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Government guidance funds and regional talent mobility: evidence from China's floating population

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Abstract

Purpose – The purpose of this study is to investigate the influence of government-guided funds (GGFs) on the cross-regional mobility of talent within China. The research aims to provide empirical evidence on how GGFs, as a policy tool for local economic development, attract highly educated labor and impact the distribution of human capital across different provinces. It also seeks to uncover the micro-mechanisms through which GGFs influence talent mobility, offering insights for talent strategy formulation and implementation.

Design/methodology/approach – The study employs a discrete choice model to analyze the impact of GGFs on interprovincial talent mobility in China using data from 2011 to 2017. It utilizes a unique dataset combining the China Migrants Dynamic Survey (CMDS) with GGF data from PrivCo. The methodology includes controlling for fixed effects and using instrumental variables to address potential endogeneity, providing a robust analysis of GGFs' influence on talent attraction and mobility.

Findings – The study finds that the establishment of GGFs significantly attracts talent from other provinces, particularly in more developed cities and those closer in geographic proximity. GGFs increase job opportunities and expected income levels, thereby enhancing a city's attractiveness to skilled labor. The impact of GGFs on talent mobility is more pronounced within the same province, suggesting that these funds effectively promote intra-provincial talent mobility and help curb the outflow of local talent.

Originality/value – This study offers original insights by examining the micro-mechanisms of how GGFs influence labor mobility, a perspective often overlooked in the literature. It provides valuable empirical evidence on the talent agglomeration effects of GGFs, contributing to the understanding of regional economic development strategies. The findings have practical value for policymakers seeking to leverage financial policies to attract and retain talent, fostering innovation and economic growth.

Keywords Government-guided funds, Talent mobility, Enterprise innovation, Agglomeration

Paper type Research article

1. Introduction

Venture capital (VC) typically entails high risk and high returns, providing crucial support for innovation in high-tech enterprises. Local governments also lean toward VC to invigorate urban economic development. In practice, VC operates diversely and flexibly to provide financial support for the establishment of enterprises, which promotes the development of emerging industries. In recent years, China's supply-side structural reforms have entered a rapid development phase. But the efficiency of market resource allocation is constrained by various issues within the investment and financing management system. The emergence of government-guided funds (GGFs) has effectively addressed this issue. Compared to strategies directly influencing enterprise development, such as tax reductions and innovation subsidies, GGFs can leverage individual VC to broaden the financing scale, thus exhibiting fiscal amplification

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effects. Moreover, when managed properly, they can generate sustainable cash flow from fund returns.

GGFs are vital instruments for fostering regional innovation by leveraging industrial policies to stimulate the interaction between regional development and talent. It assists local governments in achieving long-term economic growth with limited resources. Although China introduced VC relatively late, GGFs are gradually evolving toward maturity and high quality for continuous improvements in economic and market environments. Taking Anhui Province as an example, the government of Hefei City has effectively utilized GGFs to drive economic development. Hefei took the lead in introducing GGFs, achieving economic leaps and industrial transformations while continuously enhancing the competitiveness of its talent pool. In recent years, Hefei has attracted an increasing number of highly educated laborers [1], accompanied by a significant rise in wage levels compared to other cities. Therefore, the effective implementation of GGFs not only enhances regional economic development but also optimizes human capital.

When the government makes policies aimed at liberalizing capital markets, there are spillover effects on the demand for labor markets due to the interconnectedness of economic development. The establishment of GGFs effectively alleviates the problem of insufficient private VC, thereby activating local economic "cells." The establishment of new enterprises increases the demand for labor, especially for highly educated and skilled professionals. Capital and labor are crucial factors of production endowed in regional economies. Whether local capital open policies, such as GGFs, can attract human capital (especially high-quality labor) inflow? That is a pertinent question for enhancing the overall quality of local labor capital and revitalizing the potential for local economic development. Addressing this question contributes to a deeper understanding of talent attraction policies and government-sponsored VC (GVC), providing more insightful recommendations.

We employ data from the China Migrant Dynamics Survey (CMDS) between 2011 and 2017, combined with Chinese GGF data, to investigate the influence of urban GGF initiatives on attracting high-education human capital from other provinces. By matching CMDS data with GGFs data sourced from Private Equity Info, we construct a province-city (origin-destination) mixed cross-sectional dataset. After excluding intra-provincial migration samples, this paper measures the attractiveness of destination cities to human capital from origin provinces by the proportion of talent inflows to the destination city relative to total talent outflows from the origin province. Furthermore, it estimates the cumulative amount of GGF investment in the destination city's impact on talent attraction.

We find that the establishment of GGFs is a significant factor in enhancing urban talent attraction both statistically and economically. This positive effect remains robust even after controlling for alternative independent variables and reference provinces. Our mechanism results demonstrate that the GGFs promote talent migration through two channels: (1) stimulating new firms, which expand local employment; (2) accelerating the growth of high-tech industries, thereby enhancing regional competitiveness and attracting skilled labor from other provinces. The heterogeneity analysis reveals that GGFs exhibit a stronger capacity to attract talent in more developed cities. Moreover, GGFs tend to draw talent inflows from geographically proximate origin cities, particularly those within the same province. Lastly, GGFs primarily attract mobile talents to non-manufacturing sectors and high-tech occupations. These findings offer new insights for other countries, especially developing nations, when contemplating strategies to enhance regional talent attraction and foster the development of key industries.

The contribution of this study is threefold. Firstly, we uncover the "talent agglomeration" effect of GGFs and provide a more micro perspective of GVC. Existing literature predominantly focuses on the direct effects of GGFs on capital markets (Brander *et al.*, 2015) or beneficiary enterprises (Tian and Wang, 2014), overlooking the indirect impact of this policy tool on talent agglomeration. By examining talent mobility, we investigate the pulling

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effect of GGFs on talent. This greatly broadens the economic value of GGFs and serves as a crucial starting point for examining GVC from a more micro perspective.

Secondly, we demonstrate that GGFs serve as positive factors influencing population mobility. Existing literature explores various external factors, such as environmental pollution, social public services, housing prices and business environments, affecting population mobility (Rishi and Khuntia, 2012; Plantinga *et al*., 2013). However, by adopting a new perspective centered on GGFs, our study provides an important supplement to this field.

Lastly, we offer an important mechanism of GGFs on labor mobility. Previous literature suggests that GGFs primarily enhance the innovation performance of beneficiary enterprises by alleviating financing constraints (Lerner, 2002) and increasing the enthusiasm for innovation and entrepreneurship (Shin *et al*., 2012). But they overlook the importance of human capital. We explore the new channels of GGFs to talent mobile. The GGFs stimulate new firms and provide new jobs, and also improve the high-tech industry, which increases the activity of the regional development. Thus, concerning the research topic of how GGFs promote local enterprise innovation, in conjunction with our research findings, talent agglomeration may serve as an important influencing mechanism, which provides crucial direction for future research.

The remaining sections of this paper are organized as follows. Section 2 provides a brief description of the institutional background and proposes hypotheses. In Section 3, we derive an econometric model from the utility function of migrant workers and provide a brief introduction to the data used in the empirical analysis. Section 4 shows the empirical results, including baseline regressions, robustness checks and endogeneity tests. Section 5 provides the mechanism test, and Section 6 conducts heterogeneity analysis. Section 7 provides a comprehensive discussion of our research findings.

