DEPARTMENT OF ECONOMICS

Four Pillars of Job Applicant Screening in China

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Chinese employers practice extensive personal screening of job applicants. This study identifies four manifestations of this practice by motive – statistical, customer taste-based, employer taste-based, and regulatory – and evaluates their prevalence, economic determinants and implications for firms' performance using simultaneous-equations linear and Poisson models. Categorization of a regulatory motive for applicant sorting in China is one contribution of this study. Statistical screening is found to be related positively to employers' capital intensity, labor-market power and private ownership, and negatively to the supply of skills in provincial labor markets, as may be expected. Customer-taste screening is more prevalent in service and sales industries, as expected, and interestingly in wealthy first-tier cities. Employer-taste screening appears more prevalent at privately-owned firms, and surprisingly in skill-intensive industries and in first-tier cities, potentially reflecting difficulty at distinguishing it from customer-taste screening. Regulatory screening is related positively to firms' market power, capital intensity and state ownership, as expected. Statistical and customer-taste screening is associated with higher firm profitability, particularly in skill-intensive industries and in service and sales industries, respectively, while employer-taste and regulatory screening is associated with lower profitability, as expected. These results jointly validate our identification of the four pillars of applicant screening.

Keywords: Recruitment, job applicant screening, profiling, statistical & taste-based discrimination, hukou, China, Poisson regression, simultaneous equations model.
JEL Codes: J7, J24, D83

I. Introduction

Labor market in the People's Republic of China (PRC, China) operates under a unique mix of market rules, intervention from government and other institutions, and social norms. In recruitment, Chinese employers solve a unique optimization problem with unique constraints. Like in other countries, they seek to hire the most desirable applicants from the available pool in the presence of uncertainty about applicants' skills. But in their choice over how to recruit workers, they have different ability to infer applicants' desirability, and different limitations on their practices. Desirability of workers is also judged by different criteria.

The focus in our study is the choice of Chinese firms regarding the screening of job applicants' personal information during recruitment, the determinants and the extent of such screening, and consequences for firms' performance. This topic is important because Chinese employers practice extensive screening of applicants using factors that are illegal to consider per se, or thought of as inappropriate by various standards.[1] They inquire about applicants' political affiliation, ethnicity, marital status, family background, appearance, blood type and other personal factors. Moreover, firms' job advertisements typically also specify the gender, age, health status, appearance or family registration status of preferred applicants. This study sorts these different forms of screening into four types by their distinct motives – statistical, customer taste-based, employer taste-based, and regulatory – and evaluates which employers and which market situations are likely to produce extensive screening of each type. Categorization of a regulatory motive for applicant sorting in China is one of the contributions of this study, as it has not been discussed in economic literature previously. This classification is important because different types of screening have different implications for the firms and for job applicants. Yet, there is currently limited understanding of firms' motives, prevalence of the different practices across firms, as well as implications for society. Better understanding may help us identify pitfalls in firms' practices and in the existing public policy.

This study follows up on a survey of the recruiting market in China with a review of firms' motives for stating preferences on job advertisements and screening applicants on application forms (Hlasny and Jiang, 2013). The closest other studies (Kuhn and Shen, 2009, 2013) have evaluated employers' preferences on job advertisements, and found that they could be only partly explained by statistical and customer-taste motives, with latent cultural factors overriding them in lower-skill recruitment. This paper differs from those studies in its subject and analytical approach. It focuses on questions on firms' job application forms, as

[1] This problem is not specific to employers in China. Hlasny (2009) summarizes and compares evidence of studies from a number of countries.

the more detailed second-stage screening following the posting of preliminary minimum specifications on job advertisements. The results are compared to those for the stated preferences on job ads, in a sample of 225 application forms and 148 job advertisements of large employers from across the Chinese economy. Analytically, this study starts by classifying individual personal characteristics screened by their inferred motive into four types, and evaluating how firms' and market circumstances affect the extent of each type of screening. Secondly, it tests the implications of the four screening types for firms' profitability. As a byproduct, this test helps to validate the classification of characteristics screened into the four conceptual types.

In what follows, the study first reviews the historical context of labor relations under which Chinese firms adopt specific recruiting practices, and the applicant screening practices widely used. Section III sketches a custom model identifying theoretically the four distinct motives for applicant screening. This model yields testable predictions regarding the form and extent of screening used by employers in different settings. Section IV describes our empirical approach and information available. Finally, Sections V and VI present the empirical results and comment on their implications.

II. Background of Labor Recruitment in China

Human resource management (HRM) practices at Chinese firms today can be linked to political and economic developments in the country over the past six decades. In the 1950s, as the Chinese central government abolished free factor markets and implemented central planning to achieve a Great Leap Forward, employers came to operate under public ownership of all factors of production. Labor placement and working conditions were harmonized across the economy. In support of regional planning, a family registration (*hukou*) system was set up in 1958 by the Ordinance of Household Registration of the PRC. This system dictated where workers with agricultural or nonagricultural registrations could be employed, and restricted migration (Chan and Zhang 1999).[2] State-owned enterprises

[2] Beside the system of agricultural vs. nonagricultural registrations, regional personnel management and university admission systems were implemented to restrict free movement of people. Employers or even local Public Security Bureaus managed workers' official personnel records, and tracked workers' progress through life in these records. Depending on the content of workers' records, employers could prevent workers from changing work, moving or even getting married (Moss 1996). University entrance policies also effectively restricted movement of people, by reserving a number of university openings to candidates with local *hukou*, and by requiring students to take the entrance examination in students' place of residence. The content of the

(SOEs) were allocated workers based on workers' formal qualifications, political affiliation and *hukou*, rather than on inferred true skills (Ding and Warner 2001).

A quarter-century later, when central planning failed to spur economic growth, important economic reforms were implemented. Under the Reform of the Economic System (1978), companies in many sectors were privatized and reorganized. Firms of all ownership types were encouraged to compete for qualified labor. Private employers took advantage of looser regulation to use any means to recruit talent and to induce effort among their workforce. In hiring, promotion and compensation, employers started discriminating among workers using detailed information on workers' personal and even protected characteristics, without fear of government clampdown. Statistical discrimination – employers' strategy to hire more productive workers using information on their personal attributes and membership in particular social groups, and information on distribution of skills across social groups – and customer taste-based discrimination – employers' strategy to raise customers' willingness to pay by hiring appropriate workers – were becoming refined features in all aspects of firms' HRM.

Even before deregulation, employers' decisions had traditionally been tainted by employers' own tastes for workers' physical features, healthy looks, amenable character and fitting zodiac signs – including features that were irrelevant or unobservable to customers, and unrelated to productivity. Regulation had also forced firms to discriminate based on workers' political affiliation, class background and *hukou* registration. As employers became more educated, and labor market became deregulated and more competitive, employer taste-based and regulatory forms of discrimination faded and were replaced by statistical and customer taste-based forms. These in turn became explicit, systematic and widespread.

Economic reforms of the late 1970s and early 1980s brought growth to industrial cities along the east coast. This exacerbated the gap between urban and rural living standards (Park 2008; Meng 2012) and increased migration from rural western provinces to eastern cities. As the number of migrant workers rose, employers started taking workers' residency and ethnicity into explicit account, in view of labor-cost implications of hiring non-locals,[3]

examination varied across provinces, forcing students to spend 1-2 years in their home town to pass the local exam.

[3] Because migrant workers did not have secure housing and state-provided health and welfare coverage, they were expected to be costlier to employ. Should the employer wish to retain the worker or reassign them to a different branch, a rural *hukou* was also harder to convert to an urban one. Finally, migrant workers were expected to need to periodically travel home, and have higher turnover.

binding *hukou* registration rules, and customers' tastes over workers' dialect and demeanors. Employers' freedom to offer different working conditions to different groups of workers exacerbated the systematic discrimination and mistreatment of replaceable workers and workers without bargaining power such as migrants.

By the 1990s, following rapid economic growth, the central government started worrying about social harmony and international approval, and started pushing for equitable working conditions. Health and workplace safety regulations and antidiscrimination laws were enacted, even if not enforced, and monitoring of regional inequalities began.[4] Under the 'grasp the large and let go of the small' SOE reforms of 1993, central government kept the requirement for state and investor owned companies, and companies in industries with public stake (*strategic* industries) to report the demographic composition of their workforce. The government has also pushed to relax the *hukou* registration rules, in order to resolve the regulation-based discrimination against migrant workers and to improve their access to social services. To this day, however, the reforms have done little to promote migrants' rights (Cai 2007). The stricter workplace safety regulations also had some perverse effects on workers' rights. As hospitality and healthcare firms received a mandate to test job applicants for transmittable diseases including hepatitis B, employers in other sectors followed suit with detailed screening of applicants' health conditions beside those specified by the government.

All in all, despite market-equalizing reforms of the 1980s and 1990s, nationwide labor market remains segmented and unequal (Brandt *et al.* 2011). Across provinces, industries and firm types, employers face different applicant pools, reporting rules, and degrees of enforcement of labor regulations by regulators or labor representatives. They differ in their perceived need and ability to select job applicants based on applicants' personal characteristics, be it for statistical, idiosyncratic taste or regulatory reasons.

[4] The first anti-discrimination provisions appeared in the Constitution of the PRC (1982) and the Labor Law (1994). China started sending delegations to the International Labor Organization's conferences (first in 1983) and became an active member. Building on the provisions of the Labor Law, the Employment Services and Management Regulations (2000), Law on the Protection of the Rights and Interests of Women (2005), the Labor Contract Law (2008), and the Employment Promotion Law (2008) were subsequently introduced. In 2005, the government also ushered in the Socialist Harmonious Society calling for interregional and intergenerational equality. The Ministry of Labor and Social Security, the Labor Services Bureau, the All China Women's Federation, local Labor Dispute Arbitration Committees and individual trade unions are some institutions now set up to check on individual companies' employment practices and to resolve disputes.

1. Firms' Recruiting Practices

Most Chinese employers use formal as well as informal channels to seek out suitable candidates. Formal channels include advertising on dedicated, publicly-accessible websites, in newspapers, or through independent employment agencies that provide detailed information about openings to the general public. Informal channels include unsolicited queries from jobseekers, nepotism and referrals by influential connections or employees, or other word of mouth referrals (source: own survey). This study focuses on employers' formal practices, because they are more widespread, and information on them is more widely available and transparent.

Recruitment can typically be broken down into four steps: attracting of suitable candidates, their classification, communication with pre-selected applicants, and reaching an agreement (Chen 2002). This study focuses on the first two steps (hereafter, *documents stage*), of posting of appropriate job announcement and application instructions, and selecting of information that will be used to classify job applicants.[5] Special attention is paid to the employer-selected content of job advertisements and application forms.

Firms' job advertisements list requirements, preferences or characteristics of ideal applicants (hereafter, prerequisites). Applicants pre-selected on these criteria are then asked detailed personal questions on lengthy application forms, and may be asked to release confidential government-held records to the employers including residence, criminal, or even personal debt records. The prerequisites and information requested on application forms include detailed personal characteristics with bearing on workers' productivity, trustworthiness, sociability, or likeability among customers and colleagues. The prerequisites on job advertisements include specific age range, gender, degree of physical attractiveness, health status and *hukou*. Application forms additionally ask for applicants' photograph, family background, marital status, ethnicity, political affiliation, blood type and existence of any internal referral. Since the factors screened on firms' application forms are the focus of the present study, they are briefly introduced below. Table 1 reports their prevalence and table A1 their joint distribution across the sampled firms.

[5] Applicants retained in the documents stage are invited for written exams, personal interviews and medical examination. Since informal recruiting, and recruiting stages beyond the documents stage are ignored in this study, trends identified below are likely to be at the lower end of the true extent of applicant profiling by Chinese employers, particularly the taste-based kind.

Blood type: A minority of employers believe that blood type affects workers' personality and assign workers with a particular blood type to designated tasks or work-teams where their personality would be an asset and would not clash with others' personalities. Since there is no recognized basis for such practices, this is classified as employer taste-based. Some employers – none in our sample – even specify a prerequisite blood type on job advertisements (Liu 2001).

Ethnicity: Under China Labor Law and PRC Employment Promotion Law, employers are advised to give adequate consideration to members of ethnic minorities. State-owned employers comply with this law, and give no preferential treatment to any ethnic group. Private firms, however, have a preference over workers' ethnicity. This is because non-Han ethnic groups are thought to have lower fluency in Mandarin, lower cognitive and non-cognitive skills, and different standards in regard to work habits and lifestyle.

Family background: Employers often enquire about applicants' upbringing, current family status and living conditions, cohabitation and dependents, and family members' achievements. Screening of family background, in this study, refers to surveying of any facts regarding applicants' family history and current family circumstances. Many employers ask about the education, occupation, job title or salary of applicants' parents and siblings. Through these questions, employers may assess applicants' hereditary predispositions and personality traits, childhood and young-adulthood influences, and accumulated goodwill.

Health: Limitations on health status may come from employers' and coworkers' prejudice against applicants with unusual physical conditions, fear of violating public-safety laws, or fear of costs and legal liability over workplace accidents. The consideration of health is particularly difficult to tackle, as the national government itself imposes health standards in some industries and occupations. However, employers from across different industries have used those standards to screen health of all their applicants. In mining, food, and pharmaceutical industries, over 60% of large state-owned firms require physical examination, including for hepatitis B (Yirenping Center 2011).

Hukou: Because it is easy to assess applicants' residence status from their *hukou*, and because applicants' residence status may proxy for their relocation cost, expected turnover, social status, and other factors, many employers specify a particular *hukou* as prerequisite or preference. Many openings in coastal provinces specify "open to applicants with Beijing or Shanghai *hukou* only." Reasons include prejudice toward outsiders, fear of workers' absenteeism or termination to return home, or lack of corporate housing to accommodate commuters. Personal prejudice may come from worries over criminal background or incompatible work-place habits. Some employers, especially state-owned companies, have to follow quotas on *hukou* registrations of their workers.

