ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
SCHOOL OF BUSINESS, ECONOMICS AND LAW
UNIVERSITY OF GOTHENBURG
217

Essays on Team Cooperation and Firm Performance

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ISBN 978-91-85169-89-4 (printed)
ISBN 978-91-85169-90-0 (pdf)
ISSN 1651-4289 print
ISSN 1651-4297 online

Printed in Sweden,
Kompendiet 2014

To my family

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Acknowledgements

I had never dreamed of completing a doctoral thesis like this and becoming a PhD until I came to Gothenburg seven years ago for the sole purpose of accompanying my husband, who was doing his PhD studies at the Department of Economics. During my first days in Gothenburg, I was cordially embraced by the department, which for example allowed me to attend PhD courses. I was positively influenced by the atmosphere at the department – it was open, friendly, inspiring and strenuous. The connection to the department not only gave me a sense of social belongingness, which was critical for me in order to make a smooth transition to a new environment, but also inspired me to pursue a PhD myself. Looking back at the PhD journey, I have learned an enormous amount of knowledge and skills, and have been trained to think like an economist. More importantly, I have realized the philosophy of research – to always keep curious about the world, motivated in daily work, and diligent, patient and cheerful in the process – and am determined to devote the rest of my life to implementing it. Although a great number of challenges in various areas emerged along the way, thankfully I have never been alone.

I am profoundly grateful to my family. I would like to thank my parents, Liping Zhang and Yimin Weng, for their affection, nurturing, encouragement and support throughout my life. Their determination and effort in providing me with the good education since I was little and their respect for my decisions after I grew up have paved the way for me to reach this stage of my life. My husband, Haoran He, deserves my special thanks. Without him, I might never have travelled to Sweden as a tourist, not to mention lived there for so many years and accomplished so much. His kind love, unflinching encouragement and perpetual support have helped me overcome the fears, doubts, hesitation and difficulties that arose along the journey. Working in the same occupation, he could understand very well the reasons for my joys and times of sadness. My beloved daughter, Yibo He, joined us during my PhD studies. She has brought tremendous happiness and comfort to me and my family, and has changed my life from one revolving exclusively around work to one with more balance. This thesis is dedicated to all of you!

My deepest gratitude goes to my supervisors and co-authors Fredrik Carlsson and Måns Söderbom. I genuinely thank both of them for their relentless encouragement and unconditional support, their insightful guidance through constructive comments and useful suggestions for my papers, and their patience with my endless, and sometimes silly, questions.

Without all of this it would have been impossible for me to reach the finish line. Fredrik, I am impressed by your quick and straightforward responses during discussions, your optimism during the tough times of our project, your sound advice on both research and job planning, as well as your caring help on issues outside of research. Thanks for always replying to my emails incredibly fast and reading my drafts during nights and weekends. On top of being my supervisor, you have been a dear friend to me. Måns, I truly appreciate that you have always taken time to meet and discuss things, especially considering your many other commitments as a professor and current deputy head of the department. I have learned a lot from you, including the correct procedure for writing an empirical paper, numerous econometric techniques and Stata syntax, which I never would have figured out myself, the high standards one should set and hold when writing a paper, and the preciseness, prudence and perseverance one should keep in research, etc. You always had solutions to all the problems that sometimes seemed to have driven our projects into a dead end. Fredrik and Måns, it has been a great privilege and fantastic experience working with both of you, and I hope I will have the opportunity to continue working with you in the future.

I am also greatly indebted to the many people who have offered me invaluable help to improve my work. Jintao Xu and Xuemei Jiang gave me useful instructions when I carried out my first project for the thesis. Matthias Sutter, Martin Kocher, Maria Bigoni, Martin Dufwenberg, Peter Martinsson, and Amrish Patel shared their expertise and experience in conducting experiments, and were extremely helpful through discussions and comments on my experimental papers. Martin Kocher and Florin Maican, as external examiners, gave me insightful feedback that greatly improved my papers. Peter Berck offered me advice and help both during my exchange study at the University of California, Berkeley, and during my job applications. Jiegen Wei and Clara Villegas-Palacio acted as mentors to me during the early phase of my PhD study. They enthusiastically introduced me to research and always kept an open door for me. Yinan Li offered his knowledge and brainstormed with me on several research ideas. Xiangping Liu selflessly shared her extensive experience in both research and career planning.

