8] Here we separately examine the effects of the consumption of coworkers at positions in the same layer, the consumption of coworkers at positions that are one layer higher, and the consumption of coworkers at positions that are one layer lower.

Column (1) present results for worker-weeks at the bottom layer. The estimates demonstrates that the consumption of bottom-layer workers is more strongly related to the consumption of higher-layer coworkers than same-layer coworkers. A 10 percent increase in higher-managerial-layer (higher-income-layer) peers' average lagged consumption is related to a 0.18 (0.13) percent increase in the individual's consumption, whereas the same-sized increase in the same-managerial-layer (same-income-layer) peers' average lagged consumption is related to a 0.14 (0.03) percent increase in the individual's consumption.

Column (2) shows results for worker-weeks at the intermediate layer, who have both higher- and lower-layer coworkers. The estimates show that consumption of same-, higher-, and lower-layer coworkers all predictively affect an individual's consumption, but the strongest effect comes from

[8] We analyze worker-weeks at intermediate, top, and bottom layers, separately. Since some workers may switch between different layers, their observations are grouped into more than one of three groups. Therefore, the sum of the number of individuals in the three subsample regressions are larger than the total number of individuals in the full sample. Because some firms have only two income layers in total, observations of workers in those firms are not included in the intermediate subgroup, and that is why the intermediate subsample is relatively smaller than top or bottom subsample in Panel B of Table 3. We also run the regressions for firms with two income layers and firms with three income layers, respectively. The results are mostly robust.

same-layer coworkers. A 10 percent increase in same-managerial-layer (same-income-layer) peers' lagged consumption is related to a 0.53 (0.41) percent increase in the individual's consumption, while the effects of higher- and lower-layer coworkers are 0.27 (0.25) and 0.10 (0.17), respectively. The differences between same-layer effect and the higher -or lower-layers effects are statistically significant.

Column (3) reports results for worker-weeks at the top layer. The estimates show that the consumption of top-layer workers is more strongly related to the consumption of same-layer coworkers than lower-layer coworkers. A 10 percent increase in the same-managerial-layer (same-income-layer) coworkers' lagged consumption is associated with a 0.44 (0.33) percent increase in the individual's consumption, while a same-sized increase in lower-managerial-layer (lower-income-layer) coworkers' lagged consumption is associated with a 0.40 (0.15) percent increase in the top-layer workers' consumption.

We find similar results for both managerial and income layers. However, we focus on the results of the income hierarchy in our subsequent analyses as it has the advantage of being based on actual monthly income flow information, updated in real-time. In comparison, the managerial layer data is self-reported and may not always be updated as workers move across layers. Focusing on income layers allows us to examine a worker's dynamic position in the hierarchy, providing a unique perspective in comparison to previous studies in the literature.

The finding that the correlations vary across layers within firm also weakens the potential concern that firm-specific shock may leads to positive consumption correlations among workers. This is because if firm-specific shocks, not peer effects, drive our results, we would see that individuals have the same correlations with different groups of coworkers (e.g., higher-layer vs.

lower-layer) in the same firm.

Generally speaking, the peer effect with lower-layer coworkers is always no greater than those involving same-layer coworkers, which is consistent with more "distant" peers having less influence (De Giorgi, Frederiksen, and Pistaferri, 2020). However, the peer effects involving higher-layer coworkers are not always weaker than the same-layer effects, a finding that we find to be surprising and warrants further examination.

Finding 2. Peer effects are heterogeneous within a hierarchy. For intermediate- and top-layer workers, the consumption of coworkers of all layers is significantly related to an individual's consumption, but the effect of the consumption of same-layer coworkers is the strongest. Consumption of the bottom-layer workers is more strongly associated with the consumption of higher-layer coworkers than the consumption of same-layer coworkers.

Table 3: Peer Effects in the Hierarchy

	(1)	(2)	(3)
Dependent variable:		*Log consumption*	
Panel A: Managerial Hierarchy			
	Bottom	Intermediate	Top
Lagged peer consumption at higher layer	0.018***	0.027***	
	(0.004)	(0.002)	
Lagged peer consumption at same layer	0.014***	0.053***	0.044***
	(0.004)	(0.003)	(0.004)
Lagged peer consumption at lower layer		0.010***	0.040***
		(0.002)	(0.005)
Controls	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Firm-layer-quarter effects	Yes	Yes	Yes
Observations	449,694	1,050,456	312,325
R^2	0.278	0.268	0.282
Number of individuals	30,239	59,719	15,206

p-value (H_0: intsame=inthigher)	0.577	0.000	
p-value (H_0: intsame=intlower)		0.000	0.540
p-value (H_0: inthigher=intlower)		0.000	