Internal referral: Identifying potential job candidates through existing employees' social networks may help employers find more motivated and loyal workers, and facilitate better cohesion among the company's workforce. Employers often ask whether the applicant has any relatives or acquaintances among the company's workforce. In some consolidated industries dominated by large state-owned companies, such as tobacco or oil production, recruiting through connections and nepotism is pervasive (Chen 2012).[6]

Marital status: Married workers are commonly perceived as more stable and devoted to their jobs. On the other hand, married women of certain age are viewed as exhibiting absenteeism, lack of flexibility regarding work schedule, lack of interest in team-bonding, and risk of quitting due to child-bearing. Single women are at risk of quitting due to marriage plans. These factors affect employers' productivity and labor costs. Secondly, marital status serves as an indicator of workers' family situation, need of care for dependents, etc. By asking about marital status, employers may not need to survey applicants' more detailed characteristics.

Photograph: Photographs serve to verify job applicants' identity but also to assess first impression left by the applicants, important in interpersonal relations with customers, coworkers and business-partners. The practice of screening applicants' family background and requesting photograph is widespread in job recruiting, as well as in other spheres of life in China. In fact, private employers have adopted the practice from central-planning and social control practices of previous decades. Employers' implicit cost of asking about family background and requesting a photograph is thus low.

Political affiliation: Government agencies and state-owned companies put great emphasis on the Communist Party spirit among their workers, and indicate "Party membership required" or "priority given to Party members." Foreign-owned and private employers may use Party membership as a signal of applicants' motivation, sociability, political consciousness, or

[6] The possible explanations are that companies with monopoly rents are selective in who they share the rents with, or that these companies tend to have a patriarchal, bonding culture among their workforce.

value of reputation. The government encourages employers to give priority to Party members.[7]

The discussion above suggests four principal motives why employers screen applicants' personal characteristics. Statistical motive is that the collected information on workers' membership in various social groups may help employers infer their productivity or loyalty. Customer taste-based motive is that firms' customers may value certain characteristics in the personnel serving them, which affects their willingness to pay. Employer taste-based motive follows the hiring manager's own preferences over workers' characteristics beside their impact on firm profit. Finally, regulatory motive is to comply with explicit or implicit rules over information collection and recruitment, as perceived by the employers. Section III reviews these motives in greater conceptual detail, and section IV discusses the method for classifying each characteristic screened into the four types. The following note explains why all forms of screening of personal characteristics regardless of motive are thought to be inappropriate and of concern to public policy.

2. Public Policy Concerns over Applicant Screening

There are various standards of propriety for factors considered to select workers. This includes legality of recruiting practices and information collected; procedural justice and objectivity; consistency and unbiasedness across decision-makers and subjects; review by multiple professional decision-makers; content-fairness and relevance to applicants' merit; job-relatedness; non-invasiveness; falsification-proneness; and outcome-fairness (Arvey and Renz 1992; Gilliland 1993, 1995; Truxillo, Steiner and Gilliland 2004; Hlasny and Jeung 2014). All the screening practices described above are in violation of some of these norms.

With regards to efficiency, the identified forms of applicant profiling are inappropriate because they taint employers' view of candidates and affect their hiring and compensation choices by characteristics other than applicants' own job-related skills. Such practices result

[7] Beside factors listed above, some companies ask for additional personal information. Employers in transportation, and selected engineering, manufacturing & pharmaceutical sectors (5 employers in the sample) typically enquire about eyesight with or without glasses, and color blindness, as they require advanced precision skills in their employees. In these industries, workers' eyesight is carefully checked in physical examinations, and surveyed in application forms. However, eyesight is not included among the personal factors analyzed here, because of its direct impact on productivity in selected occupations, and low prevalence rate. Unlike in other East Asian countries, Chinese companies typically do not screen applicants' religion, military experience (but some enquire about veteran status), financial status (including real estate or car ownership, or financial status of family members), or smoking & drinking habits. For description of prerequisites on job advertisements, refer to Hlasny and Jiang (2013).

in denying of work opportunities to otherwise qualified workers, say, when employers reject them based on employers' personal preferences or because of inaccurate inference of workers' skills (Phelps 1972). Such discrimination can be systematic, and persistent even across generations in the workers' families.

The second problem with employers' recruiting practices is that they affect workers' incentives for skill acquisition and job search. Workers respond to the recruiting practices by obtaining skills and attributes that employers appear to value, even if these attributes do not make them more productive. This results in socially inefficient levels of investment and wrong allocation of workers' resources across different activities. This also prevents credit-constrained workers from disadvantaged backgrounds from moving upward socially.

While the personal characteristics screened are not related directly to productivity, many of them are correlated with workers' protected status, and their usage or even consideration is banned by relevant laws. The Employment Services and Management Regulations prohibit employers from including discriminatory factors in job advertisements, including national registration, ethnicity, gender, age, health status and religion. The Labor Act also explicitly bans employers from considering applicants' ethnicity, race, gender and religion. Employers' observed practices are thus in violation of these regulations. Gender, ethnicity, *hukou* and health prerequisites also infringe on the Employment Promotion Law of the PRC, which prohibits employment discrimination against women, ethnic minorities, rural workers, the disabled and carriers of epidemic pathogens.

Under these laws, workers encountering discrimination may lodge lawsuits in the people's courts (ILO 2011). However, lack of clarity regarding the prohibited forms of discrimination, lack of monitoring and enforcement, and workers' fear of retribution for whistleblowing still limit the effectiveness of laws at protecting workers. At the same time, applicants are required to provide the surveyed information fully and truthfully. Hence, Chinese firms are only partially constrained in their applicant screening practices, and can optimize regarding the extent of each type of screening subject to a tradeoff between the expected marginal benefits and finite expected marginal costs of each type.

III. Theoretical Model of Applicant Screening

This section outlines a custom theoretical model of applicant screening in firms' recruitment. This model casts light on the determinants of the form of screening at different firms, and the effect of different forms of screening on firms' performance. It follows theoretical models of statistical and taste-based discrimination (Becker 1971) to explore the relationship between employers' screening of applicants and their resulting performance. The model yields predictions about the form of screening used by firms facing different market and regulatory conditions.

The fundamental assumptions in our model are that firms screen applicants with the intent to hire more desirable workers, and that applicant screening affects directly the composition of firms' workforce. At the center of the model, a rational employer strives to maximize his utility with respect to the type of worker whom he hires into an opening. The decision to hire a new worker is assumed to have already been made, perhaps conditional on achieving a reservation level of expected utility. Employer's utility depends on 1) the present value of economic rent he makes over the worker's tenure with the employer; 2) the one-time cost of recruiting and screening; and 3) present value of the idiosyncratic taste from employing a particular worker over his tenure with the employer, regardless of the worker's productivity.[8] Employer's problem may be constrained by a government requirement on hiring a member of a particular demographic group.

The employer faces an applicant pool of exogenous size N, and selects a worker with the most desirable set of values of four characteristics A, B, C and D. For idiosyncratic taste-based reasons, the employer prefers hiring workers possessing high values of an inherent characteristic A. High values of A give the employer a greater idiosyncratic taste value, $g(\cdot)$, than low values of A, $dg/dA>0$. Also, workers' productivity is a function of their possession of an inherent characteristic B. Workers with high values of B tend to have greater productivity, $f(\cdot)$, than workers with low values of B, $df/dB>0$. The employer thus has an incentive to *statistically discriminate* against low-B workers. Further suppose that firm's customers prefer dealing with workers possessing high values of an inherent characteristic C.

[8] Employer's economic rent and utility from the idiosyncratic taste accrue over the worker's tenure with the employer, but this accumulation over time is not studied explicitly here, in part because we do not observe expected tenure of workers across industries or firms. Tenure is assumed exogenously fixed and constant across applicants. This essentially implies that employers cannot dismiss workers after they learn their type, and workers do not differ in their turnover. In the search theory of labor markets, such permanent matching is a standard assumption. Our basic model also assumes that workers' characteristics cannot be augmented through on-the-job training, experience or firms' acquisition of complementary factors of production. Correspondingly, there is no training cost. A more complete model would allow for differences in tenure, skill augmentation, and training costs across applicants. The employer's problem would become more complex, because he would have to infer, for each applicant, the present value of the entire expected productivity and utility profile over the worker's tenure. Applicants' productivity, taste value to the employer, tenure, learning, and training costs may be correlated in complicated ways, and the employer's expected utility monotonic in either of them.

Customers have a greater willingness to pay, *p(·)*, when transacting with workers with higher values of *C*, $dp/dC>0$. Finally, state regulator may mandate that the firm hire workers possessing particular personality or demographic characteristic *D*, say $D\geq\delta$ (or, membership in a *protected group* δ), else the firm would face a penalty or litigation cost. The employer's utility function takes the form:

$$u = u[\pi(B,C) - \mathrm{r}(\Theta_A,\Theta_B,\Theta_C) + \mathrm{g(A)}] \qquad s.t. D \geq \delta \tag{1}$$

where $= f(B) \cdot p(C) - w$. The employer's utility *u* is assumed separable in economic rent π, one-time recruitment cost *r*, and idiosyncratic taste *g*, a standard assumption. By focusing on a single hiring decision, the employer's total economic rent, taste and utility are also implicitly assumed separable in the rent, taste and utility obtained from each hire. In effect, issues such as complementarity among workers and *employee discrimination* are assumed away.

Employer's economic rent depends on the average revenue product of the worker, which depends on the worker's average productivity *f*, consumers' willingness to pay for the output good *p*, and salary *w*. Labor productivity *f(·)* comes from a general production function that may depend on the firm's chosen technology and values of all factors of production. *f(·)* is assumed to vary across workers in a predictable way, and is a monotonic function of the value of the worker's characteristic *B*. Price *p* depends on the value of the worker's characteristic *C*.

Wage *w* is assumed exogenously fixed and constant across workers, perhaps because of perfect competition in the labor market under uncertainty about workers' type. Local government regulations, coordination among local trade unions, and industry conventions contribute to this justification. Hence, we assume that starting wages are the same for all prospective job applicants, regardless of their actual productivity, of employer's or customers' taste for them, or of their protected status. Employers cannot adjust the wage even in future time periods. This is a potentially restrictive assumption, making the selection of a hire a more important decision.

Recruiting cost *r* depends on the extent of screening of each kind of characteristic, Θ_k $k=\{A,B,C\}$, conducted by the employer in an effort to identify the most desirable worker. Hence, $r(\Theta_A,\Theta_B,\Theta_C)$ depends indirectly on the values of *A*, *B*, *C* of the hired worker. Recruiting cost comprises the explicit outflow of resources for requesting, collecting, storing and analyzing of information on applicants, as well as any expected implicit loss of firm goodwill, regulatory sanctions, and litigation cost under the selected kind of applicant screening and discrimination. For simplicity, the cost of complying with regulation on hiring $D \geq \delta$ applicants is assumed to be zero here. This cost is not too important conceptually, because it cannot be avoided, and it may be lower as it does not comprise any loss of firm goodwill or litigation cost. However, regulation δ is still costly to the employer as it limits the effective applicant pool and distribution of *A*, *B*, *C* in the pool.

1. Solution under Perfect Information

Suppose the employer knows the values of characteristics *A*, *B*, *C* and *D* for each applicant. This information could be obtained at a cost, as a part of $r(\cdot)$. The solution to the employer's problem is to hire an applicant *i* whose set of values of A_i, B_i and C_i maximize the employer's utility while complying with regulation $D_i \geq \delta$.

The selected values of *A*, *B* and *C* depend on the respective first derivatives and cross-derivatives of the recruiting cost function, conditional on $D \geq \delta$: $dr/d\Theta_k \cdot d\Theta_k/dk$, $dr/d\Theta_k \cdot d\Theta_k/d\Theta_{-k} \cdot d\Theta_{-k}/d(-k)$ for $k=\{A,B,C\}$. They also depend on the first-derivatives of the average-productivity, customer-valuation, and employer-taste functions, conditional on $D \geq \delta$: df/dB, dp/dC, and dg/dA. Finally, the selected values of *A*, *B* and *C* depend on the distribution of these characteristics in the available applicant pool, and on pool size *N*. The greater the variation of these characteristics in the pool, the greater the expected values in an applicant ultimately hired.

For simplicity, assume that the values of applicants' characteristics are independent of each other, so that the joint probability distribution of the four characteristics is simply the product of the four individual probability distributions. Width of the distributions of *A*, *B*, *C* and *D* in the applicant pool, and particularly their right tails, affect the employer's rent and overall utility positively, as they increase the expected values of *A*, *B*, *C* in an ultimate hire. Size of the pool *N* affects the employer's utility similarly.

The restriction on hiring only $D \geq \delta$ applicants affects the employer's expected utility negatively as it shrinks the applicant pool and may narrow the joint distribution of *A*, *B* and *C* in the pool. Similarly, the extent to which the employer receives taste value from applicants' characteristic *A*, dg/dA, affects his expected economic rent negatively as it compels him to favor applicants with higher values of *A*, even if they have lower values of *B* and *C*. There is a tradeoff between pursuing applicants with high values of one characteristic, and pursuing applicants with high values of other characteristics.[9]

If the values of the characteristics were not independent of each other, restricting the pool to only, say, $D \geq \delta$ applicants will have a more complicated effect on the joint distribution of other variables in the remaining pool. Say, if characteristics B and D are correlated positively, the regulatory restriction will increase the prevalence of high values of B in the remaining pool. The issue of correlation among variables is discussed more in Footnote 11.