My sincere gratitude goes to all those who have shared their knowledge and thoughts with me during my coursework: Hala Abou-Ali, Renato Aguilar, Arne Bigsten, Stephen Bond, Gardner Brown, Kaiji Chen, Jessica Coria, Markus Eberhardt, Håkan Eggert, Lennart Flood, Lennart Hjalmarsson, Marcela Ibanez, Olof Johansson-Stenman, James Konow, Gunnar Köhlin, Katrin Millock, Andrea Mitrut, Katarina Nordblom, Ola Olsson, Peter Parks, Agnar Sandmo, Oleg Shchetinin, Johan Stennek, Thomas Sterner, Thomas Tangerås, Elias Tsakas, Roger Wahlberg, Hong Wu, and the researchers at the Beijer Institute of Ecological Economics.

I also wish to thank Åsa Adin, Katarina Forsberg, Elizabeth Földi, Gerd Georgsson, Mona Jönefors, Eva-Lena Neth-Johansson, Selma Oliveira, Margareta Ransgård, Katarina Renström and Jeanette Saldjoughi for the extraordinary administrative support, and the IT department for the technical support. Life became much easier and more enjoyable with their help. I am particularly thankful to Elizabeth for her kindness to always offer solutions to my problems, and to Åsa and Jeanette for aiding me with the application for parental benefits. I also thank Debbie Axlid for her excellent editorial assistance.

My nice colleagues and friends at the department made my stay in Gothenburg so much more cheerful – thanks to all of you. I am grateful that I had the privilege to start the journey together with Lisa Andersson, Jorge Bonilla, Haileselassi Medhin, Kristina Mohlin, Anna Nordén, Hailemariam Teklewold, Claudine Uwera, Michele Valsecchi, Simon Wagura, and Xiaojun Yang. The time we spent together and the laughter and complaints we shared will be treasured in my heart. Special thanks go to Haile for organizing the wonderful trip to Ethiopia. In addition, I would like to thank Yonas Alem, Andreas Kotsadam, Pham Khanh Nam, Måns Nerman, Eyerusalem Siba, Kofi Vondolia, and Conny Wollbrant, with whom I have taken courses together, for all the useful discussions and help. I also thank Karin Jonson, Elina Lampi, and Daniel Slunge for showing me the hospitality and family life of Swedes.

I would like to acknowledge the financial support from Formas through the COMMONS program and from the Jan Wallander and Tom Hedelius Foundation for my experiments, Xiujuan Zhang and Pengyuan Pei for their excellent assistance in conducting the experiments, and each and every one of the hundreds of university students who participated in the experiments. Without them, I would not have been able to complete this thesis.

Last but not least, I would like to give a big thanks to my friends. The company of, and help from, Min Hu, Yuandong Liang, Linda Schollenberg, Eric Tam, Xiuna Yang, and Xiaobing Zhang made my time alone in Gothenburg never feel lonely. Fang Jiang, Xin Qiao, and Yue Zhang, as friends since childhood, provided me not only with friendship, but also professional advice and help to my family during my absence. Thank you all!

Qian Weng

Beijing, April 2014

Abstracts

Paper I: Cooperation in teams: The role of identity, punishment and endowment distribution

Common identity and peer punishment have been identified as crucial means to reduce free riding and to promote cooperation in teams. This paper examines the relative importance of these two mechanisms under two income distributions in team cooperation. In a repeated public good experiment, conditions vary among different combinations of homogeneous or heterogeneous endowment, strong or weak identity, and absence or presence of peer punishment. We find that without punishment, strong identity can counteract the negative impact of endowment heterogeneity on cooperation. Moreover, punishment increases cooperation irrespective of income distribution. However, the impact of punishment under strong identity depends on the relative strengths of the identity-building activity and the effectiveness of punishment. Furthermore, we find no evidence of stronger punishment in teams with a strong identity. These findings provide important implications for management policy makers in organizations: implementing *ex ante* income heterogeneity within teams should be done with caution, and the decision of whether identity or punishment is a more effective norm enforcement mechanism in teams is rather sensitive to their interaction and relative strengths.

Paper II: Session size and its effect on identity building: Evidence from a public good experiment

The effect of session size has largely been ignored in experimental studies, despite the possibility that it may affect people's perception of the strength of the potential link between them and consequently the strategies used in the interactions. This paper investigates how the effect of an induced common identity on individual cooperative behavior differs depending on session size in a repeated public good experiment with constant group size and partner matching. We find that induced identity significantly enhances cooperation only when the session size is small and only in the initial period. In all other periods, induced identity does not have a significant effect on cooperation in either small or large sessions. The same null effect of identity in small and large sessions suggests that session size is not a confounding factor of identity in repeated interaction settings.