Panel B: Income Hierarchy			
	Bottom	Intermediate	Top
Lagged peer consumption at higher layer	0.013***	0.025***	
	(0.002)	(0.003)	
Lagged peer consumption at same layer	0.003	0.041***	0.033***
	(0.003)	(0.006)	(0.003)
Lagged peer consumption at lower layer		0.017***	0.015***
		(0.006)	(0.003)
Controls	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Firm-layer-quarter effects	Yes	Yes	Yes
Observations	1,143,811	394,383	620,659
R^2	0.291	0.291	0.317
Number of individuals	87,454	33,472	46,297
p-value (H_0: intsame=inthigher)	0.010	0.013	
p-value (H_0: intsame=intlower)		0.005	0.000
p-value (H_0: inthigher=intlower)		0.281	

Notes: This table shows the heterogeneous effects of lagged log average consumption of peers at different layers on the individual's current own consumption. The dependent variable is the logarithm of consumption. Panel A and Panel B present results in managerial hierarchy and income hierarchy, respectively. In column 1, the sample is restricted to observations at bottom layer of each firm. The main independent variable is lagged log average consumption of peers at the same, and higher layer, respectively. In column 2, the sample is restricted to observations at the intermediate layer of each firm. The main independent variable is lagged log average consumption of peers at higher, same, and lower layer, respectively. In column 3, the sample is restricted to observations at top layer of each firm. The main independent variable is lagged log average consumption of peers at the same, and lower layer, respectively. Control variables include lagged log own consumption, log income, log wealth, age, squared age, marital status, five education indicators, number of workers in the firm. We also control for the number of workers at the same, and higher layer in column 1, the number of workers at the same, higher, and lower layer in column 2, the number of workers at the same, and lower layer in column 3. Standard errors are clustered at the individual level and reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, 10% level, respectively.

4.3 Heterogeneity Analysis

In this section, we explore the heterogeneity in the peer effect across demographic characteristics, including age, education and gender. We use the same regression as in column (2) of Table 3 but add individual characteristics and their interaction with peers' lagged consumption one-by-one. Results are shown in Table 4.

Column (1) shows the heterogeneous effect of age. We see that peer effects with same- and lower-layer coworkers do not vary significantly with age, but peer effects with higher-layer coworkers decline significantly with age. Column (2) shows the effect of education. For employees holding an associate's or higher degree, peer effects with higher-layer coworkers are 0.015 higher (107% more than the average estimate of 0.014 for employees with high school or below education), but there are no education-related differences in peer effects with same- and lower-layer coworkers. Column (3) shows the effect of gender. For male workers, we find that the effects of the consumption of coworkers at all layers are significantly stronger than for female workers.

Overall, the results imply that young/highly educated employees have stronger peer effects with higher-layer coworkers than other employees. Male employees have stronger peer effects with all types of coworkers than female employees..

Table 4: Heterogeneity Effects across Individual Characteristics

	(1)	(2)	(3)
Dependent variable:	*Log consumption*		
Interaction variable	Age	Education (Associate's degree and above=1)	Gender (Male=1)
Lagged peer consumption at higher layer	-0.001**	0.015**	0.024***
× *Interaction variable*	(0.000)	(0.006)	(0.006)
Lagged peer consumption at same layer	0.001	0.012	0.032***
× *Interaction variable*	(0.001)	(0.012)	(0.010)
Lagged peer consumption at lower layer	0.001	0.011	0.029***
× *Interaction variable*	(0.001)	(0.012)	(0.011)
Lagged peer consumption at higher layer	0.058***	0.014**	0.009**
	(0.015)	(0.005)	(0.005)
Lagged peer consumption at same layer	0.005	0.032***	0.020**

	(0.028)	(0.010)	(0.008)
Lagged peer consumption at lower layer	-0.015	0.009	0.002
	(0.030)	(0.011)	(0.008)
Controls	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Firm-layer-quarter effects	Yes	Yes	Yes
Observations	394,383	394,383	394,383
R^2	0.291	0.291	0.291
Number of individuals	33,472	33,472	33,472

Notes: This table shows the heterogeneous consumption peer effects across age, education, and gender. The dependent variable is the logarithm of consumption. The main independent variable is lagged log average consumption of peers at higher, same, and lower layer, respectively. The three variables are interacted with age in column 1, education level in column 2, and gender in column 3. Control variables include lagged log own consumption, log income, log wealth, age, squared age, marital status, five education indicators, number of workers in the firm, the number of workers at higher, same, and lower layer. Standard errors are clustered at the individual level and reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, 10% level, respectively.

Why does the peer effect related to higher-layer coworkers vary across these individual characteristics? One possible explanation under the hieratical context is promotion motive. Indeed, both Landau (1995) and Van Veldhoven and Dorenbosch (2008) find that young employees have more career opportunities than older workers. Education level is also found to be positively related to career success (Ng. et at., 2005). Men are found to have higher promotion potential evaluations (Landau, 1995), are more likely to have career success (Ng. et at., 2005), and anticipate less barriers in career development (McWhirter, 1997), compared to women.