2. Solution under Uncertainty about Applicant Type

Suppose the employer knows the distribution of A, B, C and D in the applicant pool, but not the values of any specific applicant. Let a star denote their latent nature: A^*, B^*, C^*, D^*. Suppose that the employer cannot ask directly about A^*, B^*, C^*, D^*, either because this would violate antidiscrimination laws, or because the reported values would be imprecise and biased. Applicants may be unaware of their exact values or may intentionally misreport them. Without any additional information, the employer would hire a random applicant, with expected values $E(A^*)$, $E(B^*)$, $E(C^*)$, $E(D^*)$ in the pool – the unconditional expected type.[10]

The employer can succeed at hiring an applicant with a higher expected set of characteristics by collecting information predictive of the types for all applicants, and then selecting an applicant with the utility-maximizing set of conditional expected values. The employer may screen three sets of characteristics – sets A, B, C, D – that have bearing on the latent characteristics A^*, B^*, C^*, D^*. A, B, C, D are vectors of characteristics of a large order. Each characteristic in a set, say $A_{\theta_A}\ \theta_A \in (1, \ldots, \Theta_A, \ldots)$, takes a value $a_{\theta_A i}$ for an applicant i. The employer's problem is to select how much of each set of information to screen – the values of Θ_A, Θ_B, Θ_C and Θ_D – given that each set affects his utility function in a different way, and each marginal characteristic screened has a different predictive power for the corresponding latent quality, at different cost.[11] In this setup,

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[9] On the other hand, complementarity may exist between B and C, in the sense that $d^2\pi/dBdC>0$, but this issue is ignored here for simplicity.

[10] Say, subject to achieving at least a reservation level of expected utility from the hire, $E[u(\cdot)] \geq u(no\ hire)$.

[11] For instance, suppose that $A^* = \omega_1 A_1 + \omega_2 A_2 + \ldots + \omega_{\theta\to\infty} A_{\theta\to\infty}$ where $\omega_1, \omega_2 \ldots, \omega_{\theta\to\infty}$ are weights on individual predictive variables. We may expect $\omega_1 > \omega_2 > \ldots > \omega_{\theta\to\infty} > 0$. If the employer screened all $\theta\to\infty$ predictive variables, he would learn A^* with certainty. The employer selects the count of variables Θ_A whose predictive power $\omega_1, \ldots, \omega_A$ is sufficiently high, so that their contribution to the employer's expected taste value exceeds their screening cost. The prediction error, $\varepsilon_{A\Theta} = A^* - E(A^*|A_1, \ldots, A_\Theta) = \omega_{\Theta+1} A_{\Theta+1} + \ldots + \omega_{\theta\to\infty} A_{\theta\to\infty}$ is assumed to have zero expectation, and zero correlation with $A_1, \ldots, A_\Theta$. (This would strictly technically imply that variables A_θ in the pool also have zero expectation, a non-restrictive assumption.)

$$Eu(\Theta_A,\Theta_B,\Theta_C,\Theta_D) = Eu\left[\pi\left(\widehat{B^*},\widehat{C^*}|\Theta_B,\Theta_C\right) - \mathrm{r}(\Theta_A,\Theta_B,\Theta_C) + \mathrm{g}\left(\widehat{A^*}|\Theta_A\right)\right] \; s.t. \widehat{D^*}|\Theta_D \geq \delta \qquad (2)$$

where hats denote predicted values of latent characteristics conditional on the variables screened. Equation 2 is easier to maximize when latent characteristics are independent of each other, as well as of any of the θ_k observable predictors of other latent variables $k_{\theta_k}, k \in (A,B,C,D)$. For instance, by using taste-based screening of the extent $\Theta_A>0$, and narrowing the conditional distribution of A^* for each applicant, the employer does not learn anything about applicants' values of B^*. That is, $E(\widehat{A^*}\cdot B^*|A_1 \ldots A_{\Theta A})=0$. Restricting the applicant pool based on the screened values of $A_\theta \forall\theta$ or on the predicted values A^* does not affect the distribution of B^* in the pool, except for the fact that it decreases pool size.

In this imperfect-information setup, the employer has two problems: how much to screen applicants, and whom to hire. The second problem is analogous to that under perfect information. The employer hires the applicant with a utility-maximizing set of expected values $\widehat{A^*},\widehat{B^*},\widehat{C^*}$ complying with government regulation $D^*\geq\delta$. The selected values of $\widehat{A^*},\widehat{B^*},\widehat{C^*}$ depend on the first derivatives and cross-derivatives of the recruiting cost function, conditional on $\widehat{D^*}\geq\delta$: $dr/d\Theta_k \cdot d\Theta_k/d\widehat{k^*}$, $dr/d\Theta_k \cdot d\Theta_k/d\Theta_{-k} \cdot d\Theta_{-k}/d(-\widehat{k^*})$ for $\widehat{k^*}=\{\widehat{A^*},\widehat{B^*},\widehat{C^*}\}$. They also depend on the first derivatives of the average-productivity, customer-valuation, and employer-taste functions, conditional on $\widehat{D^*}\geq\delta$: $df/d\widehat{B^*}$, $dp/d\widehat{C^*}$, and $dg/d\widehat{A^*}$. Finally, they depend on the joint distribution of $\widehat{A^*},\widehat{B^*},\widehat{C^*}$ in the applicant pool.

The more interesting problem is how much to screen applicants. The chosen values of Θ_A, Θ_B, Θ_C and Θ_D depend 1) positively on the desired levels of $\widehat{A^*},\widehat{B^*},\widehat{C^*}$ given their effects on productivity, customer valuation, employer taste, and recruiting cost; 2) positively on the predictive power of variables A_θ, B_θ, C_θ, D_θ $\forall\theta$ – generally the difference in the moments between the conditional probability distribution of $\widehat{A^*},\widehat{B^*},\widehat{C^*},\widehat{D^*}$ and the unconditional distribution of characteristics A^*, B^*, C^*, D^* in the applicant pool; 3) positively on the applicant pool size; and 4) negatively on the incremental cost of screening $dr/d\Theta_A$, $dr/d\Theta_B$, $dr/d\Theta_C$.[12,13]

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[12] The recruiting cost may theoretically depend on both the latent type of the hire (e.g., under adverse impact laws), as well as the extent of screening (e.g., cost of collecting and analyzing information, and under adverse treatment laws).

[13] An important simplifying assumption until now has been that applicants' characteristics are independent of each other. As a result, the employer's choice over the value of one characteristic (say, B^*), or extent of one form of screening (Θ_B) had no bearing on the probability distribution of another characteristic (say, A^*) in the applicant pool, or the need for another form of screening (Θ_A), except through restricting the effective size of the

3. Solution at Heterogeneous Employers

This section distinguishes among companies facing different technologies and demands for skills, supply of skills in their applicant pools, customers' and own tastes for discrimination, recruiting costs, and regulatory restrictions. It strives to infer how much of each form of screening different companies should conduct, and how such screening should affect their performance.

First, employers differ in their average productivity of labor and in the effect of characteristic B^* on productivity. Employers differ in their need of skills B^* among their workers. For example, suppose there are two types of firms, with skill-intensive β_H or non-skill-intensive β_L technologies, $\beta_H > \beta_L$. Suppose that average labor productivity takes the form $f(\beta \cdot B^*)$, with a cross-derivative $d^2 f / d\beta dB^* > 0$. Employers with skill-intensive technology would be predicted to strive more to hire workers with high values of B^* than employers with non-skill-intensive technology. This is because $df(\beta_H \cdot B^*)/dB^* > df(\beta_L \cdot B^*)/dB^*$, while $dr/d\Theta_B \cdot d\Theta_B/dB^*$ is same for the two firms. If B^* is latent, employers with a skill-intensive technology will screen more characteristics predictive of B^* than other employers.[14]

Employers also differ in the intensity of their idiosyncratic taste for particular workers. Again suppose that there are two types of firms, with high taste intensity α_H or low intensity α_L, $\alpha_H > \alpha_L$, and that the taste value function takes the form $g(\alpha \cdot A^*)$, with a cross-derivative

applicant pool. In this section, we sketch how the solution would change if the independence assumption were relaxed. As before, we will not derive the explicit function forms of firms' problem or solution, because for that we would need to specify the joint distribution of characteristics A^*, B^*, C^*, D^* as well as of the predictive variables A_θ, B_θ, C_θ, D_θ $\forall\theta$ precisely.

When characteristics A^*, B^*, C^*, D^* are arbitrarily correlated, variables predictive of one characteristic tend to be predictive of another characteristic, too (unless all the correlation stems from correlated error terms $\varepsilon_{A\Theta}$, $\varepsilon_{B\Theta}$, $\varepsilon_{C\Theta}$, $\varepsilon_{D\Theta}$). By targeting an applicant with a high value of B^*, the employer may incidentally select an applicant with a high value of A^* too. For instance, $corr(A^*,B^*) \neq 0$, implies $corr(A^*,B_{\theta\epsilon\Theta B}) \neq 0$ or $corr(A^*,\varepsilon_{B\Theta}) \neq 0$, because, by assumption, $corr(B_{\theta\epsilon\Theta B},\varepsilon_{B\Theta})=0$. The first implies $corr(A_{\theta\epsilon\Theta A},B_{\theta\epsilon\Theta B}) \neq 0$ or $corr(\varepsilon_{A\Theta},B_{\theta\epsilon\Theta B}) \neq 0$; and the latter implies $corr(A_{\theta\epsilon\Theta A},B^*) \neq 0$ or $corr(\varepsilon_{A\Theta},B^*) \neq 0$. $B_{\theta\epsilon\Theta B}$ is then expected to be predictive of both B^* and A^* unless $corr(A^*,B_{\theta\epsilon\Theta B})=0$ and $corr(A^*,\varepsilon_{B\Theta}) \neq 0$. $A_{\theta\epsilon\Theta A}$ is predictive of both A^* and B^* unless $corr(A_{\theta\epsilon\Theta A},B^*)=0$ and $corr(\varepsilon_{A\Theta},B^*) \neq 0$.

Knowledge of $B_{\theta\epsilon\Theta B}$ affects the predictive power of $A_{\theta\epsilon\Theta A}$ for A^*, because a part of A^* that could be revealed through A_θ ($\omega_\theta A_\theta$ $\forall\theta$) gets revealed through B_θ ($\omega_\theta \cdot B_\theta\, cov(A_\theta,B_\theta)\ \forall\theta$). The effective predictive power of A_θ becomes $\omega_\theta[A_\theta - B_\theta cov(A_\theta,B_\theta)\ \forall\theta]$. Thus, under the plausible assumption of substitution in predictive power among A_θ, B_θ, C_θ, D_θ $\forall\theta$, an increase in, say, Θ_A is expected to be coupled with a reduction in Θ_B, Θ_C, Θ_D.

[14] We could also distinguish various skills needed in production, say B_1^*, B_2^*, B_3^*, … For instance, production may require intelligence, eye-hand coordination, sociability, and other qualities. Each of these latent qualities may be predictable using a unique set of variables $B_{1\theta}$, $B_{2\theta}$, $B_{3\theta}$, ...$\forall\theta = 1, \ldots, \Theta$. Production function of a company may have different skill-intensity parameters β_j for different skills j. Hence, an employer may screen a different number of characteristics predictive of skill 1 than characteristics predictive of skill 2.

$d^2g/d\alpha dA^*>0$. Taste-intensive employers will strive more to hire workers with high values of A^* than other employers, and will screen more characteristics predictive of A^*.

Similarly we can distinguish employers whose customers have high taste intensity γ_H or low intensity γ_L for particular employees, $\gamma_H>\gamma_L$, with willingness to pay of the form $p(\gamma\cdot C^*)$, with a cross-derivative $d^2p/d\gamma dC^*>0$. Employers with taste-intensive customers will strive more to hire workers with high values of C^* than other employers, and will screen more characteristics predictive of C^*. Furthermore, the regulatory constraints on employers' hiring may be differently binding for different employers: $D^*\geq\delta_H$ or $D^*\geq\delta_L$, $\delta_H>\delta_L$. Employers with more stringent constraints will screen more characteristics predictive of D^*.

Employers also differ in their incremental recruiting costs. The cost of processing applicant information, the expected repercussions for information collection, and the expected repercussions for hiring only particular types of workers may vary across employers. Suppose the marginal recruiting cost is either high or low, depending on a binary parameter ρ, $\rho_H>\rho_L$. Suppose this parameter enters the recruiting costs linearly, affecting all arguments equally: $r(\rho\cdot\Theta_A, \rho\cdot\Theta_B, \rho\cdot\Theta_C)$. The higher the cost parameter ρ, the less inclined an employer would be to search for applicants with high values of A^*, B^*, C^*.

Finally, our setup allows us to make different predictions for employers facing small versus large application pools per opening, N. The larger the applicant pool, the greater the difference between the unconditional expectation of A^*, B^*, C^* of the hired worker, and their conditional expectation thanks to the screening of A_θ, B_θ, C_θ. Hence, the greater the benefit from one-time screening of applicants.

4. Testable Hypotheses

The above model yields several predictions about the determinants and consequences of the extent of firms' screening – the chosen values of Θ_A, Θ_B, Θ_C, Θ_D – that can be tested using available data. The first set of predictions concerns the determination of the extent of screening of each kind. In sum, parameters ρ, α, γ, β, δ, N should have bearing on screening practices (as indicated in the set of equations 3 below).

Hypothesis 1: The recruiting cost parameter ρ affects negatively the extent of statistical and taste-based screening: $d\Theta_k/d\rho>0$ for $k=\{A,B,C\}$. Hence, the greater the degree of government scrutiny, and the greater the firm's reliance on operations abroad or on government contracts, the lower the expected applicant screening, if we control for other employer characteristics.