Paper III: Multi-product firms, product mix changes and upgrading: Evidence from China's state-owned forest areas

Product selection matters for a firm's productivity and long-run growth. Recent theoretical and empirical studies indicate that an important margin of adjustment to policy reforms is the reallocation of output within firms through changes in product mix decisions. This paper examines the frequency, pervasiveness and determinants of product-switching and upgrading activities in firms located in China's state-owned forest areas during a period of gradual institutional and managerial reforms (2004–2008). We find that changes to the product mix are pervasive and characterized by adding or churning products rather than only shedding products. Moreover, changes in firms' product mix have made a significant contribution to the aggregate output growth during our sample period. We also find that firms with different characteristics, human capital and market conditions differ in their propensity to diversify and upgrade product mix.

Paper IV: Is R&D cash-flow sensitive? Evidence from Chinese industrial firms

We hypothesize that research and development (R&D) is sensitive to cash-flow fluctuations due to asymmetric information and agency problems in the credit market. We adopt a variant of the *Q* model for R&D investment using the value of the firm, physical capital and employment to capture firm fundamentals as proxies for investment opportunities. We add cash flow to this specification, and estimate the augmented model separately for R&D participation and spending using data on Chinese industrial firms for the period 2001-2006. We find that R&D spending is sensitive to cash-flow fluctuations, conditional on firm fundamentals. We also find that the cash-flow sensitivity of R&D varies across firms depending on ownership. We conclude that credit market imperfections pose a constraint for R&D in Chinese industry.

Summary of the thesis

This thesis consists of four self-contained papers. While at first glance these papers seem to address quite distinct issues and use different methodologies, there are indeed some underlying links. For example, all of the papers deal with the conditions based on which gains from specialization and cooperative production within an economic organization (a firm, a household, or a market) can better be obtained. These conditions, together with the structure of the organization, are considered the two important problems facing a theory of economic organizations (Alchian and Demsetz, 1972). It is of critical interest to study these conditions for firms since firms play a critical role in the growth and prosperity of a country's economy.

The firm is seen as a contract between a multitude of parties (Holmström and Tirole, 1989). This contractual view is developed based upon the seminal work by Coase (1937). Investigating the nature of the firm, Coase (1937) argues that "organizing" production through the price mechanism is costly. Establishing a firm and allowing an "entrepreneur" to direct the resources can minimize the transaction costs between specialized factors of production. The transaction costs include the cost of discovering the relevant prices of the factors, the cost of negotiating and concluding a separate contract for each exchange transaction taking place on the market, and the cost of the impossibility to state the detailed requirement in a long-term contract at the date of contracting. Thus, the purpose of the existence of firms is to facilitate exchange and to accommodate contractual constraints rather than production constraints (Holmström and Tirole, 1989).

However, the contract between the parties may be incomplete. A prominent example occurs in team production (see, e.g., Alchian and Demsetz, 1972). Suppose that two workers cooperate to complete a task as partners. How should they be compensated for their efforts? If their inputs are observable and can be contracted upon, the answer is simply to make payments in accordance with the costs of their inputs. Under such a circumstance, it will be in each worker's interest to work up to the level that is socially efficient. But what if their inputs cannot be verified so that rewards can only be based on the team output? A free-riding problem may occur, and it is not possible to detect the cheater(s). Since teams have been increasingly viewed as an important way to enhance the efficiency of firms, it is crucial to explore the mechanisms to reduce free riding and to promote cooperation in teams. The first two papers of the thesis contribute to this discussion by presenting evidence from laboratory experiments.

Paper I examines the relative importance of common identity and peer punishment in enhancing team cooperation under two income distributions. Social identity theory (Tajfel and Turner, 1979, 1985) implies that once an individual has gone through a cognitive change and emotional investment process to categorize herself as part of a unit with shared goals, values, and norms, her behavior tends to conform to the norms of that unit, which could lead to a higher degree of team cohesion and more effective teamwork (Lembke and Wilson, 1998). Moreover, people who are inequity averse and choose to cooperate are willing to sanction the free riders at their own cost if they are sufficiently upset by the payoff inequality due to the free riding of other people (Fehr and Schmidt, 1999). Free riders on the other hand could perceive the threat of punishment to be credible and thus tend to cooperate (Fehr and Gächter, 2000). Furthermore, teams are often composed of individuals unequal in productivity, ability, and motivation, and payments tend to be differentiated partly to induce greater individual effort.

Under different combinations of conditions on income distribution, identity and punishment, we conduct a repeated public good experiment. We vary endowment distribution by giving subjects in one team the same or different endowments to create homogeneous or heterogeneous teams, manufacture the strength of identity to be strong or weak by conducting an identity-building activity or not, and allow punishment of other team members in half of the treatments. We also employ two identity-building activities and two sets of punishment effectiveness parameters to test the sensitivity of our findings to the relative strengths of identity and punishment.