Our observation of stronger peer effects related to higher-layer coworkers among workers with characteristics associated with promotion competitiveness leads to an interesting question about whether consumption peer effect in the workplace is partially driven by promotion motive, which is absent in homogenous groups. This motive hinges on a positive link between consumption peer effect and promotion. We explore this link further in the next section.

5 Consumption Peer effects and Promotion

To more directly explore whether consumption peer effect we observed is partially related to promotion in the hierarchy, we first examine how promotion probability correlates with peer effects across different levels. Then, we use an event study around the promotion to provide more compelling evidence for the promotion motive channel.

5.1 Peer Effects and the Probability of Promotion

We use the move from a lower to a higher income layer as a proxy for promotion. As mentioned in Section 2.3, we rely on income layer because the managerial position is not updated frequently in the data. The literature shows that income levels are positively correlated with managerial positions within hierarchy (Lazear and Rosen, 1981; Waldman, 1984), and managerial promotions are often associated with large income increase (Olson and Becker, 1983; Gibbons and Waldman, 1999). Admittedly some income raises are not necessarily associated with managerial promotions, but regardless of whether the promotion is salary-wise or managerial-wise, it has to be approved by higher-layer coworkers hence one may have a motive to act for it. For these reasons, we think income raises are meaningful events to study the promotion motive behind consumption peer effects.

To exclude temporal income raise such as bonus, we require the upward changes in income levels to last for at least two months to be counted as promotion events.[9] According to this definition, 21.03% of the workers experienced a promotion during the sample period.

Are stronger peer effects with coworkers linked to promotion? To evaluate the link between peer effects and promotion, we first estimate the promotion probability for each individual: we regress the promotion indicator on individual characteristics (log income, log wealth, age, age squared, gender,

[9] To ensure that this timing assumption does not drive the results, in a robustness test we further restrict the rise in income layer to last for at least four months and results are robust (shown in Online Appendix Figure A3).

marital status, education) and use the fitted value as the promotion probability.

We then run a similar regression as in Table 4 but add an interaction term between peers' lagged consumption and promotion probability. Regression results are shown in Table 5. The estimates of the interaction terms between the lagged peer consumption of higher-layer (same-layer) coworkers and the promotion probability are significantly positive, indicating that workers with higher promotion probability have stronger peer effects with higher-layer (same-layer) coworkers. But there is so such relationship for peer effect with lower-layer coworkers. These findings suggest that peer effects in a hierarchical structure, especially those involving higher- or same-layer coworkers, are strongly related to promotion.

Table 5: Peer Effects and Promotion

Dependent variable:	*Log consumption*
Lagged peer consumption at higher layer × Promotion Probability	0.229***
	(0.045)
Lagged peer consumption at same layer × Promotion Probability	0.178**
	(0.080)
Lagged peer consumption at lower layer × Promotion Probability	0.050
	(0.085)
Lagged peer consumption at higher layer	-0.019**
	(0.009)
Lagged peer consumption at same layer	0.006
	(0.016)
Lagged peer consumption at lower layer	0.007
	(0.016)
Controls	Yes
Individual fixed effects	Yes
Firm-layer-quarter effects	Yes
Observations	394,383
R^2	0.291
Number of individuals	33,472

Notes: This table shows the heterogeneous consumption peer effects across promotion probability. The dependent variable is the logarithm of consumption. The main independent variable is lagged log average consumption of peers at higher, same, and lower layer, respectively. The three variables are interacted with estimated promotion probability. The promotion probability is estimated by regressing promotion indicator on individual characteristics (log income, log wealth, age, squared age, gender, marital status, education), and keeping the estimated promotion probability for each individual. Control variables include lagged log own consumption, log income, log wealth, age, squared age, marital status, five education indicators, number of workers in the firm, the number of workers at higher, same, and lower layer. Standard errors are clustered at the individual level and reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, 10% level, respectively.

5.2 Dynamics of Peer Effects around Events of Promotion

- **Dynamic Change around a Promotion Event**

The above analysis provides only preliminary correlational evidence on the channel of promotion motive. To have more direct tests, we resort to the dynamic patterns of peer effects around the promotion event. If peer effects, especially those involving higher- and same-layer coworkers, are partially driven by promotion motive, then we should expect them to change before and after promotion, because promotion motive naturally declines after the promotion is realized.