Hypothesis 2: The intensity of the employer's (customers') taste for discrimination should affect Θ_A (Θ_C, respectively) positively: $d\Theta_A/d\alpha>0$, $d\Theta_C/d\gamma>0$. Urban and large firms, with more formal HRM policies and more professional recruiting officers, may thus be expected to use less of employer-taste screening. Service-sector and rural firms are expected to practice more of screening motivated by customer tastes.

Hypothesis 3: Skill and capital intensity of production at a firm is expected to affect Θ_B positively, $d\Theta_B/d\beta>0$, as the firm's performance is more sensitive to worker's skills.

Hypothesis 4: Stringency of the regulatory constraint on hiring affects positively firms' need to screen applicants' protected characteristics: $d\Theta_D/d\delta>0$. State-owned firms should therefore have higher Θ_D.

Hypothesis 5: Finally, applicant-pool size should affect the extent of statistical and taste-based screening positively, $d\Theta_k/dN>0$ for $k=\{A,B,C\}$. Hence, firms with market power in local labor markets, and firms facing high local unemployment rate may screen their applicants more heavily. However, these circumstances should have no effect on Θ_D, as firms merely need to satisfy $D^*\geq\delta$ no matter what the applicant pool is.

Hypothesis 6: The extent of screening of one kind should affect the extent of screening of other kinds negatively, as long as the underlying variables of interest are related non-negatively. However, to the extent that there are unobservable firm-specific characteristics, some firms may be predisposed to asking few questions of all kinds, say because they face high latent screening costs. If we fail to confirm the negative relationship among Θ_A, Θ_B, Θ_C in our sample even after controlling for economic factors, that may serve as evidence that latent firm-specific effects are systematic and important.

IV. Empirical Approach and Data

Our empirical approach is to formulate an estimable model of the role of firms' screening; collect information on firms' actual screening practices, firms' characteristics and performance, and market and regulatory circumstances; classify screening practices into the four conceptual types; and use regression analysis to evaluate the theoretical predictions and comment on the classification of screening practices.

The model in Section IV has generated several predictions about the determinants of applicant screening along the four dimensions of screening.[15] By adding together all questions of a particular kind into Θ_A, Θ_B, Θ_C, Θ_D, and regressing the four counts on firms' characteristics, we can test those predictions. Under the predictions, the counts of questions at an employer *j* are functions of the parameters of *j*'s screening costs, ρ; intensity of *j*'s taste or need for particular screening, α, β, γ, δ; and the size of applicant pool N. Because of suspected partial substitutability among the four screening types, the extent of any type of screening Θ_k is also thought to be a function of the extents of other screening types Θ_{-k}:

$$\begin{aligned}
\Theta_{jA} &= \Theta_{jA}\{\rho_j, \alpha_j, N_j, \Theta_{-A}\} + \varepsilon_{jA} \\
\Theta_{jB} &= \Theta_{jB}\{\rho_j, \beta_j, N_j, \Theta_{-B}\} + \varepsilon_{jB} \\
\Theta_{jC} &= \Theta_{jC}\{\rho_j, \gamma_j, N_j, \Theta_{-C}\} + \varepsilon_{jC} \\
\Theta_{jD} &= \Theta_{jD}\{\delta_j, \quad N_j, \Theta_{-D}\} + \varepsilon_{jD}
\end{aligned} \tag{3}$$

ε_{jk} are randomly-distributed errors stemming from the omission of firms' unobservable characteristics, possible measurement errors in variables, and the limited-variable nature of Θ_{jk}. ε_{jk} are likely heteroskedastic, because Θ_{jk} are non-negative count variables and because firms in different market and regulatory circumstances face a different number of risk factors and opportunities for applicant screening.[16]

Because of the mutual determination among Θ_A, Θ_B, Θ_C, Θ_D , and covariance among ε_A, ε_B, ε_C, ε_D, this system of equations should be estimated using a simultaneous equations model in a three-stage procedure (SEM; Zellner and Theil 1962). In the first stage, Θ_{-k} are estimated

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[15] While the model does not make any predictions about firms' usage of individual screening questions A_{θ_A}– because that depends on unobservable correlations between the underlying characteristics of interest and alternative screening questions, as well as among various screening questions – it makes predictions about the extent of each kind of screening.

[16] For instance, small firms may exhibit greater heterogeneity of screening practices than large firms. The Breusch-Pagan test rejects homoskedasticity for all screening types except for customer-taste screening. In the small sample, this is interpreted as clear evidence of heteroskedasticity.

using only exogenous variables, satisfying rank and order conditions for valid SEM instruments. In the second stage, equations 3 are estimated using predicted values of Θ_{-k} among explanatory variables. In the third stage, standard errors are re-estimated by accounting for the covariance among ε_k.[17] As a benchmark specification, equations 3 are specified as linear equations. Alternatively, because Θ_k take on only several non-negative integer values, the relationship between explanatory variables and Θ_k may be modeled as exponential, and the distribution of errors characterized as Poisson.[18,19] Since the means of question counts in table 2 are typically smaller than the respective variances, mild underdispersion is suspected. Coefficient standard errors in all models are corrected for arbitrary heteroskedasticity, and in Poisson models – for arbitrary dispersion.

1. Data Collection

Data for the empirical analysis come from several public sources. Job application forms available on employers' own recruitment webpages represent the main source of information. We considered only employers' own recruiting practices and restricted the sample to advertisements and application forms on employers' own websites. We did not analyze generic job application forms available from online job portals, because it was unclear how representative those application forms were of decisions taken by individual employers in specific hiring situations.[20]

A convenience sample of the largest 250 companies in China is compiled based on firms' 2010 sales revenues. The application forms were for the 2010 recruiting season. 215 of the

[17] This method allows consistent identification of coefficients on all regressors provided that instruments are valid, and that order and rank conditions are satisfied – essentially that several exogenous variables appear only in first-stage equations, and several exogenous variables appear only in a subset of second-stage equations. This method also produces a corrected covariance matrix of residuals in the four equations. After estimating the SEM, one can test whether endogeneity was a significant problem in the first place, and can comment on the validity of (overidentifying) instruments, although small sample size may render the tests inconclusive.

[18] Under Poisson distribution and exponential functional form, $E(\tilde{\Theta}_k|x) = var(\tilde{\Theta}_k|x) = exp(x\sigma)$, where x are all the explanatory variables and σ are the corresponding estimable parameters. The probability that $\tilde{\Theta}_k$ takes a particular integer value $\tilde{\theta}_k$ is $(\tilde{\theta}_k|x) = exp[-exp(x\sigma)][exp(x\sigma)]^{\tilde{\theta}_k}/\tilde{\theta}_k!$ (Hlasny 2014).

[19] As a test of robustness to misestimation in a small sample, equations 3 are also estimated using separate ordinary least squares (OLS) or Poisson regressions (with or without $\tilde{\theta}_{-k}$ among explanatory variables). These specifications correct standard errors for arbitrary heteroskedasticity. These models may be inconsistent and less efficient as they treat ε_A, ε_B, ε_C, ε_D as independent. Their results are available on request.

[20] Intermediate agencies may be influenced by their own objectives, resource availability, and information environments. Employers' webpages inform us of employers' own decisions regarding recruiting practices, rather than of decisions taken by intermediate hiring agencies or workers themselves. Evidence on employers' webpages reflects the decisions by firms' own personnel departments regarding information to be sought from job applicants, and what position to adopt vis-à-vis anti-discrimination laws. In any case, the vast majority of firms recruit workers by themselves, rather than using recruiting agencies.

250 surveyed companies had application forms for openings on their websites. Among the 215 companies, we collected 225 unique application forms.[21] The SEM requires a balanced panel, which in our sample means omission of one firm with missing data.

The content of firms' application forms and prerequisites in their job advertisements (henceforth, the *documents-stage* screening practices) are linked to other information on firms' characteristics, and their market and regulatory circumstances. The information for all 215 firms (225 application forms), available from companies' own websites and annual reports, includes companies' sales revenue, value of assets, number of employees, operations abroad, ownership, main industry group, and the province of headquarters. Profit rate is available for a subset of 149 companies (156 applications). Labor-market indicators at the province level include unemployment rate and proportion of college-educated workers. Table 3 provides the description and summary statistics of variables used.

On firms' application forms, we limit our analysis to ten personal questions that may be problematic from a legal or ethical viewpoint, and that were asked by more than five employers: *hukou* (asked by 81% of employers); marriage status (69%); party affiliation (65%); ethnicity (60%); photograph (47%); height and weight (43%); family background (31%); health (12%); blood type (8%); and internal referral (5%).[22] Questions related to education, work experience or habits are omitted because it could be argued that employers are justified in asking them. While employers may have discriminatory motives for asking those questions, evidence of this is lacking. Secondly, personal questions asked by fewer than five employers are omitted, because the cases could be outliers and could influence other results. Reasons why these firms ask the rare questions are unknown, and could differ across firms or be subject to randomness. Inclusion of these cases would only sidetrack our analysis.

[21] Eleven companies used different application forms for different openings. For instance, positions for experienced candidates, and for recent graduates used different application forms and advertised different prerequisites. Of the 215 firms, 201 use the same application form to recruit both groups of workers, and recruit them on their own. 12 of the 215 firms apply different standards to different groups, and 2 firms only ask for free-style resumes. Of the 12 firms using different standards, 6 firms conducted 'experienced recruitment' themselves but entrusted campus recruitment to recruiting agencies; 6 firms recruited both groups themselves.

[22] In addition, 52% of companies asked about applicants' hobbies or interests; 92% about present or expected salary; 56% about work, other experience or training; 37% about years of experience, present job or reasons for switching jobs; over 40% about educational major, classes failed, awards won or other special skills. Some companies also asked about reasons for applying, self-evaluation, career plans, military experience, experience abroad, tenure of membership in the Communist party.

2. Classification of Questions into Four Conceptual Types

Applicants' individual personal characteristics (A_θ, B_θ, C_θ, D_θ $\forall\theta = 1, \dots, \Theta_k$) help employers to infer applicants' values of variables of interest (A^*, B^*, C^*, D^*), say, from observable population statistics on how A_θ, B_θ, C_θ, D_θ are correlated with A^*, B^*, C^*, D^*. Employers can thus exploit personal characteristics in their choice over whom to hire for statistical, customer-taste, employer-taste, or regulatory reasons.

To test our predictions about the extent of different types of screening under different market conditions, and the implications for employers' performance, it is first necessary to classify questions on application forms into the four conceptual kinds.[23] The underlying hypothesis is that each personal characteristic screened by employers has a purpose: to ascertain applicants' values of A^*, B^*, C^* and D^*. Clearly we expect some overlap in factors ascertaining the four characteristics. One option for classifying the screened factors is to attach each question asked to a single characteristic of interest. The advantage of this method is that the sum of the four imputed counts would equal the true gross count of all factors, $\sum_{k=A,B,C,D} \tilde{\Theta}_k = \sum_k \Theta_k$. The disadvantage is that $\tilde{\Theta}_k$ imputed in this way may not measure precisely the volume of information that an employer used to predict characteristic k^*, and may systematically underestimate it, $\tilde{\Theta}_k < \Theta_k \; \forall k$. Due to uncertainty regarding the exact motives at each firm for each characteristic screened, and due to the likely duplication of factors among the four sets $A_1 \dots A_\Theta$, $B_1 \dots B_\Theta$, $C_1 \dots C_\Theta$, $D_1 \dots D_\Theta$ (e.g., $A_1 \dots A_\Theta \cap C_1 \dots C_\Theta \neq \emptyset$), we opt to assign each factor screened to one or more characteristics of interest. If it is plausible that firms inquire about a particular characteristic for multiple reasons, or different firms for different reasons, the factor is classified under multiple categories. For example, height appears important both as a statistical as well as a customer-taste factor. Health may be surveyed to predict applicants' productivity as well as to comply with health-screening regulations. It is unclear which of the two motives dominates. If the classification is done carefully, we would ideally obtain $E(\tilde{\Theta}_k - \Theta_k) = 0 \; \forall k$ although $\sum_{k=A,B,C,D} \tilde{\Theta}_k > \sum_k \Theta_k$.

Our classification of characteristics screened is as follows: Questions about height and weight, family background, marital status, health and internal referral are classified as

[23] As a first cut, we could treat all personal factors screened as equivalent to one another and study the gross count of factors screened on firms' application forms and the gross count of prerequisites on job advertisements regardless of motive, as $\tilde{\Theta}$. Firms in the sample screen 0-9 personal factors on their application forms (mean 4.22), and use 0-4 personal factors as prerequisites on advertisements (mean 1.39). Regressions of these counts have been estimated, but have an unsatisfactory theoretical interpretation, given the diversity of motives for screening individual characteristics.

statistical factors. Height and weight, ethnicity, and requests for a photograph are classified as customer taste-based factors. Blood type and internal referral are classified as employer taste-based factors. Applicants' party affiliation, *hukou*, ethnicity and health are classified as regulatory factors.

This classification was performed by considering 1) the questions' perceived information content; 2) patterns of joint occurrence across application forms; and 3) prevalence across firms with different labor needs. With respect to information content, questions about height and weight, family background, marital status, health and internal referral strive to identify agile, strong, socially skilled and dependable workers (Hlasny and Jeung 2014). Height and weight, ethnicity, and good looks on photographs are attributes that are thought to be easily noticeable and valued by firms' customers in their short interactions with the firms. Certain blood types and internal referrals are traditionally used in East Asia as predictors of workers' personality and long-term relations – with no scientific base – and are only detectable by the employer, not by customers. Finally, party affiliation, *hukou*, ethnicity and health may be screened in perceived compliance with equal-opportunity or information-collection laws, or by employers copying recruiting processes at state-owned companies.