2. Literature review and institutional background

2.1 Literature review

The positive impact of GVC on firm performance has garnered widespread recognition in existing literature. Several studies suggest that GVC helps start-ups overcome information asymmetry issues with risk capital management institutions, thereby increasing their chances of securing VC. Specifically, governments can signal to capital markets through credit guarantees, which enhances the recognition of start-ups receiving GVC investments (Jeng and Wells, 2000; Jääskeläinen *et al*., 2007; Hall and Lerner, 2010). Finally, it alleviates the financing constraints of start-ups (Lerner, 2002; Allen *et al*., 2005). For instance, Lerner (2002) proposed early on that GVC increases market confidence in the future profitability of assisted start-ups since government agencies are better positioned to identify promising start-ups. Several studies mainly explore the impact of GGFs on the performance of assisted enterprises from a micro perspective. For example, GGFs can enhance future sales revenue and employee growth rates of funded enterprises (Lerner, 2000; Li *et al*., 2024a, b), promote research and development innovation (Manso, 2011; Zhang *et al*., 2024) and increase the probability of successful exits (Brander *et al*., 2015). Given a higher tolerance for short-term failures, firms funded by GVC are more likely to engage in risky, long-term, high-failure-rate research and development activities (Manso, 2011; Tian and Wang, 2014), resulting in increased innovation output in the long run.

Some literature discusses the impact of GVC on capital markets. Brander *et al*. (2015) demonstrated that GVC and private VC are complementary, increasing the scale of VC and the number of funded enterprises. Moreover, companies receiving mixed financing have a higher probability of successful exits than those receiving single-source financing. In comparison to these existing studies, our research delves into the macroscopic impact of GGFs on regional labor markets, enriching the study of GVC and providing new insights into the mechanisms by which GVC promotes enterprise innovation.

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Another relevant literature pertains to studies on labor mobility. According to the "push-pull theory" in labor economics, population mobility often depends on the comparison of living conditions between destination and origin areas (Bogue, 1959). Existing research mainly discusses the factors influencing individual migration decisions from two aspects: individual characteristics and external environments. Individual characteristics primarily include age (Bernard *et al*., 2014), gender (Dang *et al*., 1997), family status (Fan *et al*., 2011) and educational level (Schwartz, 1976), among others. External macro factors mainly include housing prices (Plantinga *et al*., 2013), environmental pollution (Rishi and Khuntia, 2012), expected income (Kennan and Walker, 2011), social public services (Bayoh *et al*., 2006) and household registration systems (An *et al*., 2024). For the talent migration, the mobility of highly skilled individuals is more sensitive to related factors than general labor mobility. Chen *et al*. (2022) found that regions with higher levels of educated populations are more prone to talent outflows due to air pollution. Facchini *et al*. (2019) discovered that uncertainty in urban trade policies mainly increases the influx of high-skilled labor, while the influx of low-skilled labor remains relatively unchanged. In terms of the migrant talent utility, we are the first to investigate the impact and mechanisms of GGFs on talent migration, expanding the research boundaries in the field of talent mobility.

As a government-led investment tool with policy guidance functions, GGFs have played a significant "pull factor" in attracting high-skilled labor. First, the resource effect of GGFs reduces the financing constraints of enterprises (Chen *et al*., 2024a, b), provides financial support for local enterprises, especially high-tech enterprises (Hao *et al*., 2025) and promotes the improvement of their production capacity and innovation capabilities. With the support of GGFs, enterprises can expand their scale and develop new businesses, thereby creating more employment opportunities and increasing wages (Li *et al*., 2024a, b). Especially in high-tech industries, GGFs' investment is often concentrated in scientific and technological innovation and high-tech industries, which have a large demand for high-skilled labor and therefore attract a large influx of talent.

In addition to being a "pull factor" to attract talent inflow, GGFs may also form a "push factor" by promoting the innovation capabilities of the inflow areas. GGFs often focus on innovation-driven and industrial upgrading (Zhang *et al*., 2024) and enhance the innovation vitality and capabilities of local enterprises through investment in strategic emerging industries (Li *et al*., 2024a, b). This improvement not only enhances the industrial competitiveness of the inflow area but may also widen the gap in economic development levels with other regions. With the acceleration of innovation-driven and the optimization of industrial structure, the technological and economic advantages of the inflow area have gradually become prominent, resulting in the outflow of high-skilled labor in other regions due to limited development opportunities. Therefore, the investment of GGFs not only promotes the economic growth of the inflow area but also indirectly widens the economic gap between regions, forming a "push factor" that promotes the outflow of talent from other regions.

Taking into account the role of GGFs, we believe that its impact on talent mobility is dualistic: on the one hand, by improving the employment environment in the inflow area, including increasing employment opportunities and improving income levels, GGFs enhance the region's attractiveness to high-skilled labor; on the other hand, GGFs further aggravate the economic gap between regions by promoting innovation vitality and innovation capability, weakening the ability of other regions to retain high-skilled labor. Therefore, the establishment of GGFs not only attracts high-skilled labor in the inflow area but also may promote the outflow of talent from other regions, forming a two-way dynamic mechanism. Based on the above analysis, we propose Hypothesis 1:

The establishment of regional GGFs will enhance the region's attractiveness to high-skilled labor by improving the employment environment and promoting innovation development.

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2.2 Institutional background

GGFs represent a governmental initiative derived from the adaptation of GVC models to the political and economic landscape of China. The earliest GVC initiative globally was the Small Business Investment Company Fund (SBIC) established by the U.S. Small Business Administration (SBA) in 1958, benefiting world-renowned innovative enterprises such as Intel, Apple and FedEx. Subsequently, this policy-driven fund model was emulated by other countries and evolved into various modes of operation, such as the United States' capital market-oriented model, Israel's government-led model and Japan's bank-led model.

China's GGFs primarily draw inspiration from the government-led model. Initially, the government invests in establishing a parent fund, which then participates in other newly established industry investment funds through market-oriented operation models, employing methods such as capital injection, forming an operational process of "government–parent fund–subsidiary fund." In comparison to Israel's investment funds, the Chinese government's involvement in fund management is significantly higher. That means the closer government–enterprise ties and the greater risk-taking by the government will result in significant operational differences between the two modes. Furthermore, borrowing operational models from federal systems like the United States, China's GGFs rely on the administrative system. Depending on the contributing entities, funds are established at national, provincial, municipal or county/district levels, providing greater flexibility and local characteristics.

GGFs in China commenced relatively late, with the first recognized GGF being the Zhongguancun (Chinese: 中关村) VC Guidance Fund established in 2002. Following this pioneering project, the state and various levels of government continuously introduced new management methods for GGFs, enhancing their efficiency and industrial guidance effects. With the continuous standardization of management practices, the development of GGFs has become more market-oriented, professional and diversified. Based on the developmental characteristics of GGFs, we categorize their evolution into four stages:

The Exploratory Stage (2002–2008): This phase was primarily an exploratory period, marked by pilot initiatives such as the "Interim Measures for the Management of Special Funds for the Development of Small and Medium-sized Enterprises." The establishment of GGFs was cautious, with relatively low numbers and amounts.

The Initial Stage (2009–2014): During this period, GGFs began to emerge with both the number and amount of funds showing growth trends, albeit at relatively modest levels.

The Rapid Development Stage (2015–2016): Following the implementation of new laws such as the "Budget Law of the People's Republic of China" and the "Interim Measures for the Management of Special Funds for the Development of Small and Medium-sized Enterprises" in 2015, local governments at all levels accelerated the establishment of GGFs.

The Standardization and Adjustment Stage (2017–2024): During this phase, efforts were directed toward establishing comprehensive regulations and policy frameworks for GGFs, strengthening budgetary control constraints and enhancing risk prevention and control measures.

Through these stages, the evolution of GGFs in China reflects a gradual maturation process, characterized by increasing institutionalization and refinement of management practices, ultimately contributing to the promotion of industrial development and innovation within the country.