We conduct an event study to investigate how peer effects vary before and after the promotion events. Promotion events are defined in the same way as that in Section 5.1. To carry out the event study, we specify a regression model that permits dynamic changes in the peer effect:

$$\ln c_{iljt} = \alpha + \left[\beta + \sum_{s=-5}^{s=6} \psi_s 1_s \right] \ln c_{l+1,j,t-1} + X_{iljt}\gamma + \lambda_i + \eta_{ljq} + \sum_{s=-5}^{s=6} \delta_s 1_s + \varepsilon_{iljt} \qquad (5)$$

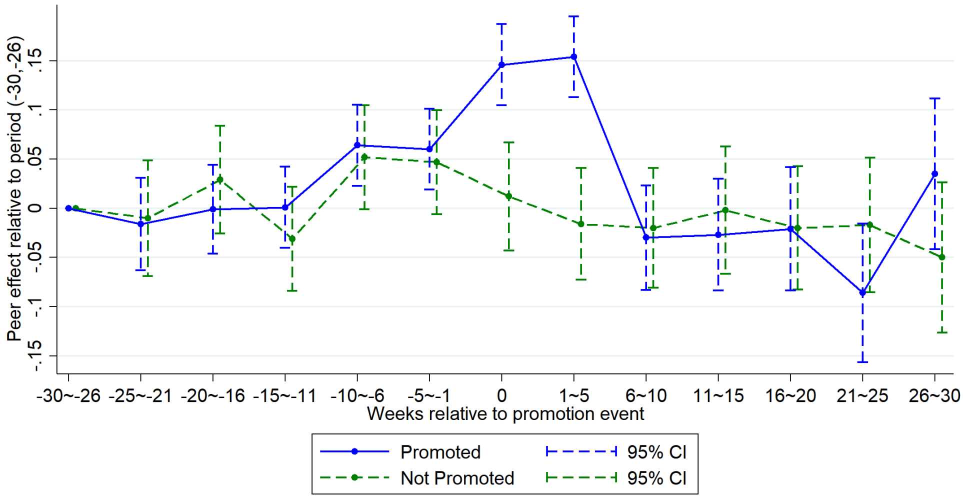
where $\ln c_{l+1,j,t-1}$ is the lagged log average consumption of coworkers at a higher layer before the promotion, who become same-layer coworkers after that. In our model, $s$indexes time relative to the promotion event: $s=0$ denotes the month of the promotion event, $s=-1,-2,...$ each denotes a 5-week intervals before the event, while $s=1,2,...$ each denotes a 5-week intervals after the event. We focus on 30 weeks before and 30 weeks after each event as well as the month of the event, giving us six intervals before ($s=-6,-5,...,-1$), one interval during ($s=0$), and six intervals after each event ($s = 1,2,...,6$).[11] The benchmark period is the $s = -6$ time interval, [-30, -26] weeks before the event. X_{iljt} is a vector of time-varying characteristics, including log income, log wealth, age, squared age, marital status, education, number of workers in the firm, number of coworkers at higher and the same layers, and the lagged log own consumption of worker i . The definitions of other variables are the same as those in Equation (3). Importantly, we interact the time indicators $s = -6, -5, ..., -1, 0, 1, ..., 5, 6$ with the lagged log average peer consumption that allow the peer effect to vary over time. We are interested mainly in the coefficient ψ_s, which dynamically measures the strength of the peer effect before and after the promotion event relative to the baseline period. Standard errors are clustered at the individual level.

To control for any unobservable common trend across workers within the same firm, we use propensity score matching to construct a sample of workers who are similar to the promoted ones but do not get a promotion.[12] We then apply the regression in Equation (5) to both the promoted and matched non-promoted groups to estimate and compare the dynamic changes around the event.

Figure 1: Estimated Peer Effect Dynamics (with Higher-layer Peers)

[11] We focus on the first promotion event for each worker to facilitate construction of the event time. If a worker experiences more than one promotion event, we exclude the period during and after the second event.

[12] We first estimate the propensity score based on a logit regression using a rich set of individual-level independent variables (peer effects with same-layer, higher-layer, lower-layer coworkers, log income, log wealth, age, squared age, gender, marital status, education). For each worker getting a promotion, the potential matched workers are those at the same layer in the same firm before the promotion, but have not been promoted during our sample period. We match each promoted worker to the nearest neighbor based on the propensity score in this potential group.



Notes: This figure plots the entire paths of coefficients ψ_s, along with their corresponding 95 percent confidence intervals, of peer effects with higher-layer coworkers relative to the baseline time interval as estimated from Equation (5). The blue solid line represents workers who experience a promotion event during the sample period, and their peers are those at a higher layer before the promotion and become same layer after the promotion. The green dash line shows matched workers with no promotion, and their peers are those at a higher layer. The *x*-axis denotes the time intervals around the promotion event. The time interval of the -30 to -26 weeks before the promotion event is the omitted category in the regression.