With respect to joint occurrence of these individual questions across application forms, table A1 indicates that questions classified as being of the same type are more highly and significantly correlated with one another, in part due to apparent hierarchical relationships (Hlasny 2011, 2014): Firms are significantly more likely to screen workers' party affiliation if they also screen *hukou*, and ethnicity if they screen party affiliation and *hukou*. Similarly, firms are significantly more likely to screen height and weight if they also screen marital status, and health if they screen marital status, height and weight, or family background. Firms screening health are much less likely to screen blood type.[24] These patterns suggest that employers follow a systematic routine when designing their application forms, with specific motives in mind. More detailed and intrusive questions of any type are asked only if more general questions of that type are asked first. These patterns help to verify the proposed

[24] Of the firms screening workers' *hukou* (183 cases), 71% also screen party affiliation. Of the firms that do not screen *hukou* (43 cases), only 39% ask about party. Questions about *hukou* thus apparently serve as a 'prerequisite' for questions about party. Restricting our attention to the 183 cases screening *hukou*, we find that firms screening party affiliation are more likely to screen ethnicity (78% of the 130) than firms that do not (30% of the 53). Similarly, firms screening marital status are more likely to screen height and weight (50% of the 155) than firms that do not (27% of the 71). Restricting attention to the 155 cases screening marital status, firms screening height and weight are more likely to screen health (19% of the 78) than firms that do not (9% of the 53).

clustering of questions, particularly for statistical and regulatory motives. Customer and employer taste-based factors are not as clearly delineated, presumably because characteristics that are thought to appeal to customers – in employers' view – appeal to employers themselves.

The final test of the clustering is based on the prevalence of individual questions on application forms of firms of various types. Firms' reliance on various worker attributes (self-coded Likert scale), detailed industry classification, strategic nature of industry, and Herfindahl-Hirschman index in the industry labor market were considered. Since these variables are not used in the structural models – due to missing values, consideration for degrees of freedom, or collinearity with other factors – their usage here does not directly affect empirical results. This test confirms that the screening of family background, marital status and internal referral is significantly more prevalent at firms relying more on workers' cognitive skills, self-motivation, professionalism and trustworthiness, indicating a statistical motive for screening them. Similarly, screening of height and weight, marital status, and health is more prevalent among firms relying on precision and physical skills, flexibility and irregular-status labor. Employers relying more on workers' social skills – services, retail sales, high technology manufacturing and telecommunications – screen height and weight, ethnicity and internal referrals more frequently than other firms, indicating customer or employer tastes as motives. Firms in strategic industries, and in public utility, mining and construction industries are more likely to screen party affiliation, *hukou*, ethnicity and health, suggesting regulatory motives. Finally, firms with greater market power are more likely to screen most of the questions, especially party affiliation, marital status and health, suggesting regulatory and statistical motives for screening them.

Tables 1 and 2 and figure A1 in the appendix summarize the resulting classification. Figure A2 shows the joint distribution of the types of screening in the sample. Regardless of the overall extent of screening, most employers practice some regulatory screening. Firms screening few factors tend to screen statistical and regulatory factors. Firms screening more factors than others tend to screen more for statistical and regulatory motives. Only employers practicing other forms of screening extensively also choose to screen factors motivated by employer taste.

A final note is warranted. While this classification allows us to test the specific predictions from Section IV, this is attained at a potential cost of inaccuracy in the subjective classification. If OLS regressions of the extent of each type of screening $\tilde{\Theta}_k$ (equations 3) do not include $\tilde{\Theta}_{-k}$ among regressors, the dependent variables should proxy as well as possible for the latent true extent of screening of each type. It is then appropriate to include height in both $\tilde{\Theta}_B$ and $\tilde{\Theta}_C$, health in both $\tilde{\Theta}_B$ and $\tilde{\Theta}_D$, etc. However, since the simultaneous equations model controls for the joint determination of the four counts of screening, such duplicate classification likely biases the estimated correlation among Θ_A, Θ_B, Θ_C, Θ_D and among ε_{jA}, ε_{jB}, ε_{jC}, ε_{jD} upward. Controlling for $\tilde{\Theta}_{-k}$ in a fully specified SEM model, this issue is not likely to substantially affect the consistency and efficiency of other coefficients of interest, but we must carefully evaluate the potential consequences when interpreting the results of alternative specifications.[25]

V. Findings

Table 4 presents the results of two SEM specifications explaining jointly the extent of the four types of personal screening on firms' application forms, $\tilde{\Theta}_k \; \forall k$. These models assume linear functional form in the determination of $\tilde{\Theta}_k$ and normality of ε_k.[26] Columns 1-4 present a benchmark model using only theoretically-motivated explanatory variables, while columns 5-8 present a full specification, using additional control variables that were deemed conceptually and empirically relevant. Coefficients in table 4 can be interpreted as the average marginal impacts of a unit-increase in the explanatory variables on the count of personal factors screened, $\tilde{\Theta}_k$. To preserve space, we will not discuss individual coefficients but merely qualitative trends apparent across columns.

[25] Another criticism of the above approach is that screening of personal factors may have different motives at different firms. For instance, height may be screened for customer-taste reasons in service occupations, statistical reasons in manual-work occupations, and employer-taste reasons elsewhere. To deal with this issue, Hlasny and Jiang (2013) reclassified questions into the four conceptual types based on their information content as well as firms' characteristics: 1) skills and availability they require of their workers, 2) main customer type, 3) ownership, 4) level of competition in the relevant labor market, 5) other features of the relevant industry or geography and 6) government role. But this more flexible classification is susceptible to inaccurate assignment at individual firms, and endogeneity in regressions. Regression results using this approach are generally stronger but likely biased.

[26] Results of the sets of four separate OLS or Poisson regressions, without controlling or instrumenting for $\tilde{\Theta}_{-k}$, or systems of seemingly-unrelated regressions, are omitted for lack of space. Their results are generally weaker than the main SEM results and are likely biased. Hausman's and Wooldridge's specification tests, and Breusch-Pagan error-covariance tests indicate that the SEM specification is more appropriate than SUR, 2SLS or OLS specifications. Finally, SEM models in which different employers are allowed to have different motives for screening individual personal characteristics also yield qualitatively similar – but stronger and likely biased – results as those reported. These results are available on request (also refer to Hlasny and Jiang 2013).

Table 5 presents the equivalent specifications where Θ_k are modeled as Poisson-distributed. Coefficients in these regressions are the percentage impacts of a 0.01-unit increase in explanatory variables on the count of personal questions. When multiplied by the sample mean of the count of questions ($E(\Theta_k)$), these coefficients can be interpreted as the average partial effects, and can be compared to OLS coefficients. On the one hand, Poisson specifications are preferable to linear specifications given the distribution of dependent variables. On the other hand, Poisson models are more sensitive to distributional assumptions on Θ_k and ε_k, and Poisson marginal impacts are cumbersome to evaluate. A glance at table 5 also reveals that Poisson results are similar to linear-model results in table 4, and Poisson regressions perform slightly less well in terms of overall fit. Hence, tables 4 and 5 will be discussed jointly, and only qualitative differences between them will be noted.

Statistical screening

In Section IV, statistical screening was predicted to be driven by firms' demand and workers' supply of skills, and any regulatory constraints on statistical screening. Under a hypothesis that statistical screening is important for firms whose performance is sensitive to workers' skills, we expect that firms in skill- and capital-intensive industries will practice it most extensively. The lower the mean educational achievement in the province, the greater the right skew of the distribution of skills may be, and the greater the risk that firms would hire a low-skill worker – hence, the greater the benefit of statistical screening. Finally, employers operating under stricter labor-market constraints, such as in foreign jurisdictions, are less able to statistically screen candidates. We may also think that state-owned firms and firms facing more competition in labor market have lower incentives and ability to practice statistical screening.

Column 1 in table 4 (as well as in the Poisson specification, table 5) reports on the benchmark specification of the statistical-screening equation, while column 5 uses additional explanatory variables. These specifications provide modest support for most of our conjectures. While coefficients on skill-intensive industry fail to confirm that firms with demand for skills ask more questions on application forms, coefficients on capital-labor ratio carry the expected positive sign (significant in the Poisson specification). Proxying for the supply of skills in the applicant pool, the share of college-educated population in a province is associated negatively with firms' screening as expected (significant in 3 of 4 specifications), suggesting a lesser need for the screening of applicants' skills. Firms' output-market share, the available proxy for employers' ability to choose their workers in the labor market, is associated positively with statistical screening, also as expected. However, firms' size in terms of their employment carries negative coefficients (marginally significant) that are difficult to interpret in tandem with the coefficients on market share.

Coefficients on state ownership and on reliance on government contracts carry the expected signs in five of six instances (insignificant), weakly supporting the conjecture that these firms have lesser motives for financial optimization (lower β) or more stringent constraints on their decision-making practices. Finally worth noting, operations abroad exhibit a small or negative effect across model specifications, failing to support a conjecture that foreign jurisdictions impose constraints on firms' aggressive screening.

Beside these theoretically motivated variables, the extent of screening of other types, selected industry indicators, and unemployment rate in the province are also controlled for. The coefficients on screening-count variables are surprisingly large and significant across all columns in tables 4 and 5, implying that a large portion of a firm's decision to screen one set of applicant characteristics can be explained by the firm's decision to screen other characteristics. (This finding holds even when we use a non-duplicative classification of factors screened.) The coefficients are for the most part positive, in contrary to our hypothesized substitutability between screening types. Having screened one set of characteristics does not appear to make it less marginally beneficial or more costly for a firm to screen additional characteristics. Since our model does not control for firms' recruiting systems or screening costs explicitly, the extent of one type of screening at a firm may proxy for the firm's proficiency at collecting and processing information, or (inversely) for the firm's effective screening costs. Empirically the positive signs correspond with the fact that firms screening any personal characteristics typically screen multiple characteristics, of various types.

The effects of the rest of explanatory variables are empirically mixed or have an unclear interpretation. While unemployment rate was expected to have a positive effect on statistical screening – as an indicator of the size of the applicant pool from which firms choose their workers – the negative coefficient may be caused by latent business-cycle, geographic or demographic effects.

Customer-taste screening

Prevalence of direct interaction between workers and customers, and the nature of customers should have bearing on screening motivated by customer tastes. Employers in service and sales industries are expected to conduct more of this screening. Firms' reliance on public-sector orders and on business abroad may be related negatively to the extent of taste-based screening, because public-sector and overseas customers are thought to have less taste for discrimination and to shun intrusive taste-based practices. Regulation in these sectors is also expected to present stricter constraints on firms' practices. Finally, urban employers may conduct more or less of customer-taste screening, depending on whether the willingness to pay of urban consumers is more responsive to workers' characteristics than that of rural consumers, and how effective regulatory and media oversight is in first-tier cities versus elsewhere.

The results in columns 2 and 6 confirm that employers in service and sales industries screen more personal characteristics on application forms (significant in table 5). Prevalence of government customers has a small, mixed effect on customer-taste screening, failing to confirm our a priori conjecture. There is only weak evidence that employers with operations abroad practice less of customer taste-based screening.

Employers in first-tier cities screen more customer taste-based questions on application forms than rural employers (significant in table 5), suggesting that urban consumers' valuation depends more on the appearance and demographic features of company representatives. This corroborates anecdotal reports that urban residents discriminate against non-urban residents, and urban middle-class consumers like to see themselves transacting with equals. Among other results, surprisingly, larger firms and firms in skill-intensive industries appear to practice more of customer-taste screening, statistically significant.

Employer-taste screening

We have hypothesized that employers' taste-based screening depends negatively on the formality of employers' HRM, and on the stringency of the regulatory climate they face. Columns 3 and 7 evaluate these hypotheses empirically. Unfortunately, there are only imprecise proxies available for the two factors. Proxying for the formality of firms' HRM are the firms' size, state ownership, and location in cities. Proxying for regulatory climate are firms' market share, firm size, and an indicator for whether firms have primarily government customers. Operation in a strategic industry was also considered but eventually omitted from the structural models for collinearity with firms' size, industry indicators, ownership and main customer type.

Empirical evidence of the role of the formality of firms' HRM is mixed. On the one hand, state-owned firms screen applicants less extensively for taste-based reasons (very significant in table 5), as expected. This reflects the fact that state-owned firms operate more bureaucratically, and are more closely overseen by the government. However, unexpectedly, larger firms are shown to practice taste-based screening more extensively. Furthermore, firms in large cities are also estimated to screen applicants more extensively than rural firms. Both of these results are very significant statistically.

Evidence of the role of firms' regulatory constraints is equally mixed. Firms' market share has a small but expected negative effect on the extent of taste-based screening (all coefficients significant), but firms' size has an unexpected positive effect, as noted above. Reliance on government contracts was also considered as a proxy for regulatory constraints, but was omitted due to poor results – small and insignificant coefficients of opposite signs in tables 4 and 5 – and in order to satisfy the rank condition for valid instruments across columns.

Among other findings, employers in skill-intensive industries and in provinces with a high prevalence of college education screen more for employer-taste reasons than others, against our expectations. The most plausible explanation for these results is omitted variables, or imprecise classification of personal factors by motive: If customer taste-based factors were confounded with employer taste-based factors, we may indeed find large and urban employers screening more in line with the results for customer taste factors.

Regulatory screening

Regulatory pressures for appropriate screening are thought to be strongest at state-owned firms, and large firms with high market power in the output market – because securing of a preferential market position or sufficient capital requires administrative intervention, and because labor at more powerful firms is likely to interact with public authorities. Firms relying on government contracts and those in large cities are also expected to face stricter regulations. On the other hand, firms with operations abroad may be exempted from strict regulatory standards, so that they could comply with equal-opportunity laws and norms in foreign jurisdictions.