Figure 1 shows the distribution of newly established and cumulative GGFs from 2009 to 2022. It is evident that the amount of newly established local GGFs showed slow growth from 2009 onwards, experienced a rapid increase in growth rate after 2014, peaked in 2016, and gradually declined thereafter, stabilizing at a relatively consistent level. The trend in cumulative GGFs amounts aligns closely with this pattern. Since 2017, the growth rate of cumulative GGFs has maintained relative stability. Therefore, we chose the period from 2011 to 2017 as the sample period as it encompasses three critical phases of robust development in

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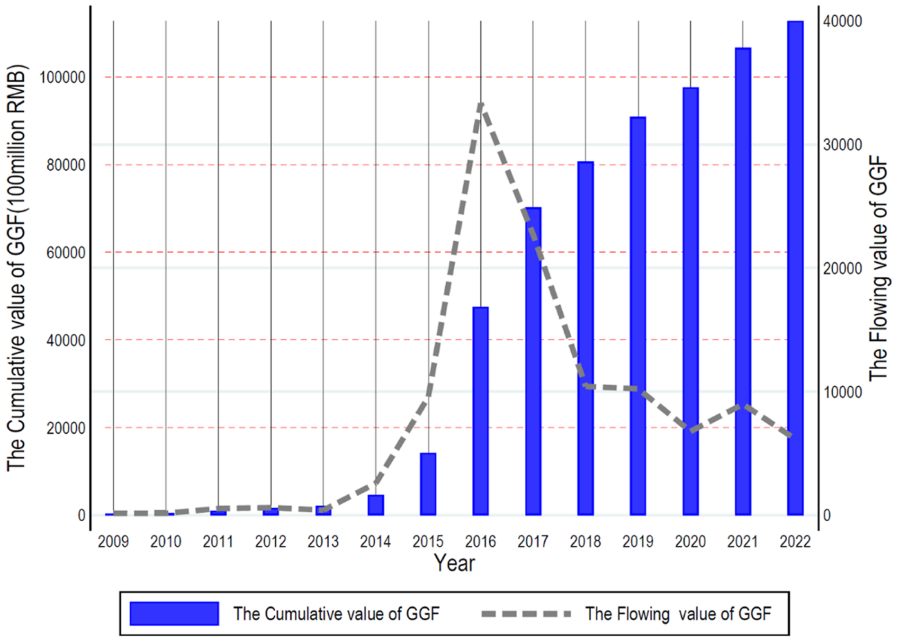

Figure 1. Development trend of the Chinese GGFs from 2009 to 2022. Source(s): Authors' own work

China's GGFs. This period allows for a comprehensive understanding of the policy impact of GGFs and is deemed reasonable for analysis.

China's GGFs are gradually maturing toward a direction of high quality, boasting several successful case studies. Hefei, in particular, stands out as a typical city in China that has achieved economic prosperity and industrial transformation through GGFs. Over the course of 20 years, it transitioned from a city primarily focused on household appliance assembly to an innovation hub with a series of globally leading achievements. Its GDP surged from 59 billion RMB to 1.2674 trillion RMB, a transformational journey often referred to as the "Hefei Model." In 2008, Hefei strategically introduced Beijing Oriental Electronics (BOE) Technology Group Co., Ltd. with a model combining GGFs and industrial chain processes. Leveraging the entry of this leading enterprise, Hefei attracted a large influx of related talents, capitalized on the rise in stock prices and reinvested profits into new industries through stock reduction, thus perpetuating a cycle of development. Through this developmental paradigm, Hefei has made remarkable achievements in industries such as semiconductors, displays and industrial robotics.

Hefei's case suggests that GGFs may drive economic development through upgrading the labor force structure. To validate our hypothesis, we draw inspiration from Moretti (2004) and define individuals with a diploma or above as high-skilled labor. Using the 2017 cumulative amount of local GGFs, we generate a heatmap and plot talent outflow from Shaanxi Province to visualize migration patterns. Thicker arrows represent larger volumes of talent mobility, as illustrated in Figure 2. Coastal cities in the eastern regions and cities with higher administrative levels exhibit larger amounts of GGF allocation. Simultaneously, most of Shaanxi Province's population migrates to surrounding areas or coastal regions in the east. The former is due to spatial proximity advantages, while the latter shows a positive correlation with the spatial distribution of GGFs. This suggests that GGFs can enhance urban talent attraction to a certain extent. Certainly, rigorous causal identification is required to further understand the relationship between talent mobility and local guidance funds.

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Figure 2. The distributions of GGFs and talent mobility in China's mainland province. Source(s): Authors' own work

3. Data and model

3.1 Model

The literature on labor mobility commonly employs Conditional Logit models (McFadden, 1974). However, the limitations of the Conditional Logit model primarily lie in its acceptance of explanatory variables that vary with scenarios, leading to the independence of respondents from different years or locations. Additionally, the Conditional Logit model imposes stringent requirements on sample data, necessitating data filling for all possible alternative scenarios, which may result in sample selection bias. Therefore, this paper innovatively adopts a discrete choice model commonly used in empirical industrial organization studies (Berry, 1994).

In the model, each year, each place of residence is considered as a relevant market. Labor force respondents choose their workplace based on the principle of maximizing their own utility, which is related to regional GGFs and other development. The sum of choices made by all labor constitutes the observed labor mobility share in the data.

The utility function for representative labor i selecting alternative j out of J options is expressed as follows:

$$U_{ij} = \alpha GGF_j + \beta X_j + \xi_j + v_{ij}, i \in \{1, 2, 3, \ldots, N\}, j \in \{0, 1, 2, .., J\} \quad (1)$$

This study investigates the impact of regional government-led funds on labor mobility in China. Using data from 2011 to 2017, we employ a discrete choice modeling approach to analyze the factors influencing labor migration decisions. Specifically, we consider the development level of GGFs in each region (GGF_j), observable characteristics (X_j) and unobservable characteristics (ξ_j) as determinants of labor migration. Additionally, we

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incorporate the heterogeneity of utility (ν_{ij}) derived by representative labor i relocating to region j. Notably, due to the minimal proportion of labor inflows to Xinjiang and Tibet, we treat these regions as the baseline or external choice ($j = 0$).

Given that the first three terms in Equation (1) are unrelated to labor characteristics, we define the average inflow utility for region j as

$$\delta_j = \alpha GGF_j + \beta X_j + \xi_j \tag{2}$$

Hence, the utility of labor i choosing workplace j is rewritten as $U_{ij} = \delta_j + \nu_{ij}$. Let S_j denote the proportion of labor inflows to region j relative to all laborers in their respective domiciles. Assuming ν_{ij} follows a Type I extreme value distribution and applying the principle of utility maximization ($U_{ij} \geq U_{ik}$; , $\forall k \neq j$), we can derive the share of labor inflows from domicile c to region j. (See Appendix for the detailed derivation process)

$$S_j = \frac{exp\left(\delta_j\right)}{1 + \Sigma_k exp\left(\delta_k\right)} \tag{3}$$

If the utility of the benchmark scenario's labor force selection is standardized to 0, then

$$S_0 = \frac{1}{1 + \Sigma_k exp\left(\delta_k\right)} \tag{4}$$

According to Eqs. (2)–(4), we have

$$lnS_j - ln\,S_0 = \alpha GF_j + \beta X_j + \xi_j \tag{5}$$

where c is the domicile, j is the destination and t is the year, by summing up the labor force migration utilities as described above. Then we obtain the labor force migration shares between different regions. The final econometric model is as follows:

$$ln\left(S_{cjt}\right) - ln\left(S_{c0t}\right) = \alpha + \beta \times GGF_{jt} + \gamma X_{jt} + FE_{ct} + FE_j + v_{cjt} \tag{6}$$

The specific definitions of each variable are as follows: (1) Dependent variable $\ln(S_{cjt}) - \ln(S_{c0t})$: the difference in the logarithm of labor force migration shares, where S_{cjt} represents the share of the labor force from province c migrating to city j in year t and S_{c0t} represents the share of the labor force from province c migrating to the reference province in year t; (2) Independent variable GGF_{jt}: the logarithmic value of the cumulative amount of GGFs established locally, and we also use the cumulative quantity of GGFs for robustness checks; (3) Control variables X_{jt} include a series of other factors that attract labor force migration to cities, such as the population count (*Population*) to measure city size, the annual average housing price (*House price*) to measure living costs, the annual emission of industrial sulfur dioxide (SO_2) to measure city environment, the amount of annual research and development expenditure (*RD*) to measure enterprise innovation and the per capita gross domestic product (*PGDP*) to measure the economic development of regions. v_{cjt} is the random error term.