Figure 1 shows the estimated coefficients ψ_s along with their corresponding 95% confidence intervals for both the workers who get the promotion (blue solid line) and the matched workers who do not (green dashed lines). The full regression results are reported in Appendix Table A.2, where each regression coefficient represents either the baseline peer effect or the change in peer effect in a five-week window around the promotion event.

For workers who get a promotion, an interesting dynamic change is observed in the estimates of peer effects involving higher-layer coworkers, as shown in both Figure 1 and Table A.2. Starting from 10 weeks before the promotion ($s=-2$ and -1), there is a gradual increase by 0.064 in the estimated peer effects with higher-layer coworkers compared to the baseline [-30, -26 week] time interval ($s=-6$). The increase is both statistically (at the 1% level) and economically significant (0.064/0.025$\approx$2.6 times the average peer effect with higher-layer workers shown in Table 3). The estimated peer effect with higher-layer coworkers for the promoted worker reaches a peak (with an increase of 0.146, which is $0.146/0.025 \approx 5.8$ times the average estimate) during and shortly after the promotion ($s = 0$ and $s = 1$), and then return to the baseline level six weeks after the promotion ($s = 2$). The change in peer effects with the (previous) higher-layer coworkers are insignificant and close to zero in four of the five time intervals beyond the sixth week (i.e., beyond the $s = 1$ time interval), except for the $s = 5$ time interval where the coefficient is significantly negative at the 5% level.

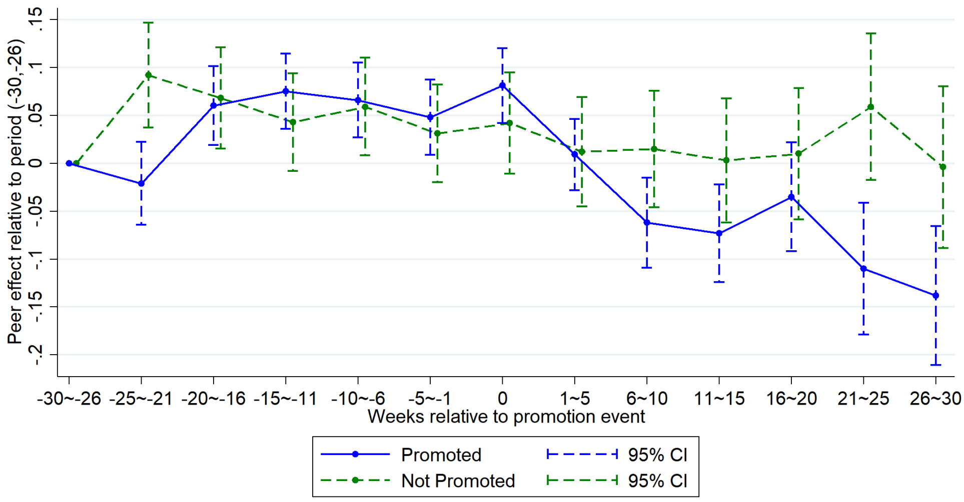
In contrast, for workers who do not get the promotion, the pre-event trend is similar to that of promoted workers: the peer effects with higher-layer coworkers increase by 0.052 (*p* value=0.058) and 0.047 (*p* value=0.084) at six to ten weeks ($s = -2$) and one to five weeks ($s = -1$) before the promotion, compared to the baseline time interval ($s = -6$). The difference between promoted and non-promoted workers emerges at the promotion period ($s = 0$): while promoted workers' peer effects peak, non-promoted workers' peer effects drop to the baseline level and remain stable afterward. .

Figure 2 presents the dynamic change in peer effects with same-layer coworkers (who become lower-layer coworkers after the promotion) around the promotion event. We find that, for promoted workers, the peer effect estimates increase slightly before the promotion and then decline significantly during and after the event. The post-event decline for promoted workers make sense as the same-layer coworkers become lower-layer coworkers, with whom the peer effects are lower. For workers without promotion, there is similar increase in estimated peer effects before the event but the change in peer effects become insignificant during and after event.

Figure 3 also shows the results involving lower-layer coworkers. We find no significant dynamic change in the peer effects estimates for either promoted or non-promoted workers around the event..