The results in columns 4 and 8 confirm that state-owned firms, firms with a stronger market position, and capital intensive firms practice more of regulatory screening, significant statistically in most instances. The results fail to confirm the conjectures about the impact of firms' government contracts, city size or operations abroad on firms' regulatory screening, as their coefficients are insignificant or switch signs. Among other results, firms in skill-intensive industries, in provinces with a high prevalence of college education and high unemployment appear to screen less for regulatory reasons. These results are difficult to interpret.

Overall, models estimated in table 4 explain firms' screening practices reasonably well, explaining 9.1-21.3% of variation in them across firms (4.3-17.4% in the Poisson specification in table 5). Wald tests indicate that the models are significant compared to intercept-only or limited-controls model alternatives. Hence, the benchmark hypotheses of no systematic variation in personal screening can be rejected. Most coefficients in tables 4 and 5 support our hypotheses regarding firms' motives for screening, consistently across columns, particularly for statistical and customer-taste screening.[27] This helps to validate our classification of questions by employers' motives, with the possible exception of customer and employer taste based questions, which appear to be driven by similar factors.

The results are also consistent across functional forms in table 4 versus table 5, albeit the results differ quantitatively and in the degree of significance. Linear specification appears to provide a better fit, probably because the distribution of question counts diverges from Poisson distribution, and individual equations suffer from different degrees of under-dispersion, issues that are not easily offset in the small sample.

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[27] Analogous regressions were estimated to explain the count of prerequisites on firms' job advertisements. Their results are not as significant as those for screening on application forms, in part because prerequisites have very limited variation in the sample. Conceptually, application-form screening is arguably a more effective method for applicant selection than applicant-pool truncation via prerequisites, and can thus be better explained by economic factors. Screening on application forms gives firms' better control over applicant selection than rigid prerequisites, and does not lead to explicit adverse treatment that would explicitly violate some laws. This explains why application-form screening is more prevalent and extensive, and why cross-firm variation in this practice is more open to statistical analysis.

Correlation between the count of factors on application forms and the count of prerequisites is for the most part positive, and is insignificantly different from zero. This is true for the overall counts regardless of motive ($r=+0.056$), as well as for the counts of screening of each motive. Correlation for statistical prerequisites and screened factors is $r=+0.061$; for customer taste-based factors it is $r=-0.001$; for employer taste-based factors it is $r=-0.054$; and for regulatory factors it is $r=+0.184$. Hence, omission of the prerequisites from tables 4 and 5 does not appear to affect coefficients qualitatively.

Estimating the four types of screening using a system of simultaneous equations model has yielded consistent and more efficient results than a set of independent regressions or a seemingly-unrelated regressions specification – available on request. The addition of alternative screening methods (instrumented) among regressors allows a more precise estimation of the contribution of each regressor in the structural equations.[28,29]

VI. Discussion

This study has described the information environment and the optimization problem that Chinese employers face in recruitment, and identified four distinct motives for applicant screening – statistical, customer taste-based, employer taste-based, and regulatory. The model yielded testable predictions regarding the extent of each form of screening by employers in different economic circumstances, and the implications for firms' observed performance. Using a system of simultaneous equations with linear and Poisson regression specifications, we have evaluated the theoretical predictions.

On the most fundamental level the study confirms that, on the skill-demand side, the form of applicant screening is systematically related to capital and skill intensity of firms' production, their industry, and their main customers. On the supply side, firms' position in the labor market, urban versus rural locality, and local demography affect screening. Finally, government oversight over industries, firms' ownership, and operation under foreign

[28] After estimating the structural model, we evaluate whether error-correlation or endogeneity was a concern in the first place. The Breusch-Pagan test of correlation among ε_A, ε_B, ε_C, ε_D rejects a hypothesis of independence (p-value 0.001), justifying the SEM specification over independent 2SLS regressions. The Hausman specification test of the difference between the consistent SEM and the potentially inconsistent SUR coefficients also shows marginally significant difference in the basic model (p-value 0.159) and highly significant difference in the complete model (p-value 0.001). Wooldridge's heteroskedasticity-robust regression-based specification test performed on four independent 2SLS regressions confirms this by marginally rejecting the baseline hypothesis of exogeneity (p-values 0.131-0.977 in basic models, 0.165-0.777 in complete models).

[29] Instruments for $\tilde{\Theta}_{-k}$ used in the SEM appear valid although their strength may be modest. Tables 4 and 5 confirm that the order condition on the exclusion of some exogenous variables from a subset of equations is satisfied. First-stage equations include the entire set of exogenous variables and also include three variables from outside of the second-stage equations (strategic industry, city–strategic industry interaction, and public utility indicators). The results of first-stage regressions, in table A1 in the appendix, also satisfy the rank condition on the significance of instruments. First-stage regressions achieve a modest overall fit with an R-squared of 0.11-0.22. One quarter of coefficients in table A1 are significant, with coefficient signs for the most part mirroring those in table 4. Variables excluded from the second-stage equations (e.g., for $\tilde{\Theta}_{-k}$ in column 1 in table 4 this means 1st-tier city, gov. customers, service & sale industry, unemployment rate, construction, manufacturing, strategic industry and public utility in columns 2-4, respectively, in table A1) are jointly highly significant. Wooldridge's heteroskedasticity-robust score test of overidentifying restrictions fails to reject the hypothesis that the additional instruments are valid (p-values 0.232-0.979).

jurisdictions contribute. These findings validate some predictions about the role of statistical, customer taste-based, and regulatory screening in firms optimization problem.

Across the different motives for screening, statistical and regulatory screening appears the most prevalent, by the number of factors screened and by the number of firms employing it. Statistical screening is related positively to employers' capital intensity, labor-market power and private ownership, and negatively to the supply of skills in provincial labor markets. These results in principle agree with the predictions from the theoretical model. Customer taste-based screening is linked positively to service and sales industries, in agreement with theory, and interestingly to wealthy first-tier cities. The determinants of employer taste-based screening are less significant and clear, in part because it is far less prevalent among firms. The best predictors of taste-based screening appear to be private ownership and, surprisingly, location in major cities. This presumably reflects some confoundedness between employer-taste and customer-taste screening. Either our classification of the two forms of screening is imprecise, or employers are subject to the same biases that they are aware of in their customers. Like Kuhn and Shen (2013), we conclude that taste-based screening observed at firms corresponds to our economic understanding only partially. Regulatory screening is well explained by firms' market position, capital intensity, and ownership by the state (all positively), agreeing with our institutional understanding.

In sum, many results of empirical results of this study agree qualitatively with the predictions from the theoretical model. This validates the model as well as the classification of factors screened by firms into four categories by motive. Employers conduct applicant screening in a systematic manner that can be explained by their economic and institutional circumstances and surprisingly even quite systematic tastes. Moreover, screening practices appear to have the expected effect on firms' performance (refer to the appendix), providing further justification for the classification method used: Statistical and customer-taste screening is associated positively with firms' profit rate, while employer-taste and regulatory screening is associated negatively with it. These results hold both for screening on firms' application forms and for prerequisites on job advertisements. Statistical screening appears particularly beneficial to employers in skill-intensive industries, and customer taste-based screening to employers in service and sales industries. If we could interpret these relationships causally, they would support our predictions. These results are in contrast with those reached in previous studies from other countries that firms embracing diversity in recruitment tend to be more successful in terms of stock valuation (Wright et al. 1995) and profit rate (Hlasny and Jeung 2014).

These findings should prompt greater introspection by firms' HR departments and local regulators into which applicant-screening practices are justified with respect to market-performance and social-welfare objectives. Regulators should enforce market conditions conducive to desirable practices for the collection and management of information by employers – possibly through relaxation of certain regulatory constraints, providing firms with essential information on workers in more transparent and coordinated ways, civic education campaigns publicizing appropriate social norms, and stricter enforcement of minimum standards of responsible recruiting practices.

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Table 1. Factors Screened on Applications: Prevalence & Classification by Presumed Motive

	Prevalence (%)	Statistical	Customer-taste	Employer-taste	Regulatory
Blood type	8.41			Y	
Ethnicity	59.73		Y		Y
Family background	31.42	Y			
Height & weight	42.92	Y	Y		
Health status	12.39	Y			Y
Hukou	80.97				Y
Internal referral	4.87	Y		Y	
Marital status	68.58	Y			
Party affiliation	65.04				Y
Photo	47.35		Y		

Note: Prevalence is among 225 application forms.

Table 2. Summary Statistics of the Count of Screened Personal Factors by Presumed Motive

	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Firms with #>0
All questions	4.217	2.104	0	9	-0.057	2.518	96.02%
Statistical	1.603	1.151	0	5	0.656	3.554	81.42%
Customer-taste	1.500	0.953	0	3	-0.123	2.076	81.86%
Employer-taste	0.142	0.375	0	2	2.563	6.046	13.27%
Regulatory	2.181	1.130	0	4	-0.434	2.242	90.27%

Note: Summary statistics are for 225 application forms. Statistical, customer taste-based, employer taste-based or regulatory motive is inferred from the content of screening, from prevalence across different types of employers, and from the joint occurrence of various characteristics screened.

Table 3. Evaluated Variables, Data Sources and Summary Statistics

Variable	Source	Description (Units)	Mean (St.Dev.)
Province	NBSC (2011)	Province of headquarters (Binary for the 28 provinces represented in the sample)	--
Unemployment rate	--	Unemployment rate, by province (%)	3.180 (0.792)
% college-edu. in province	--	Percent of population college-educated, by province (%)	9.254 (7.641)
Industry	Companies' websites	Main industry group (Binary for manuf.; retail & wholesale; services; finance & insurance; real estate; pharma; textiles; agri & forestry; food processing & hotels; mining; energy & utilities; transport & post; constr & engin; high-tech & telecom)	--
Log(employees)	Annual Reports[i], Companies' websites	Logarithm of firm's workforce	9.643 (1.351)
1^{st}-tier city	Companies' websites	Binary for headquarters in Beijing, Shanghai, Guangzhou, Shenzhen or Tianjin	0.193 (0.396)
State-owned	--	Binary for state-owned firms	0.421 (0.495)
Government customers	--	Firm has government customers (Binary)	0.219 (0.415)
Strategic industry	--	Firm's industry is metals manuf.; mining; food processing, pharma; aviation; constr & engin; real est; fin & bank (Binary)	0.456 (0.499)
1^{st}-tier city×strat	--	Interaction term (Binary)	0.136 (0.344)
Skill-intensive industry	--	Firm's industry is manuf., retail, wholesale, services, finance & insurance, pharmaceutical, textiles, agriculture, food processing, metals, energy, transport (Binary)	0.750 (0.434)
Revenue	China.org.cn[ii], Annual Reports	Sales revenue in 2010 (RMB million)	37,211 (51,267)
Market share	--	Firm's revenue as portion of industry revenue (%)	6.579 (12.650)
Operations abroad	Annual Reports	Firm has operations abroad (Binary)	0.185 (0.389)
Capital-labor ratio	--	Assets / employees in 2010 (RMB million / worker) for 207 firms	2.550 (6.694)
Profit rate	Damodaran (2012) China.org.cn, Annual Reports	Profit / assets in 2010 (%) for 156 firms	4.918 (4.229)

Note: All variables are evaluated in a sample of 225 application forms, except for capital-labor ratio & profit rate (as indicated). All monetary variables are deflated to 2010 RMB, using midyear national CPI.

[i] Annual Reports provide information on listed firms' operations and financial performance, published on firms' own websites or on the Shenzhen stock exchange, http://www.cninfo.com.cn/information/lclist.html.

[ii] China.org.cn, national online news service, china.org.cn/business/2011-09/03/content_23344983.htm.

Table 4. Results of a Simultaneous Equations Model, Instrumenting for the Extent of Screening of Other Types

	Basic Model (224 Observations)				Complete Model (204 Observations)			
	Statistical	Customer-taste	Employer-taste	Regulatory	Statistical	Customer-taste	Employer-taste	Regulatory
Skill-intensive industry	-0.184 (0.172)	0.185* (0.107)	0.162*** (0.064)	-0.441** (0.188)	-0.045 (0.916)	0.066 (0.165)	-0.001 (0.011)	-0.012 (0.231)
Market share	0.012** (0.006)	-0.006 (0.004)	-0.005** (0.002)	0.012* (0.007)	0.049* (0.027)	-0.007 (0.006)	-0.020** (0.009)	0.015** (0.007)
Log(employ.)	-0.113* (0.061)	0.077** (0.036)	0.056** (0.025)	-0.140** (0.070)	-0.230 (0.214)	0.072* (0.042)	0.100 (0.071)	-0.077 (0.055)
% college-edu. in province	-0.005 (0.004)			0.003 (0.003)	-0.048* (0.026)	0.004 (0.006)	0.022** (0.009)	-0.017** (0.007)
1st-tier city			0.191** (0.083)	-0.408* (0.229)		0.207 (0.202)	-0.133 (0.275)	0.102 (0.210)
State-owned	-0.077 (0.138)		-0.09 (0.059)	0.251* (0.144)	0.697 (0.575)		-0.103 (0.157)	0.078 (0.120)
Government customers		0.039 (0.057)			-0.523 (0.782)	-0.007 (0.195)		-0.179 (0.199)
Operations abroad	0.237 (0.154)	-0.105 (0.105)		-0.025 (0.144)	-0.134 (0.598)	-0.072 (0.129)	-0.054 (0.189)	0.041 (0.146)
Service & sale industry		0.006 (0.079)				0.203 (0.214)		
Statistical count		0.448*** (0.149)	0.203** (0.093)	-0.321 (0.314)		0.361** (0.179)	0.806*** (0.246)	-0.619*** (0.190)
Customer-taste count	1.278*** (0.370)		-0.592*** (0.163)	1.654*** (0.355)	3.602** (1.743)		-1.534*** (0.454)	1.177*** (0.341)
Employer-taste count	1.249* (0.674)	-0.625 (0.463)		2.123*** (0.745)	2.894*** (0.518)	-1.045 (0.717)		0.764*** (0.113)
Regulatory count	-0.28 (0.267)	0.457*** (0.103)	0.281*** (0.083)		-3.998*** (0.386)	0.397** (0.182)	1.305*** (0.201)	
Capital-labor ratio					0.047 (0.058)		-0.026 (0.020)	0.02 (0.016)
Unempl. rate					-0.421 (0.363)	0.011 (0.087)	0.217* (0.128)	-0.166* (0.097)
Construction industry					-2.566** (1.204)		0.820** (0.404)	-0.629** (0.287)
Manufacturing industry					-2.136*** (0.840)	0.253 (0.193)	0.767*** (0.218)	-0.588*** (0.148)
Constant	1.346** (0.600)	-0.963*** (0.358)	-0.549** (0.237)	1.478** (0.678)	9.676*** (3.559)	-0.773 (0.772)	-3.983*** (1.350)	3.054*** (0.958)
Pseudo R-squared	0.106	0.134	0.091	0.159	0.166	0.151	0.121	0.213
Wald Chi^2	46.40***	92.05***	31.39***	61.44***	115.22***	64.57***	58.52***	146.02***

Covariance-corrected standard errors are in parentheses. Effects are significant at 1% (***); 5% (**); 10% (*) level, two-sided tests. All monetary variables are deflated to 2010 RMB using midyear national CPI. Count of questions on application forms is as reported in table 2. Results of first-stage instrumenting for them are reported in table A2.