Additionally, we incorporated various fixed effects into the analysis. The first is the "origin × year" fixed effect, which helps control for common characteristics of labor markets in each place of origin, thus partially eliminating differences among them [2]. The second is the "destination province" fixed effect, which controls for common trends at the provincial level, such as policy measures enacted by provincial governments [3] that may affect cities within the province differently.

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3.2 Data description

Our analysis is based on detailed information on talent migrant labor and regional GGFs applications. To achieve the empirical objectives of this paper, we constructed a unique analysis dataset by integrating data from different sources.

3.2.1 Talent migrants. The primary data utilized for the empirical analysis of migrants are derived from the China Migrants Dynamic Survey (CMDS) [4]. This survey, conducted annually by the National Health Commission of China (formerly the National Population and Family Planning Commission of China) since 2009, specifically focuses on migrants [5] employed in over 300 cities across 31 provinces throughout the country. The survey employs a stratified probability proportional to size sampling (PPS) method, ensuring that the sample size corresponds proportionally to the total number of migrants in each city.

It is important to note that the CMDS is a repeated cross-sectional dataset rather than a panel dataset. The main advantages of CMDS for our study purpose are that it has a large sample size (approximately 1 million migrant records from 2011 to 2017) and its representative migrants. To our knowledge, there is no existing panel dataset with a comparable sample size that tracks migrants over time in China. The challenges associated with large-scale, longitudinal tracking of migrants in China may contribute to the absence of such datasets. Therefore, we focus on CMDS for the analysis of migrants.

We have detailed information on each respondent's wages (more specifically, the wage income of the previous month before the survey), as well as key demographic information such as education, mobile type and birthplace, where the education includes that "Not enrolled," "Primary school," "Junior high school," "Senior high school," "Secondary vocational school," "College (Associate degree)," "Undergraduate (Bachelor's degree)" and "Graduate school." We are interested in the migration patterns of labor forces with at least a college education. Our interest lies in the migration patterns of labor forces with at least a college education.

We process the raw data via the following procedures. First, we drop individuals whose mobile type, current city and province of Hukou (Chinese: 户口) are missing. Second, we delete the province of Hukou, which includes Taiwan, Hokang, Macao and Foreign, since this paper focuses on the China's inland talent mobile. Then, we delete those samples from the province of Hukou, which are the reference provinces, Xinjiang and Tibet. Finally, we aggregate the total migrants at the province of Hukou level and sum the talent labor in the province (Hukou) city (destination city). These procedures lead to the working sample of 26,614 talent labor migrant records at the province and city level from 2011 to 2017.

3.2.2 Government-guided fund. The second pivotal dataset is GGFs, which is collected from the China PEDATA Database. This dataset encompasses crucial details about GGFs introduced in various cities across China from 2000 to the present, including information such as fund names, registered regions, establishment dates and target scales. Given the limitations of talent mobility samples and the developmental trajectories of guided funds, this paper focuses on the period from 2011 to 2017, characterized by a rapid increase in the ascent of GGFs. The sample is further refined through the following steps: firstly, excluding samples with missing registration region information and extracting relevant city details; secondly, aggregating monthly data for establishment time to the annual level; finally, we aggregate fund-related data to the city-year level and construct this dataset detailing the value and quantity of GGFs.

We also need additional control variables at the city-year level, which are sourced from the China Urban Construction Statistical Yearbook (http://www.mohurd.gov.cn). The database includes annual per capita GDP (PGDP), sulfur dioxide emissions (SO_2), research and development investment (RD), housing price levels (Housing price), labor supply (Population) and other relevant indicators for each city.

Finally, we finished the main data needed to support the empirical analysis by matching the city-year level information of talent labor migrants with the fund value data, which are collected from CnOpenData. The statistical descriptions of all the variables we needed are shown in Table 1.

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Table 1. Descriptive statistics

Variable	*N*	Mean	SD	Min	Max
Talent	26,614	0.001	0.007	0	0.420
GGFValue	26,614	3.446	4.175	0	14.348
Population	26,614	12.108	2.010	5.659	16.575
Hourseprice	26,614	10.400	1.219	0.693	13.183
SO2	26,614	10.766	0.611	8.773	13.056
RD	26,614	8.510	0.498	7.457	10.792
PGDP	26,614	7.127	0.882	5.017	10.107

Source(s): Authors' own work

4. Empirical results

In this section, we present the results of the estimations from the linear regression model (Eq. (1)). The first subsection focuses on the impact of GGF's cumulative fund value on China talent migrant share. We then study the potential endogeneity issues that may threaten identification and address potential estimation bias by constructing an IV. Finally, we conduct a series of sensitivity analyses to confirm the robustness of the results.

4.1 Baseline results

This subsection discusses and presents the estimates from Eq. (1) and its extensions. The objective is to identify the effect of city-year level GGF's application on talent labor migrant.

Table 2 reports the ordinary least squares (OLS) estimates from Eq. (6). Results point to a significant effect of GGF on talent migrants. In the first column, we control the migrated labor's province of Hukou and year fixed effects to absorb differences between provinces of Hukou that vary over time, including province's economic development, education investment and house price level. Results suggest that increasing 1% value of GGF in the city, the ratio of talented labor migrating into this city increases 0.215% compared with those who migrate into Xinjiang and Tibet. The effects decrease 0.25 times when we additionally control for the province of mobile city (Column 2). Since there are many factors influencing individual migration to destination cities and the weak variation caused by fixing city fixed effects, this paper employs fixed effects at the destination provincial level. This method aims to absorb as many relevant factors associated with destination cities as possible, such as the provincial economic development, housing prices, living environment and educational levels. Therefore, the coefficient is decreased to 0.156. It means that controlling for the destination provincial fixed effects to some extent mitigates the impact of the city's non-time-varying factors. However, there are still concerns of omitted variables at the city level, necessitating further consideration of relevant control variables for destination cities.

The effect is reduced by half once we additionally control the destination city's house price in the third column. The housing prices in China have experienced sustained growth, even significantly outpacing the increase in wages (Zhang *et al.*, 2017). We find that house prices indeed affect the talent mobility, but in a positive way attract labor, since housing prices, serving as a characteristic signal of alternative cities, mitigate the uncertainty of expected future income and augment the utility of talents. Furthermore, we find the effect further declines after sequentially controlling for labor supply and per capita GDP in destination cities (columns 4 and 5). City labor supply and per capita GDP denote the concentration of the labor force and the economic development, rendering it easier to attract highly educated talent.