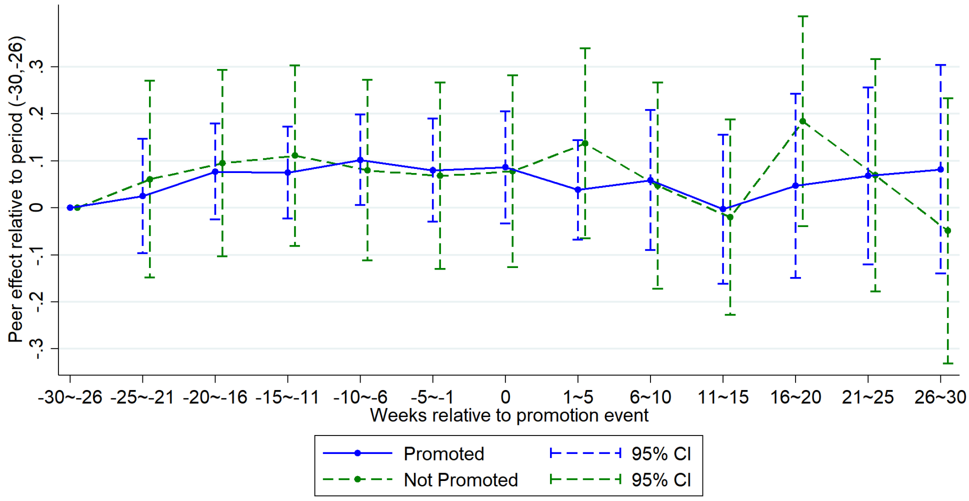
These overall patterns suggest that the dynamic change in peer effects around the promotion events is unlikely to be driven by a systematic and permanent change in income or relative position; rather, it seems to be a temporary and strategic motive that changes the peer effects for promotion-related purposes.

Figure 2: Estimated Peer Effect Dynamics (with Same-layer Peers)



Notes: This figure plots the entire paths of coefficients ψ_s, along with their corresponding 95 percent confidence intervals, of peer effects with same-layer coworkers relative to the baseline time interval. The blue solid line represents workers who experience a promotion event during the sample period, and their peers are those at the same layer before the promotion and become lower layer after the promotion. The green dash line shows matched workers with no promotion, and their peers are those at the same layer. The *x*-axis denotes the time intervals around the promotion event. The time interval of the -30 to -26 weeks before the promotion event is the omitted category in the regression.

Figure 3: Estimated Peer Effect Dynamics (with Lower-layer Peers)



Notes: This figure plots the entire paths of coefficients ψ_s, along with their corresponding 95 percent confidence intervals, of peer effects with lower-layer coworkers relative to the baseline time interval as estimated from Equation (5). The blue solid line represents workers who experience a promotion event during the sample period, and their peers are those one layer lower before the promotion and two layers lower after the promotion. The green dash line shows matched workers with no promotion, and their peers are those one layer lower. The *x*-axis denotes the time intervals around the promotion event. The time interval of the -30 to -26 weeks is the omitted category in the regression.

Finding 3. Among workers who get a promotion, their peer effects with previously higher- and same-layer coworkers gradually increase before the promotion event and decline thereafter. The pattern is more salience with higher-layer coworkers. We observe no similar pattern in non-promoted workers.

- **Discussion of Mechanisms**

In this section we discuss several possible mechanisms to explain our findings on the patterns around the promotion event.

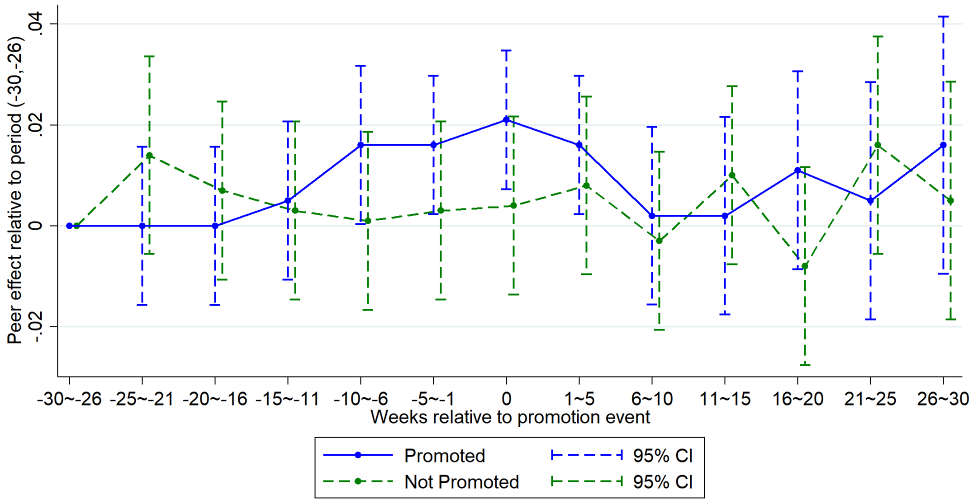
The first mechanism is strategic reaction to promotion. The consumption peer effect heterogeneity across age, gender and education as well as the positive relationship between promotion probability and consumption peer effect provide suggestive evidence for the promotion motive, while the dynamic pattern from the event study provides more compelling evidence that workers may strategically manipulate the consumption peer effect for promotion purpose.