Table 5. Results of a Poisson Simultaneous Equations Model, Instrumenting for the Extent of Screening of Other Types

	Basic Model (224 Observations)				Complete Model (204 Observations)			
	Statistical	Customer-taste	Employer-taste	Regulatory	Statistical	Customer-taste	Employer-taste	Regulatory
Skill-intensive industry	-0.009	0.124**	1.342**	-0.142***	0.125	0.070	0.126	0.014
	(.137)[.104]	(.113)[.061]	(.646)[.604]	(.093)[.046]	(.196)[.124]	(.160)[.080]	(1.038)[.786]	(.067)[.085]
Market share	0.004**	-0.002	-0.031**	0.004***	0.008**	-0.003	-0.065*	0.005***
	(.004)[.002]	(.004)[.002]	(.018)[.014]	(.003)[.001]	(.006)[.004]	(.005)[.003]	(.051)[.036]	(.004)[.001]
Log(employ.)	-0.041	0.057***	0.380**	-0.043**	-0.047*	0.040*	0.458***	-0.019
	(.049)[.032]	(.040)[.023]	(.211)[.161]	(.038)[.019]	(.049)[.028]	(.041)[.022]	(.238)[.159]	(.037)[.016]
% college-edu. in province	-0.005*			-0.000	-0.012***	0.000	0.047	-0.005***
	(.004)[.003]			(.003)[.001]	(.007)[.005]	(.005)[.002]	(.050)[.036]	(.005)[.002]
1st-tier city			1.773***	-0.114*		0.141*	0.321	0.088
			(.650)[.480]	(.155)[.067]		(.165)[.078]	(1.175)[.828]	(.142)[.060]
State-owned	-0.094		-0.941**	0.110**	-0.006		-1.833**	0.112***
	(.129)[.100]		(.539)[.427]	(.098)[.049]	[.099]		(.918)[.782]	(.098)[.043]
Government customers		0.073			-0.133	0.002		-0.052
		(.129)[.068]			(.220)[.151]	(.173)[.087]		(.135)[.056]
Operations abroad	0.154*	-0.051		0.011	0.074	-0.025	0.246	-0.024
	(.120)[.085]	(.118)[.059]		(.107)[.046]	(.130)[.089]	(.117)[.056]	(.534)[.425]	(.095)[.040]
Service & sale industry		0.099				0.196**		
		(.165)[.073]				(.198)[.093]		
Statistical count		0.105	0.776*	-0.065		0.096*	0.596	-0.093
		(.163)[.083]	(.700)[.476]	(.177)[.077]		(.146)	(.973)[.558]	(.163)[.069]
Customer-taste count	0.415*		-2.472**	0.581***	0.407		-4.536**	0.234**
	(.317)[.242]		(1.461)[1.060]	(.223)[.104]	(.585)[.398]		(2.675)[2.236]	(.248)[.101]
Employer-taste count	0.477	0.108		0.447***	0.063	-0.425**		0.239*
	(.424)[.336]	(.427)[.250]		(.436)[.172]	(.583)[.409]	(.498)[.199]		(.465)[.144]
Regulatory count	0.11	0.250***	0.625		-0.259	0.254***	5.174*	
	(.224)[.174]	(.130)[.075]	(1.012)[.940]		(.546)[.385]	(.167)[.089]	(3.596)[2.818]	
Capital-labor ratio					0.015**		-0.006	0.006**
					(.012)[.008]		(.089)[.080]	(.009)[.003]
Unempl. rate					-0.126**	-0.002	0.365	-0.045*
					(.099)[.061]	(.070)[.031]	(.638)[.402]	(.061)[.025]
Construction industry					-0.202		3.559	-0.420***
					(.479)[.332]		(3.133)[2.559]	(.202)[.096]
Manufacturing industry					-0.246	0.144	3.117**	-0.227***
					(.315)[.206]	(.184)[.102]	(2.122)[1.491]	(.097)[.048]
Constant	-0.022	-1.001***	-5.701***	0.417***	1.372*	-0.785**	-15.250**	1.013***
	(.478)[.302]	(.365)[.193]	(1.933)[1.483]	(.346)[.156]	(1.215)[.834]	(.660)[.344]	(10.14)[7.333]	(.582)[.229]
Corr[Θ,E(Θ)]^2	0.060	0.080	0.043	0.129	0.111	0.115	0.129	0.174
Wald Chi^2	32.64***	52.96***	23.99***	66.42***	100.22***	69.96***	68.49***	109.07***
Pearson *var(ε)* overdispersion	0.790	0.590	0.930	0.556	0.736	0.559	0.848	0.510
E(Θ$_k$)	1.603	1.500	0.142	2.188	1.632	1.559	0.137	2.255

Regular standard errors are in parentheses; overdispersion and heteroskedasticity-robust, covariance-corrected standard errors are in brackets. Effects are significant at 1% (***); 5% (**); 10% (*) level using robust standard errors, two-sided tests. All monetary variables are deflated to 2010 RMB using midyear national CPI. Count of questions on application forms is as reported in table 2. First-stage instrumenting for them is conducted using Poisson analogs of specifications in table A2.

Appendix

Impact of Firms' Screening Practices on Profitability

Discussion in sections III and IV has suggested that statistical and customer taste-based screening appears driven by firms' desire to hire workers who will increase firms' revenue-product, given employers' and customers' skill demand, workers' skill supply, and constraints on intrusive screening. Regulatory and employer taste-based screening appears motivated by non-pecuniary motives, and may represent a constraint on firms' profit-maximization.

To evaluate hypotheses regarding the effect of screening practices on performance, regressions of firms' profitability π_j are used. π_j is made a function of the extent of the four kinds of screening Θ_{jk}; sensitivity of profit with respect to Θ_{jk}, through β_j, γ_j; skill availability and tightness of the factor market that firm j faces, proxied for by N_j; and other cost and revenue shifters X_j at the level of firm and relevant market:

$$\pi_j = \pi_j \{ \Theta_{jk} , N_j , \beta_j, \gamma_j, X_j \} + e_j \qquad k=\{A,B,C,D\} \tag{A1}$$

X_j includes interaction terms between Θ_k and firms' relevant characteristics (ρ, α, δ, γ, β, N), because the two sets affect firms' performance in a complementary fashion, through $f(\beta B)p(\gamma C)$. e_j are randomly-distributed errors stemming from the omission of firms' unobservable characteristics, and possible measurement errors in variables. e_j are likely heteroskedastic, because, for one, firms of different size and labor-intensity are differently susceptible to labor-market constraints and opportunities. To mitigate the risk of endogeneity of regressors, Θ_{jk} from a mid-year hiring season are linked to year-end profit.

Equation A1 is estimated using OLS. By controlling for other firm-specific factors potentially correlated with screening practices and with performance, and by mitigating endogeneity of Θ_{jk} and its interaction terms through lagging, we may hope to infer causal effects of firms' screening practices on profitability. However, because of the limited information on firms' operations beside recruitment, we expect to explain only a part of the variation in π_j across firms. The remaining unexplained part, e_j, should be uncorrelated with our variables of interest Θ_{jk} as long as the rest of explanatory factors take care of the possible correlation of Θ_{jk} with omitted factors.

In our simple theoretical setup in equations 1–3, firms' observed financial performance should depend non-positively on α, δ and ρ, because these represent taste-based, regulatory and technological constraints on firms' optimizing behavior in recruiting: $d\pi/d\alpha \leq 0$, $d\pi/d\delta \leq 0$ and $d\pi/d\rho \leq 0$. As long as ρ is not too high, firms' performance should depend non-negatively on N, as a larger pool size allows firms to be more selective in whom they hire: $d\pi/dN \geq 0$.[30] The effects of job skill intensity β, intensity of customers' taste γ are unclear, as they depend on firms' ability to seek out high-B^* and high-C^* candidates.

In line with these predictions, we can infer the indirect implications of firms' observed screening choices for their financial performance, and test them empirically.

Hypothesis A1: Firms' profitability may depend negatively on the observed extent of screening motivated by employer's taste, Θ_A, and by the regulatory constraint, Θ_D. Screening of Θ_A is costly, while it does not affect $\pi(\cdot)$. Also, firms may face a tradeoff between the

[30] These predictions would not hold if higher screening cost, or smaller pool size, mainly prevent firms from attempting to recruit higher-A^* applicants.

screening of taste-based factors A_θ, versus factors related to productivity or consumer value B_θ and C_θ, because of marginally increasing screening costs, or partial substitutability in their predictive power. Observing high Θ_A may imply that an employer's utility is more sensitive to his taste value $g(\cdot)$ than to his profit $\pi(\cdot)$. High Θ_D may imply that an employer faces a stringent regulatory constraint (or irrationally over-complies with regulation).

Hypothesis A2: The observed extent of statistical screening and screening motivated by customer tastes, Θ_B and Θ_C, may be related positively to firms' performance. Higher Θ_B and Θ_C yield higher expected values of B^* and C^* in the hired worker, possibly at a low one-time cost of screening and nontrivial benefits $d\pi/dB^* \cdot dB^*/\Theta_B$, $d\pi/dC^* \cdot dC^*/\Theta_C$.[31] These qualitative predictions would hold even while accounting for firms' characteristics ρ, α, δ, γ, β and N.

As a test of these propositions, and of the sensibility of our classification of factors screened, we regress firms' profit rate on the extent of the four types of screening.[32] Table A3 presents the results of these OLS regressions. Coefficients in table A3 can be interpreted as the expected marginal impacts of a unit-increase in $\tilde{\Theta}_k$ on year-end profit rate. Column 1 shows a simple regression of profit rate on the count of factors screened on firms' application forms, controlling only for firms' basic economic variables. Column 2 also accounts for the extent of statistical screening on firms' job advertisements; Column 3, for other types of screening on advertisements; and Column 4, for firms' capital-intensity, operations abroad and one industry indicator. Column 4 is the complete model controlling for all types of screening on firms' advertisements and for circumstances where screening should be most influential – using interactions of the extent of statistical screening on application forms with firms' skill intensity, customer-taste screening with a service-industry indicator, and employer-taste screening with operations abroad.

The first row in table A3 confirms that statistical screening affects profit rate positively. If interpreted causally, an additional factor screened is predicted to raise firms' profit rate by 0.7 percentage points, a large statistically significant effect that is very consistent across columns. The only exception is the last column that controls for screening-industry interaction. Even in this specification, statistical screening is predicted to have a positive effect in skill-intensive industries as well as a positive average affect overall (of -0.474+1.293*0.75 = 0.5 pc.pt.). Similarly, customer-taste screening is estimated to raise profitability in most columns, but the effect is relatively small and varying across columns. Employer-taste screening has a negative effect on profit rate, of consistent size across columns, 0.8-1.1 percentage points per question screened. Regulatory screening also has the expected negative effect in most columns, of varying magnitudes, 0.09-0.49.[33] Hence, the

[31] These predictions were made under an implicit assumption that the four characteristics A^*, B^*, C^*, D^* were approximately jointly independent in the applicant pool, and that screening of one set of variables (say A_θ) did not affect the predictive power of other variables (B_θ, C_θ) positively. Generally, the effects depend on the correlation among the variables of interest and their predictors, and their full joint distribution.

[32] These regressions may potentially suffer from endogeneity of explanatory variables as firms make recruiting decisions with specific expectations about their future performance, so the coefficients here may not have a precisely causal interpretation. Instrumenting for the extent of screening should be considered. However, no instruments come readily to mind, since factors that affect firms' recruiting decisions likely affect firms' financial performance too. Instruments would also likely be weak, and yield imprecise and inefficient estimates in the small sample.

[33] If we take coefficients in column 4 at face value, we may infer that firms could influence their profit rate by up to 7.8 percentage points (5×0.698 + 3×0.440 + 2×0.977 + 4×0.248), by screening the maximum number of statistical (5) and customer-taste (3) factors, and zero employer-taste (out of 2) and regulatory (out of 4) factors.

vast majority of coefficients on screening variables have the expected signs and are quite consistent across columns. This again helps to validate our classification of questions by employers' motives. However, most coefficients are not significant statistically, due to the amount of noise in the sample and small sample size.