The effect changes only slightly when we include city research and development expenditure and the level of sulfur dioxide emissions in columns 6 and 7. The former signifies the city's innovation and development potential, while the latter indicates the degree of

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Table 2. The effects of GGF on talent labor migrant

	$lns_j - ln\,s_0$ (1)	(2)	(3)	(4)	(5)	(6)	(7)
GGFValue	0.2151***	0.1639***	0.0754***	0.0600***	0.0535***	0.0511***	0.0504***
	(0.0218)	(0.0122)	(0.0083)	(0.0088)	(0.0082)	(0.0082)	(0.0081)
Hourseprice			1.5871***	1.3487***	1.1787***	1.1462***	1.2018***
			(0.1072)	(0.1215)	(0.1317)	(0.1387)	(0.1457)
Population				0.2517***	0.2680***	0.2266***	0.2135***
				(0.0659)	(0.0647)	(0.0647)	(0.0665)
PGDP					0.2139***	0.1536**	0.1316*
					(0.0660)	(0.0662)	(0.0676)
RD						0.0504*	0.0437
						(0.0282)	(0.0279)
SO2							0.0471
							(0.0366)
Constant	−3.5776***	−3.4013***	−16.6030***	−16.3149***	−17.2646***	−16.6450***	−17.1956***
	(0.0525)	(0.0370)	(0.8924)	(0.8496)	(0.8960)	(0.9534)	(1.0581)
$Prov_i \times Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Prov_j$	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,614	26,614	26,614	26,614	26,614	26,614	26,614
R^2	0.540	0.601	0.625	0.628	0.629	0.629	0.629

Note(s): Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Source(s): Authors' own work

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environmental pollution. The impact of urban environmental pollution on talent mobility is negligible. These procedures suggest that GGFs robustly attract talent mobility.

4.2 Robustness

Despite controlling for strict fixed effects and as much as control variables at the city level, there remains the possibility of unobservable time-varying factors at the city level simultaneously affecting the development of the GGF and the talent mobility. This potential correlation between the independent variable and the error term introduces endogeneity bias. In this subsection, we conduct various additional robustness checks to address additional concerns. These supplementary robustness checks include substituting the core explanatory variable, dependent variable and constructing the IV.

4.2.1 Alternative independent variable. Firstly, we ignored the selection bias of the government for introducing the GGF, and the scale economy effects of the GGF's quantity. We find that cities implementing GGFs exhibit a higher propensity to attract well-educated talents when we apply the difference of difference method in Column 1 of Table 3. For the quantity of GGF, there is also a significant positive effect on talent mobility in Column 2. Therefore, our results consistently underscore the driving role of regional GGF development for internal talent mobility behavior.

4.2.2 Alternative dependent variable. Secondly, the labor force with at least an associate degree, potentially leading to an underestimation of the impact of guided funds on the mobility of individuals with higher education levels. To address these concerns, we replaced the reference provinces for talent mobility and computed the flow of talents with a bachelor's degree or higher for separate estimations. Column 3 of Table 3 shows that when replacing talents with higher education levels, guided funds still exerted a significantly positive impact on talent mobility, but with a coefficient relatively smaller than the baseline results. A plausible explanation is that guided funds primarily target investments in small and micro-enterprises. Those firms exhibit a relatively lower demand for highly educated talents than those with lower educational backgrounds, due to the limitations of high wage costs. It is fitted into the

Table 3. Robustness: alternative key variables

	Alternative explanatory variables		Alternative dependent variables
	(1)	(2)	(3)
	Dummy	Numbers	Bachelor's degree or higher
GFFDummy	0.2560***		
	(0.0612)		
GFFNumber		0.3076***	
		(0.0510)	
GFFValue			0.0327***
			(0.0059)
Constant	−18.3779***	−16.5258***	−11.8781***
	(1.0607)	(1.1291)	(0.9761)
Control Variables	Yes	Yes	Yes
$Prov_c \times Year$	Yes	Yes	Yes
$Prov_j$	Yes	Yes	Yes
Observations	26,614	26,614	26,614
R^2	0.628	0.630	0.708

Note(s): The new base provinces include Tibe, Xijiang, Ningxia and Gansu. The control variables are *PGDP, Population, RD and SO2* in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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truth that the proportion of migrants with university degrees is relatively low. Overall, guided funds robustly manifest a positive attracting effect on talent mobility.

4.2.3 Sample selection and alternative fixed effects. The selection of reference group provinces plays a critical role in shaping the interpretation of our dependent variable as variations in reference groups inherently influence observed migration decisions, even after controlling for origin province-by-year fixed effects. Furthermore, while the baseline analysis excludes samples from Xinjiang and Tibet to mitigate region-specific anomalies, such exclusions raise potential endogeneity concerns related to sample selection bias. To address this limitation systematically, we conducted sensitivity analyses focusing on two key dimensions: substituting alternative reference group provinces and reintegrating Xinjiang and Tibet into the regression sample (Table 4, columns 1–2).

Table 4 demonstrates remarkable consistency across specifications: the positive and statistically significant effect of GGFs on talent migration persists when employing alternative reference groups (Column 1). The marginally attenuated coefficient magnitude in Column 2 aligns with our theoretical expectations, primarily attributable to the inherently lower baseline migration rates within reference group cities. These robustness checks substantiate the stability of our core findings while systematically addressing methodological concerns regarding reference group selection.

Given that the GGF variable operates at the city-year level, only controlling for destination province fixed effects cannot reduce the unobserved city-level heterogeneity. To address this concern, Column 3 of Table 4 extends the analysis by introducing a city-level fixed effects model, replacing with the destination-province. The results continue to robustly support our baseline findings, with GGFs maintaining statistical significance.

4.2.4 Add talent policy controls. While our baseline specification employs destination province and origin province-by-year fixed effects, potential unobserved factors influencing talent mobility may remain unaccounted for. To improve our empirical robustness, this section introduces supplementary controls to address these concerns.

We incorporate a talent attraction policy intensity variable (*TalentPolicy*) following the methodology of Chen *et al.* (2024a, b). Drawing on text analysis of municipal government work reports, this metric systematically quantifies annual city-level policy efforts through keyword extraction and frequency weighting, encompassing subsidies, welfare provisions and recruitment initiatives. As shown in Column 1 of Table 5, the estimated coefficient of

Table 4. Robustness: alternative reference province and fixed effects

	New reference provinces (1)	Include reference provinces (2)	Add city fixed effects (3)
GGFValue	0.0500***	0.0492***	0.0149**
	(0.0082)	(0.0081)	(0.0068)
Constant	−18.1440***	−17.18***	−0.5214
	(1.0501)	(1.0635)	(2.2323)
Control Variables	Yes	Yes	Yes
$Prov_i \times Year$	Yes	Yes	Yes
$Prov_j$	Yes	Yes	
$City_j$			Yes
Observations	25,459	27,078	26,614
R^2	0.584	0.643	0.659

Note(s): The New reference provinces include Tibe, Xijiang, Ningxia and Gansu, including reference provinces means that our sample re-includes the reference province of Tibe and Xijiang. The control variables are PGDP, Population, RD, and SO2 in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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Table 5. Robustness: add more control variables