Understanding the exact channels through which consumption peer effect maps to promotion is important yet very challenging given our observational data. There could be different ways this happens. One way is that workers try to build better relationships with their coworkers by having similar consumption or more common interests. This can help them get promoted because people tend to like those who are similar to them (Berscheid and Hatfield, 1969; Byrne, 1971; Walter and Bruch, 2008) and good relationships matter for career advancement (Seibert, Kraimer, and Liden, 2001; Forret and Dougherty, 2004; Wolff and Moser, 2009; Zinovyeva and Bagues. 2015; Fisman et al., 2018; De Janvry et al. 2023). Another way is that workers give gifts to their coworkers based on what they usually consume and hope that their coworkers will return the favor (Dodlova and Yudkevich, 2009; Kube, Maréchal, and Puppe, 2012; Cao, Li, and Liu, 2020). This can also help them get promoted because gift exchange can create social obligations and gratitude (Shleifer and Shleifer, 1993; Rosenblatt, 2012; Chen and Kung, 2019). We cannot test these ways directly with our data, but we can show some clues from different types of consumption.

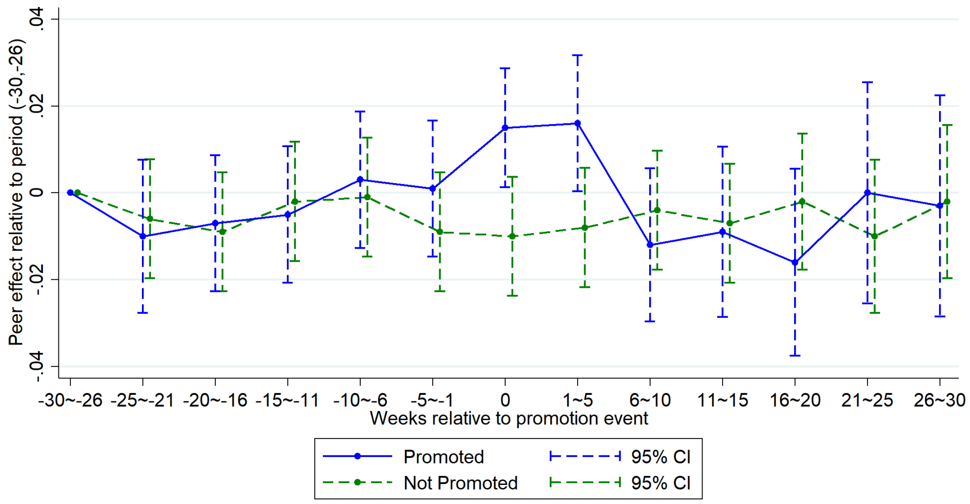
We look at different kinds of consumption: restaurants, luxury goods, and other daily things (e.g., clothes, books, movies, etc.). Figure 4 shows how peer effects change around the promotion event for these categories. We see that the changes we found before are mainly in restaurants and luxury goods. Eating out is a common way to socialize in Asian cultures and can improve relationships. This fits with the relationship-building idea. Buying luxury goods like peers may also help with building relationships or giving gifts. These results suggest that both ideas could explain the peer effect related to promotion. More data on individual behavior would help us understand better how promotion motive affects peer effects on consumption.

Figure 4: Estimated Peer Effect Dynamics with Higher-layer Peers in Three Consumption Categories