In column 4, interaction terms on screening extents and market conditions also give us mostly the expected coefficients. Statistical screening is particularly profitable at skill-intensive firms, in indirect agreement with Kuhn and Shen's (2009, 2013) results, and customer-taste screening is particularly profitable in service and sales industries (the former result significant nearly at the 5% level). However, the interaction term of employer-taste screening and an indicator for operations abroad gives an unexpected positive coefficient.[34]

Table A1. Pairwise Correlation among Individual Questions on Application Forms

	Party affiliation	Height & weight	Blood type	*Hukou* register	Family bacgrnd.	Photo	Ethnicity	Marital status	Health status
Height & weight	0.045								
Blood type	0.144^{x}	0.181^{y}							
Hukou register	0.164^{x}	0.056	0.089						
Family bacgrnd.	0.313^{y}	0.144^{x}	0.201^{y}	0.166^{x}					
Photo	0.385^{y}	-0.053	0.053	0.096	0.295^{y}				
Ethnicity	0.479^{y}	0.051	0.208^{y}	0.082	0.219^{y}	0.236^{y}			
Marital status	0.087	0.179^{y}	0.088	0.008	0.071	-.009	0.012		
Health status	0.207^{y}	0.124*	0.027	-0.023	0.259^{y}	0.198^{y}	0.187^{y}	0.061	
Internal referral	0.115*	0.088	-0.072	0.100	0.197^{y}	0.150^{x}	-0.037	0.053	0.287^{y}

Sample size is 217, restricted to applications with non-zero number of factors screened. Pearson correlation coefficient is significant at 10% (*), 5% (^{x}), 1% (^{y}) level, non-directional t test with 215 (217-2) degrees of freedom.

This of course presupposes that the ratio of marginal benefits and marginal costs of screening is similar for the observed and the infra- and extra-marginal factors screened, which is unlikely to hold precisely.

[34] Among other results of interest, prerequisites on job advertisements appear to have unclear effects on performance, much less clear than the screening on application forms – positive for statistical prerequisites and negative for regulatory prerequisites, as expected, but of unexpected signs on customer-taste and employer-taste prerequisites. Firm size, market share and capital-intensity appear to have negative effects on profit rate, significant for firm size. This may be due to regulatory climate in China, in which larger firms face more stringent regulatory oversight or protection, possibly leading to a lesser profit drive. Skill-intensive firms tend to be more profitable, while firms in the service industry tend to be less profitable.

Table A2. Linear Simultaneous Equations Model First-Stage Results

	Basic Model (224 Observations)				Complete Model (204 Observations)			
	Statistical	Customer-taste	Employer-taste	Regulatory	Statistical	Customer-taste	Employer-taste	Regulatory
Strategic industry	-0.157	0.165	0.032	0.140	-0.323	0.119	-0.002	0.149
	(0.230)	(0.188)	(0.069)	(0.217)	(0.236)	(0.197)	(0.074)	(0.226)
1st-tier city ×strategic	0.293	0.311	-0.197*	0.239	0.067	0.279	-0.252**	0.048
	(0.428)	(0.350)	(0.120)	(0.405)	(0.433)	(0.362)	(0.125)	(0.414)
Public utility	-0.673**	-0.140	0.025	0.127	-0.581*	-0.096	0.036	0.118
	(0.346)	(0.299)	(0.109)	(0.346)	(0.350)	(0.301)	(0.112)	(0.344)
Skill-intensive industry	0.238	0.123	0.009	-0.068	0.332	0.195	-0.019	0.077
	(0.280)	(0.229)	(0.084)	(0.264)	(0.286)	(0.239)	(0.089)	(0.273)
Market share	0.005	-0.002	-0.003*	0.000	0.013	0.004	-0.002	0.011*
	(0.007)	(0.006)	(0.002)	(0.007)	(0.009)	(0.007)	(0.003)	(0.007)
Log(employ.)	0.037	0.102*	0.016	0.051	-0.006	0.027	0.025	-0.014
	(0.072)	(0.059)	(0.022)	(0.068)	(0.079)	(0.066)	(0.025)	(0.075)
1st-tier city	0.440	0.237	0.315***	0.277	0.314	0.142	0.283***	0.348
	(0.358)	(0.293)	(0.107)	(0.339)	(0.361)	(0.302)	(0.107)	(0.345)
State-owned	-0.100	0.132	-0.120***	0.238	-0.008	0.229*	-0.110**	0.305*
	(0.176)	(0.144)	(0.048)	(0.166)	(0.181)	(0.141)	(0.055)	(0.173)
% college-edu. in province	-0.017**	-0.009	0.001	-0.01	-0.023***	-0.011*	0.000	-0.015**
	(0.008)	(0.007)	(0.002)	(0.008)	(0.009)	(0.007)	(0.003)	(0.007)
Government customers	0.084	0.052	-0.121*	-0.228	-0.009	-0.038	-0.118*	-0.243
	(0.291)	(0.238)	(0.070)	(0.276)	(0.293)	(0.245)	(0.071)	(0.280)
Service & sale industry	0.253	0.670**	0.041	0.668*	-0.076	0.500	0.008	0.428
	(0.391)	(0.320)	(0.117)	(0.370)	(0.416)	(0.348)	(0.130)	(0.397)
Operations abroad	0.248	-0.010	0.055	-0.025	0.064	-0.108	0.018	-0.129
	(0.200)	(0.163)	(0.060)	(0.189)	(0.203)	(0.170)	(0.063)	(0.194)
Unempl. rate	-0.139	-0.05	-0.029	-0.155	-0.234**	-0.098	-0.047	-0.164
	(0.118)	(0.096)	(0.035)	(0.112)	(0.115)	(0.102)	(0.038)	(0.116)
Construction industry	-0.496	-0.356	0.004	-0.981***	-0.417	-0.374	0.007	-0.930***
	(0.379)	(0.310)	(0.113)	(0.358)	(0.386)	(0.323)	(0.120)	(0.367)
Manufacturing industry	-0.448	0.046	0.039	-0.315	-0.562*	0.004	0.058	-0.390
	(0.330)	(0.269)	(0.099)	(0.312)	(0.345)	(0.292)	(0.109)	(0.333)
Capital-labor ratio					0.045***	0.018**	0.007	0.019**
					(0.015)	(0.008)	(0.005)	(0.009)
Constant	1.955**	0.427	0.056	2.346***	2.789***	1.322*	0.059	2.985***
	(0.878)	(0.717)	(0.262)	(0.830)	(0.914)	(0.764)	(0.285)	(0.873)
R-squared	0.131	0.153	0.111	0.191	0.182	0.157	0.125	0.216
Chi-squared	31.65***	37.50***	25.80**	49.20***	41.44***	34.88***	26.72*	51.36***

Standard errors are in parentheses. Effects are significant at 1% (***); 5% (**); 10% (*) level. All monetary variables are deflated to 2010 RMB using midyear national CPI.
Count of questions on application forms is as reported in table 2.

Table A3. Regression Results for Firms' Profit Rate

	[1]	[2]	[3]	[4]	[5]
Statistical appl.-form question count	0.727**	0.720*	0.657	0.698*	-0.474
	(0.37)[0.36]	(0.47)[0.44]	(0.49)[0.50]	(0.47)[0.42]	(1.09)[0.71]
Customer-taste appl.-form question count	-0.688	0.068	0.250	0.440	0.261
	(0.55)[0.63]	(0.68)[0.71]	(0.68)[0.65]	(0.67)[0.67]	(0.70)[0.71]
Employer-taste appl.-form question count	-0.755	-1.070	-0.924	-0.977	-1.008
	(1.07)[0.77]	(1.48)[0.98]	(1.48)[1.07]	(1.40)[0.88]	(1.65)[1.20]
Regulatory appl.-form question count	0.099	-0.487	-0.373	-0.248	-0.090
	(0.44)[0.46]	(0.59)[0.54]	(0.60)[0.58]	(0.57)[0.54]	(0.60)[0.63]
Log(employees)	-0.755**	-0.683**	-0.701*	-1.005***	-1.198***
	(0.33)[0.30]	(0.42)[0.34]	(0.43)[0.36]	(0.42)[0.29]	(0.46)[0.34]
Skill-intensive industry	1.107*	1.210	1.276	1.279	-0.840
	(0.78)[0.67]	(1.06)[0.93]	(1.05)[0.92]	(1.01)[0.85]	(2.02)[1.57]
Market share	-0.039	-0.024	-0.018	-0.004	0.010
	(0.04)[0.03]	(0.06)[0.05]	(0.06)[0.05]	(0.06)[0.05]	(0.06)[0.05]
Statistical job-ad question count		0.129	2.854*	0.420	1.562
		(0.43)[0.40]	(1.72)[1.69]	(0.42)[0.44]	(1.74)[1.66]
Customer-taste job-ad question count			0.548		-0.557
			(1.60)[1.58]		(1.66)[1.41]
Employer-taste job-ad question count			-1.604		0.074
			(1.95)[1.93]		(2.03)[1.73]
Regulatory job-ad question count			-3.688*		-1.029
			(1.91)[2.12]		(2.01)[1.98]
Capital-labor ratio				-0.096***	-0.138***
				(0.06)[0.03]	(0.08)[0.03]
Operations abroad				1.855	1.787
				(1.13)[1.61]	(1.32)[1.78]
Service & sale industry				-3.295***	-7.656***
				(1.45)[0.68]	(4.87)[2.30]
Statistical appl.-form q. × skill-intensive ind.					1.293*
					(1.12)[0.76]
Customer-taste appl.-form q. × services ind.					2.231*
					(2.33)[1.14]
Employer-taste appl.-form q. × abroad					0.885
					(3.54)[2.06]
Constant	11.74***	10.934***	10.61***	12.762***	16.516***
	(3.29)[3.02]	(4.13)[3.28]	(4.22)[3.43]	(4.02)[2.54]	(4.89)[3.25]
Observations	154	105	105	104	104
R-squared	0.116	0.103	0.144	0.219	0.246
Wald Chi^2	39.83***	23.60***	0.043	75.35***	85.68***

Regular standard errors in parentheses, standard errors robust to arbitrary heteroskedasticity in brackets. Effects are significant at 1% (***); 5% (**); 10% (*) level using robust standard errors, two-sided tests. All monetary variables are deflated to 2010 RMB using midyear national CPI.
Count of questions on application forms is as reported in table 2.
In the complete model (column 5), the benchmark comparison group corresponds to small labor-intensive firms without operations abroad, in skill-unintensive industries.

Figure A1. Distribution of the Counts of Factors Screened by Presumed Motive

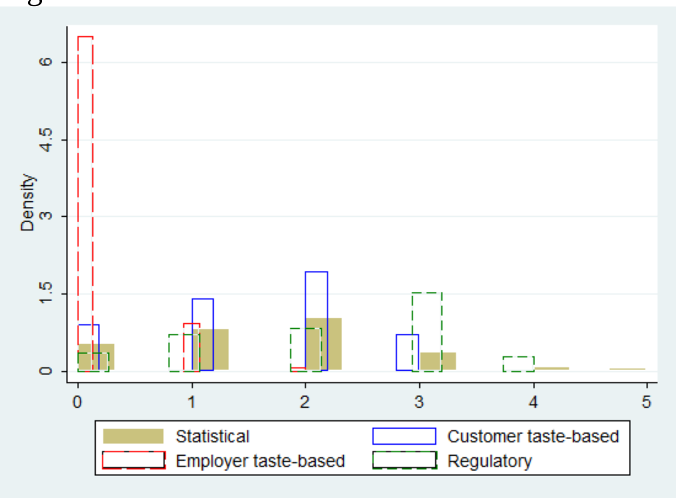
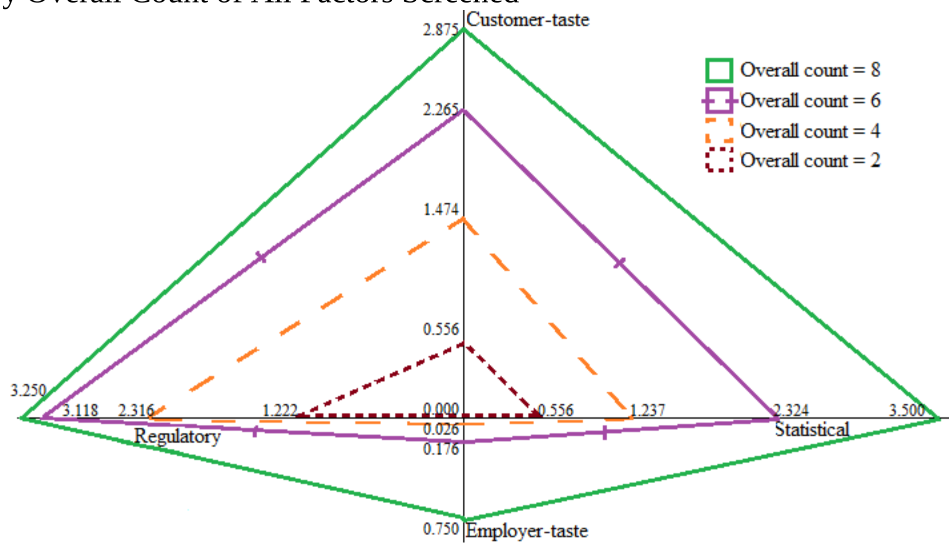


Figure A2. Mean Count of Personal Factors Screened on Application Forms by Presumed Motive, by Overall Count of All Factors Screened



Note: Each line shows the count of personal factors by motive used by a typical firm screening 2, 4, 6 or 8 personal factors in total, respectively. For instance, a typical firm screening 8 personal factors screens 3.5 statistical, 2.9 customer-taste, 0.8 employer-taste and 3.3 regulatory factors.