	$lns_j - ln\,s_0$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GGFValue	0.0563***	0.0511***	0.0492***	0.0473***	0.0466***	0.0470***	0.0427***
	(0.0090)	(0.0089)	(0.0088)	(0.0088)	(0.0088)	(0.0086)	(0.0086)
TalentPolicy	0.0628*	0.0636**	0.0654**	0.0620*	0.0609*	0.0554*	0.0487
	(0.0326)	(0.0319)	(0.0320)	(0.0320)	(0.0316)	(0.0314)	(0.0316)
Indu_struc		0.3507***	0.3348***	0.3819***	0.3878***	0.4038***	0.3414***
		(0.0938)	(0.0936)	(0.0924)	(0.0904)	(0.0911)	(0.0896)
lnwage			0.5537**	0.6885***	0.7402***	0.7569***	0.7224***
			(0.2463)	(0.2481)	(0.2450)	(0.2407)	(0.2391)
Unemploy				−0.1418**	−0.1324**	−0.1041*	−0.1147*
				(0.0550)	(0.0544)	(0.0621)	(0.0599)
Edulevel					−0.4029**	−0.2314	−0.2778
					(0.1888)	(0.2479)	(0.2329)
lncityage						−0.3313	−0.2246
						(0.3347)	(0.2994)
Medical							0.4081***
							(0.1077)
Constant	−17.28***	−17.07***	−21.38***	−22.37***	−20.15***	−19.62***	−17.87***
	(1.1748)	(1.1885)	(1.9724)	(2.0529)	(2.3384)	(2.3792)	(2.3317)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Prov_i \times Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Prov_j$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	26,614	26,614	26,614	26,614	26,614	26,614	26,614
R^2	0.540	0.601	0.625	0.628	0.629	0.629	0.629

Note(s): Standard errors clustered at the city level. The control variables are *PGDP, Population, RD* and *SO2* in GGF's city. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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TalentPolicy demonstrates strong positive effects on talent inflows, corroborating existing evidence that localized incentive programs significantly drive migration decisions (Jin and Zhang, 2024). Crucially, the inclusion of this control preserves the statistical significance of GGFs, confirming the stability of our core findings against potential policy confounders.

To strengthen the empirical foundation of our analysis, we expand the set of control variables to account for local education systems, public service provision, labor market dynamics, industrial structure, income levels and demographic characteristics, utilizing data from the China City Statistical Yearbook. Labor market conditions are proxied by the annual urban unemployment rate (*Unemploy*), calculated as the proportion of registered unemployed individuals relative to the total population. Educational quality is measured through the student-to-teacher ratio in compulsory education (*Edulevel*), derived from the combined counts of secondary and primary school teachers divided by the corresponding student populations (expressed in 10,000s). Public service accessibility is operationalized as the number of medical practitioners per capita (*Medical*). Economic and demographic controls include the logarithm of average wages (*lnwage*), the proportion of residents aged 65 and above (*lncityage*) and the ratio of tertiary to secondary industry GDP (*Indu_struc*).

The inclusion of these variables addresses two critical analytical objectives. First, it mitigates biases arising from city-level heterogeneity – structural characteristics such as economic opportunities and service infrastructure that inherently influence migration patterns independent of individual attributes. Second, it disentangles the distinct mechanisms through which GGFs and other talent attraction policies operate, thereby enhancing causal identification.

As presented in Table 5, our main findings remain robust to these extensions. The estimated coefficient for GGFs retains statistical significance, with lower unemployment rates and higher medical resource availability emerging as significant predictors of talent inflows. While educational quality exhibits limited explanatory power, the talent policy intensity variable (*TalentPolicy*) demonstrates a strong positive association, underscoring the pivotal role of targeted policy interventions. These refinements not only reinforce the internal validity of our conclusions but also broaden the study's contribution to understanding the multidimensional drivers of urban talent mobility.

4.3 Endogeneity analysis

Due to the inherent policy selectivity in the establishment of GGFs, their implementation may be simultaneously shaped by endogenous factors such as local economic development, talent supply and fiscal capacity, thereby introducing potential endogeneity bias into OLS estimates. In addition, talent mobility may itself influence the local government's propensity to establish GGFs, further complicating the identification of causal effects. To address these concerns and improve the reliability of causal inference, this study employs an IV approach to re-estimate the effect of GGFs on talent mobility.

To mitigate endogeneity concerns in assessing the impact of local GGFs on the intercity talent migration, we construct an interaction term, *sea_port* × *Num_PEFM*, as the IV. Here, *sea_port* is a binary indicator equal to 1 if a city was designated as a treaty port prior to the end of the Qing Dynasty and 0 otherwise. *Num_PEFM* captures the number (or aggregate scale) of nationally registered private equity fund management institutions in each year. The historical opening of treaty ports was an institutional arrangement that did not directly affect the current talent migration. Furthermore, the number of nationally established private equity fund management institutions represents a macro-level phenomenon and does not directly determine talent flows at the individual city level. Thus, the IV satisfies the exclusion restriction. Historically, cities that opened as treaty ports were early adopters of international trade and financial systems, leading to stronger contemporary local financial foundations. Combined with the nationwide expansion of private equity fund management institutions, these cities are more likely to facilitate the establishment of GGFs. The interaction term

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between these two factors significantly explains the heterogeneity in GGF establishment, thereby satisfying the relevance condition for the instrumental variable.

Table 6 presents the IV regression results examining the impact of local GGFs on the intercity talent migration. The findings indicate that GGF positively and significantly promotes the inflow of talent at the 1% significance level, thus supporting the conclusions drawn from the baseline regression. Furthermore, the results of the under-identification test (Kleibergen–Paap rk LM statistic) and the weak instrument test (Kleibergen–Paap rk Wald F statistic) confirm the validity of the IV employed in this study.

5. Mechanism discussion

Based on previous theoretical derivations, GGFs promote talent mobility through two complementary mechanisms: on the one hand, GGFs play an attractive role for high-skilled labor by improving the employment environment and income expectations in the inflow areas (pull factor); on the other hand, GGFs widen the regional development gap by improving the innovation capabilities and industrial upgrading levels of the inflow areas, thereby weakening the incentives for other regions to stay and prompting talent outflow (push factor).

Specifically, GGFs promote local economic vitality and increase employment opportunities by easing corporate financing constraints, encouraging innovation and entrepreneurship and improving wage expectations through improved corporate profits, which directly enhances the attractiveness of the inflow area to talents. Therefore, if the pull mechanism is established, we should observe an increase in the number of new enterprises, new jobs and average income levels at the city level after the establishment of GGFs.

In addition, GGFs focus on high-tech industries and strategic emerging industries as investment directions, accelerate technological innovation and industrial upgrading in the inflow area and enhance the local economic growth potential. This development advantage widens the gap with other regions, thereby reducing the attractiveness of backward regions to talent. If the push mechanism is established, it should be observed that after the establishment of GGFs, the innovation vitality (such as the increase in the proportion of high-tech enterprises) and innovation output (such as the increase in the number of patent applications) of the inflow areas will be significantly improved.

Based on the above analysis, we conduct empirical tests around the above two mechanisms, examining the impact of GGFs on employment opportunities, expected income, industrial

Table 6. Robustness results: IV (2SLS)

	(1) First stage: GGFValue	(2) Second stage: $lns_j - ln\,s_0$
sea_port × *Num_PEFM*	0.1998***	
	(0.0100)	
GGFValue		0.2005***
		(0.0370)
K-P rk LM	377.12	
K-P rk Wald F	397.40	
Control Variables	Yes	Yes
$Prov_c \times Year$	Yes	Yes
$Prov_j$	Yes	Yes
Observations	26,614	26,614

Note(s): The control variables are *PGDP, Population, RD* and *SO2* in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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upgrading and innovation capabilities, in order to verify the internal path of GGFs in promoting talent mobility. To test the above cost effects, we estimate the following mechanism identification equation:

$$Mech_{jt} = \beta_1 GGF_{jt} + \beta_2 X_{jt} + FE_j + FE_t + \nu_{jt}$$

where $Mech_{jt}$ represents the above mechanism variables at the city year level. Specifically, new enterprises are measured by the number of enterprises established in different cities in the year in the China Industrial and Commercial Registration Data, and new positions are obtained by crawling websites such as Zhaopin.com to obtain the number of job openings in different cities in the year. For expected income, we use the income of each person in the previous month in the CMDS data and aggregate it to the city's annual level. We use the proportion of high-tech enterprises among new enterprises to represent innovation vitality, and the innovation capacity is measured by the city's patent applications. The control variables are consistent with the benchmark equation. Additionally, we control for city fixed effects and year fixed effects to account for time-invariant differences among cities and overall supply–demand fluctuations in different years.