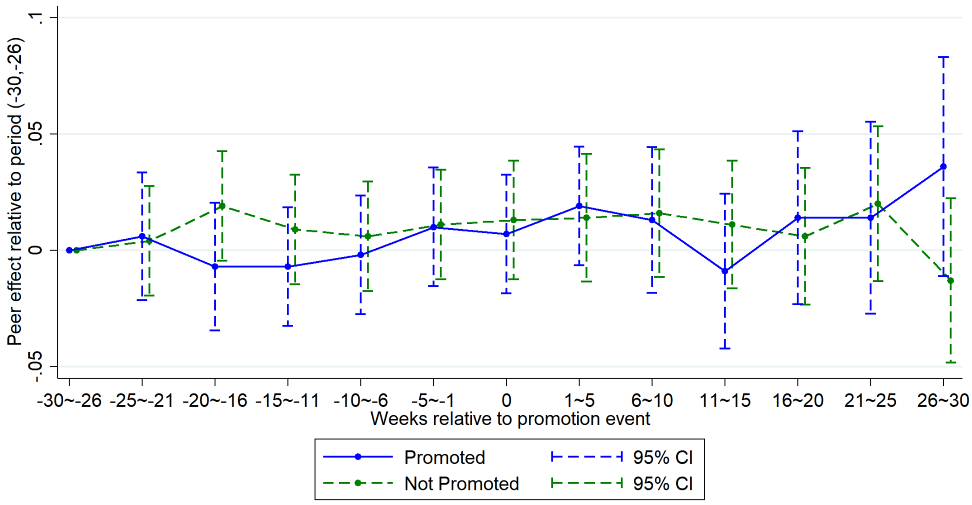
Panel A Restaurant



Panel B Luxury goods



Panel C Others



Notes: This figure plots the entire paths of coefficients ψ_s, along with their corresponding 95 percent confidence intervals, of peer effects with higher-layer coworkers relative to the baseline time interval, in three categories of consumption. The blue solid line represents workers who experience a promotion event during the sample period, and their peers are those at a higher layer before the promotion and at the same layer after the promotion. The green dash line shows matched workers with no promotion, and their peers are those at a higher layer. The *x*-axis denotes the time intervals around the promotion events. The time interval of the -30 to -26 weeks is the omitted category in the regression.

The second possible mechanism is social learning. Previous studies have shown that peer effects can happen because people learn from each other about the quality of a product and then buy similar things (Banerjee, 1992; Moretti, 2011; Banerjee, Chandrasekhar, Duflo, and Jackson, 2013; Bursztyn, Ederer, Ferman, and Yuchtman, 2014; Dahl, Loken, and Mogstad, 2014; Cai, De Janvry, and Sadoulet, 2015). This could mean that getting a promotion makes one more aware of new products and lifestyles and increases the correlations in consumption with peers. However, this does not explain why the correlations decreases after the promotion event.

The third possible mechanism is social conformity and status-seeking. Some studies have attributed peer effects to the preferences to follow the norms or behaviors of a social group to fit in or to signal one's social status (Bernheim, 1994; Bursztyn, et al., 2014; Bursztyn and Jensen, 2015; Chen, Lu, and Zhang, 2017; De Giorgi, Frederiksen, and Pistaferri, 2020; Agarwal, Qian, and Zou, 2021).

However, these preferences are likely to be stable over time (Stigler and Becker, 1977), so they do not account for any temporal change around the promotion event. Another concern is that promotion may indicate a positive change in income and in status, which under social conformity and status-seeking theory can lead to a change in consumption correlation. But again it is hard to understand why such correlation drops after the event.

Moreover, the anticipation of future promotion may explain the change in consumption correlation. In particular, the promotion event may be anticipated and workers may adjusted their consumption to match their expected income level, which rises on the event and persist onward in time. However, it is again difficult to explain the decline in peer effects six to ten weeks after promotion. A related concern is that workers may increase peer effects due to the announcement of managerial promotions before income raises. But this would only affect promoted workers, not non-promoted ones. But we find that both groups have similar pre-event increase in peer effects with higher-layer coworkers, which reject this explanation.

Lastly, some unobserved worker characteristics may lead to higher probability of promotion as well as higher level of peer effect. For instance, ambitious workers may be more likely to get promotion and to emulate higher-level peers' behavior. However, this does not explain the dynamic changes in peer effects around the promotion unless these characteristics are also influenced by promotion. In that case, the effect may be also driven by the promotion motive.

6 Conclusions

This paper uses a unique dataset comprising high-frequency consumption records and employer-employee information to study the formation of individual consumption in the social processes, and more specifically in the non-homogeneous groups of hierarchy levels in the firm. We find that individuals' consumption is positively associated with that of coworkers in the same firm. For intermediate- and top-layer workers, coworkers of all layers exert significant peer effects, although stronger effects are observed among coworkers of the same layer. For bottom-layer workers, the consumption of higher-layer coworkers has a stronger effect. We also find interesting heterogeneity across individual characteristics: the estimated peer effects with higher-layer coworkers are stronger among young and highly educated employees. Men are more responsive to the consumption of all types of coworkers than women. According to the literature, young, well-educated and male workers are generally more competitive, the heterogeneity leads us to consider the promotion motive underlying the estimated consumption peer effects.

To test the promotion motive mechanism, we first examine how peer effects vary with promotion probability and find that they are stronger with higher- and same-layer coworkers for workers who are more likely to be promoted. We then use an event study approach to explore how peer effects evolve before and after a worker's promotion. We find that promoted workers begin to exhibit increased peer effects with higher-layer coworkers 10 weeks before the promotion event, and these effects continue to increase until five weeks after the promotion event before fading. For non-promoted workers, their consumption peer effects with higher-layer have similar increase before promotion, but decrease during the promotion period. These patterns are visible primarily with respect to the consumption of restaurant services and luxury goods. Peer effects with previously same-layer coworkers also increase slightly before the event and decline sharply during and after the event for promoted workers. No dynamic changes in peer effects with previously lower-layer coworkers are observed.

These newly documented dynamics in peer effects highlight that the motivation of promotion is a key mechanism underlying consumption peer effects in a hierarchy. Further research is needed to explore the role of other hierarchical structures in peer effects among individual and firms, as well as the role of hierarchical consumption peer effects in financial markets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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