According to the results of Table 7, columns 1–3 show that the establishment of GGFs significantly improves the local employment environment and columns 4–5 show that the establishment of GGFs significantly promotes local economic development. Based on this, we have confirmed that GGFs can promote the influx of talent by improving the local employment environment and widening the gap in economic development with other regions.

6. Heterogeneity analysis

We investigate the heterogeneous treatment effects of GGFs on talent mobility across multiple dimensions, including city type, spatial distance, employment sector and job characteristics. Exploring the heterogeneous impacts of urban characteristics on talent flows in China substantially enriches our study and strengthens the causal validity of our conclusions.

6.1 Urban development levels

We conduct a heterogeneity analysis from the perspective of urban development level to explore how the effectiveness of GGFs in attracting talent varies across different regional development contexts. From a theoretical standpoint, a city's level of development not only shapes the

Table 7. Mechanism analysis results: employment

	Employment environment			Innovative development	
	(1) New firms	(2) New job	(3) Expected income	(4) Innovation vitality	(5) Innovation capability
GGFValue	0.0070***	0.0194**	0.0036*	0.0545**	0.0295***
	(0.0025)	(0.0082)	(0.0020)	(0.0211)	(0.0039)
Constant	4.2383***	2.4851	6.0244***	−6.0628	−2.2743**
	(0.6502)	(3.2455)	(0.4636)	(5.8821)	(1.0559)
Control Variables	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	1867	1,046	1865	1867	1867
R^2	0.842	0.678	0.633	0.793	0.820

Note(s): The control variables are *PGDP*, *Population*, *RD* and *SO2* in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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efficiency with which policy resources are implemented but also profoundly influences the transmission mechanism through which policies affect firm and talent behavior. Highly developed cities typically offer more complete innovation and entrepreneurship ecosystems, stronger fiscal capacity and more attractive living and employment conditions. These factors are likely to amplify the positive effects of GGFs on the local employment environment and urban development. In contrast, cities with lower development levels may experience weaker policy effects due to delayed institutional implementation and insufficient industrial agglomeration. Thus, analyzing heterogeneity through the lens of urban development levels helps clarify how GGFs influence migration decisions under varying regional conditions, further reinforcing the explanatory logic of the "policy–industry–employment–talent" mechanism chain.

Specifically, we construct a binary variable (*Higher development city*) that takes the value of 1 if a city is classified statistically as at least a third-tier city, and 0 otherwise. Based on this, we generate an interaction term (*GGFValue* × *Higher development city*) to capture the heterogeneous policy effects across different levels of urban development. The results, reported in Column 1 of Table 8, show that the coefficient of the interaction term is 0.058 and statistically significant at the 1% level. This finding suggests that GGFs have a significantly stronger effect on talent inflows in more developed cities. It provides important implications for policymakers: increasing support for GGFs in cities with an established industrial base and growth potential could yield more pronounced talent agglomeration effects.

6.2 Spatial distance

We explore the spatial heterogeneity of GGFs' impact on talent mobility by examining differences in geographic distance between origin and destination cities. Spatial distance is a critical factor in interregional migration decisions. Shorter migration distances often imply lower relocation costs, higher cultural and institutional similarity and stronger social network support. As a result, in short-distance migration contexts, individuals tend to be more responsive to "pull" factors such as job quality and development prospects, and policy incentives are likely to exhibit stronger marginal effects. To capture this, we construct a dummy variable (*Closer cities*) equal to 1 if the geographic distance between the provincial

Table 8. The heterogeneous effects of GGFs

	(1) Higher development city	(2) Closer cities	(3) Intra-provincial mobility
GGFValue × *Higher development city*	0.0580***		
	(0.0124)		
GGFValue × *Closer cities*		0.0505***	
		(0.0092)	
GGFValue × *Intra-provincial mobility*			0.0634***
			(0.0118)
Constant	−15.4781***	−17.8587***	−17.8538***
	(1.0859)	(1.0782)	(1.0258)
Control Variables	Yes	Yes	Yes
$Prov_c \times Year$	Yes	Yes	Yes
$Prov_j$	Yes	Yes	Yes
Observations	26,614	26,614	28,444
R^2	0.632	0.641	0.671

Note(s): The control variables are *PGDP*, *Population*, *RD* and *SO2* in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

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capital of the origin and the destination city is no more than 500 kilometers, and 0 otherwise. Column 2 of Table 8 presents the results, showing that the interaction term has a coefficient of 0.0505 and is statistically significant at the 1% level. This suggests that the effectiveness of GGFs in enhancing local employment appeal is more pronounced in low-cost migration scenarios. The finding lends further support to our mechanism analysis: GGFs can improve urban employment conditions and promote industrial upgrading, thereby strengthening a city's structural capacity to attract talent – especially in regions that are geographically closer and better connected.

Building on this, we further analyze spatial heterogeneity from the perspective of intra-provincial mobility to assess how institutional and cultural similarities influence migration decisions. We define a binary variable (*Intra-provincial mobility*) that equals 1 if the origin and destination are within the same province, and 0 otherwise. As shown in Column 3 of Table 8, the interaction term has a coefficient of 0.0634 and is also significant at the 1% level. This indicates that GGFs have a significantly stronger effect on attracting talent within provincial boundaries, suggesting higher resource allocation efficiency in contexts with consistent institutional and governance structures. These findings reinforce our earlier conclusion that GGFs are more effective in settings with lower spatial frictions and additionally highlight the efficiency gains from institutional consistency in policy implementation.

6.3 Employment sector and job characteristics

To further explore how GGFs shape cross-regional talent flows, we examine industry-level heterogeneity by distinguishing between manufacturing and non-manufacturing employment among incoming workers. Different industries attract talent through distinct mechanisms – manufacturing typically demands more technical and skilled labor, whereas non-manufacturing sectors, such as services and management, rely more on soft skills and professional expertise. Analyzing how GGFs affect talent inflow across these sectors helps clarify how the policy influences migration through pathways of industrial transformation and regional development. As shown in columns 1–2 of Table 9, GGFs significantly promote talent inflows into non-manufacturing sectors (coefficient = 0.053, significant at the 1% level), but have no statistically significant effect on manufacturing. This suggests that GGFs primarily enhance a region's attractiveness by stimulating the development of services and emerging industries. One possible explanation is that non-manufacturing firms – especially those in tech services, finance and IT – tend to be more dependent on capital and thus more responsive to

Table 9. The heterogeneous effects of talent mobile

	(1) Manufacture	(2) Non-manufacture	(3) High-Tech job	(4) Low-tech job
GGFValue	0.0044	0.0530***	0.0390***	0.0197***
	(0.0046)	(0.0081)	(0.0068)	(0.0052)
Constant	−3.3655***	−16.5069***	−14.0386***	−8.0713***
	(0.5327)	(1.0288)	(1.0027)	(0.5883)
Control Variables	Yes	Yes	Yes	Yes
$Prov_c \times Year$	Yes	Yes	Yes	Yes
$Prov_j$	Yes	Yes	Yes	Yes
Observations	26,614	26,614	26,614	26,614
R^2	0.728	0.638	0.653	0.776

Note(s): The control variables are *PGDP, Population, RD and SO2* in GGF's city. Standard errors clustered at the city level. Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

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public fund injections. This finding also implies that GGFs, by fostering emerging sectors, help raise employment quality and growth expectations, which in turn attract talent.

Building on this, we investigate heterogeneity across job types by distinguishing between high-skill and low-skill positions. High-skill jobs are typically concentrated in tech-intensive and innovation-driven industries, where startups and capital play a key role. GGFs may create financial spillovers in these areas – expanding the supply of high-skill positions and attracting more qualified professionals. The results, reported in columns 3–4 of Table 9, reveal that GGFs have a stronger effect on high-skill talent inflow (coefficient = 0.039, significant at the 1% level), though they also significantly increase low-skill labor inflow (coefficient = 0.0197, significant at the 1% level). This indicates that GGFs not only boost the total volume of talent inflow but also improve the overall skill structure. The increase in low-skill employment may reflect the complementary labor needs of rapidly expanding startups, suggesting that the policy generates spillover effects in broader job creation.

It is worth noting that our classification of job types is based on the occupational information available in the dataset, which may be relatively coarse. For example, the distinction between high- and low-skill jobs may not fully capture the variation in required skills or actual job content, and some positions may straddle the two categories depending on industry context. Despite these limitations, our heterogeneity analysis offers useful insights into how GGFs affect the structure of talent inflows. Future research could incorporate finer-grained individual-level data to refine these classifications and improve analytical precision.

7. Conclusions

Local policies activate entrepreneurial innovation and also increasingly attract outstanding talents, thereby contributing to the overall economic welfare of the localities. This paper focuses on the establishment of GGFs in China starting from 2002, to analyze their impact on local talent mobility across mainland Chinese cities. It expands the research landscape of local financing policies and labor mobility welfare assessment literature. By utilizing data from the CMDS in major Chinese Cities between 2011 and 2017, alongside GGF data from PrivCo for various cities, this study delves into the influence of the establishment and cumulative fund size of GGFs within cities on interprovincial talent migration.

By controlling for additional fixed effects and constructing corresponding IV where possible, we find that the establishment of GGFs in cities significantly stimulates the inflow of talent from other provinces. In addition, mechanism analysis shows that the introduction of GGFs greatly promotes financing, directly and indirectly sharing the innovation risks of enterprises. Attract talents from other provinces by creating more job opportunities, increasing expected wage levels and promoting innovative development. This helps to revitalize the urban economy. The heterogeneity analysis reveals that GGFs exhibit a stronger capacity to attract talent in more developed cities. Moreover, GGFs tend to draw talent inflows from geographically proximate origin cities, particularly those within the same province. Lastly, GGFs primarily attract mobile talents to non-manufacturing sectors and high-tech occupations.

GGFs not only promote innovation and structural transformation in physical enterprises but also generate positive effects on the accumulation of human capital, as advantageous tools for local governments to leverage economic development. Our study reveals several policy implications:

Refining the industrial focus of GGFs. It is recommended that GGFs in underdeveloped regions focus primarily on human capital–intensive industries such as high-tech services, artificial intelligence, healthcare, new energy and the digital economy. Local governments should be encouraged to establish “special sub-funds for high-skilled talents,” specifically supporting the growth of technology-based SMEs, startups and R&D platforms, thereby fostering an industrial ecosystem conducive to high-skilled employment.

Introducing a cross-regional fund cooperation mechanism. As high-development cities exert a siphon effect on talent, underdeveloped regions often struggle to attract talent

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independently. To address regional disparities, local governments could explore the establishment of "enclave-style GGFs," jointly built by economically developed and underdeveloped regions, with shared returns but with project implementation mandated in underdeveloped areas. In addition, national-level fiscal matching incentives could be provided to encourage capital from the eastern and central regions to flow toward talent and project concentration in the western regions.

Developing an integrated policy package of "Fund + Platform + Services." The effectiveness of GGFs in promoting talent inflow should be amplified through integration with other urban policy tools. For instance, when establishing funds, governments could include requirements for the development of "innovation and entrepreneurship incubation platforms," providing incoming talents with comprehensive resources such as project matching, office space and investment and financing services. Furthermore, soft incentives like housing subsidies, support for children's education and facilitation of household registration should be implemented to enhance the residential attachment of high-skilled talents in underdeveloped regions.

In conclusion, the above policy recommendations are conducive to narrowing regional disparities and achieving the goal of common prosperity.

Appendix

Derivation process of labor selection model:

The utility equation of labor i choosing working place j is expressed as

$$u_{ij} = \delta_j + \varepsilon_{ij}$$

If ε_{ij} attributes the first type of extreme value distribution, its cumulative distribution function is $\Pr(\epsilon_{ik} \le x) = F(x) = exp(-\exp(-x))$, and its probability density function is $f(x) = \exp(-x)F(x)$.

For the household registration place e, the share of the labor force that finally chooses the work place j is the probability that the representative labor force chooses the work place j:

$$s_j = Pr\left(U_{ij} \ge U_{ik}\right), \forall k \ne j$$

$$= Pr\left(\delta_j + \epsilon_{ij} \ge \delta_k + \epsilon_{ik}\right), \forall k \ne j$$

$$= Pr\left(\delta_j + \epsilon_{ij} \ge \delta_1 + \epsilon_{i1}, \delta_j + \epsilon_{i2} \ge \delta_1 + \epsilon_{i2}, \ldots, \delta_j + \epsilon_{ik} \ge \delta_1 + \epsilon_{ik}\right), \forall k \ne j$$

$$= Pr\left(\epsilon_{i1} \le \delta_j - \delta_1 - \epsilon_{ij}, \epsilon_{i2} \le \delta_j - \delta_2 - \epsilon_{ij}, \ldots, \epsilon_{ik} \le \delta_j - \delta_k - \epsilon_{ij}\right), \forall k \ne j$$

$$= \prod_{k \ne j} Pr\left(\delta_j - \delta_k - \epsilon_{ij}\right)$$

$$= \int_{-\infty}^{+\infty} exp\left(-e^{-\delta_j + \delta_1 - x} - e^{-\delta_j + \delta_2 - x} - \ldots - e^{-\delta_j + \delta_k - x}\right) f(x)dx, \forall k \ne j$$

$$= \int_{-\infty}^{+\infty} exp\left\{-e^{-x}\frac{\sum e^{\delta_k}}{e^{\delta_j}}\right\} dF(x), \forall k \ne j$$

$$= \int_{-\infty}^{+\infty} F(x)^{\frac{\sum e^{\delta_k}}{e^{\delta_j}}} dF(x), \forall k \ne j$$

$$= \int_0^1 \frac{1}{\frac{\sum e^{\delta_k}}{e^{\delta_j}} + 1} t^{\frac{\sum e^{\delta_k}}{e^{\delta_j}} + 1} dt, \forall k \ne j$$

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$$= \frac{e^{\delta_j}}{\sum e^{\delta_k}}, \forall k \neq j$$

Note

1. http://paper.ce.cn/pc/content/202307/11/content_277233.html
2. The S_{c0t} is absorbed by this fixed effect in the specific data processing process.
3. Such as Jiangsu Province "333" Talent Project.
4. Data can be found at http://www.chinaldrk.org.cn/wjw/#/data/classify/population/yearList
5. According to the National Health Commission of China, migrants are people who leave their Hukou residence and live or work somewhere else for at least 6 months.

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