The results show that without punishment, strong identity can counteract the negative impact of endowment heterogeneity on cooperation. Moreover, punishment increases cooperation irrespective of income distribution. However, the impact of punishment under strong identity depends on the relative strengths of the identity-building activity and the effectiveness of punishment. Furthermore, we find no evidence of stronger punishment in teams with a strong identity. These findings provide important implications for management policy makers in organizations: implementing *ex ante* income heterogeneity within teams should be done with caution, and the decision of whether identity or punishment is a more effective norm enforcement mechanism in teams is rather sensitive to their interaction and relative strengths.

Paper II follows the line of Paper I to study how the effect of an induced common identity on individual cooperative behavior differs depending on session size in a repeated public good experiment. Session size represents the number of participants in an experimental session. The effect of session size has largely been ignored in experimental studies, despite the possibility that it may affect people's perception of the strength of the potential link between them and consequently the strategies used in the interactions. While the interactive effects of identity and session size on cooperation has real-world implications, this paper focuses on the methodological aspect of testing whether session size could be a confounding factor of identity.

We vary the session size to be small or large with 8 or 24 subjects in a session, and manufacture the strength of identity to be strong or weak by conducting one of the identity-building activities from Paper I or not. We find that induced identity significantly enhances cooperation only when the session size is small and only in the initial period. In all other periods, induced identity does not have a significant effect on cooperation in either small or large sessions. The same null effect of identity in small and large sessions suggests that session size is not a confounding factor of identity in repeated interaction settings.

The focus of the last two papers of this thesis is shifted to firm performance in terms of the input and output of technological change in firms. In growth theory, continuing advances in technological knowledge in the form of new goods, new markets or new processes have been considered a necessary condition for sustaining a positive long-run per capita growth, regardless of whether technological change is characterized as being exogenous or endogenous to the economic system (Aghion and Howitt, 1998). Endogenous growth models typically treat technological progress in the form of an expansion of the number of varieties of products, or of quality improvements for an existing array of products (Barro and Sala-i-Martin, 2003). The link between a country's technological change and economic growth also applies at the industry and firm level.

Paper III investigates the patterns of product selection, switching and upgrading, and the determinants of these activities in firms located in China's state-owned forest areas during a period of gradual institutional and managerial reforms from 2004 to 2008. Product mix change is a topical issue in both a macro and micro perspective. At the macro level, endogenous growth models suggest that specializing in the production of some products is more growth promoting than specializing in others. At the micro level, resource reallocation within multi-product firms through adding and dropping products is also an important margin of adjustment in response to policy reforms besides firm entry into and exit from an industry (Bernard et al., 2010). Having obtained detailed firm-product level data including product name and sales, we map all reported product names into the codes of two harmonized national standards and define product, industry and sector accordingly.

Our results show that product-specific value added has a very wide dispersion, indicating that what type of product firms produce matters for their overall efficiency and long-run development. Within the same industry, multi-product firms tend to be larger, more productive and more likely to export than single-product firms. Our results further display that changes in firms' product mix are pervasive and characterized by adding or churning products rather than only shedding products. Moreover, changes in firms' product mix have made a significant contribution to the aggregate output growth during our sample period, accounting for approximately 86% of the net increase in the aggregate output with the remaining 14% attributed to growth of the existing products. Furthermore, firm age, size, human capital and market conditions are important driving factors of product mix change and upgrading decisions.

Technological change in Chinese industry originates from three different sources: time-driven autonomous change, in-house research and development (R&D), and purchase of imported technology (Fisher-Vanden and Jefferson, 2008). As one of the major sources, R&D has become an increasingly more important type of investment in China in recent decades. Comparing the gross domestic expenditure on R&D as percentage of GDP in China with that in Japan, which is the world leader in R&D, we see a huge gap in the early 1990s and a rapid convergence during the last twenty years: the percentage for China was merely around 20% of that for Japan in the early 1990s but increased to approximately 60% in 2012.

A natural question to ask then is how R&D gets financed. Features of R&D such as uncertain return, easy spillover, and lack of collateral value tend to make firms that invest in R&D face more pronounced asymmetric information and agency problems than firms that invest in physical capital. Hence, it may be more costly to finance R&D through external funds. **Paper IV** estimates the sensitivity of R&D to internal finance conditional on controlling for investment opportunities for Chinese industrial firms over the period 2001-2006. We adopt a variant of the *Q* model for R&D investment using the value of the firm, physical capital and employment to capture firm fundamentals as proxies for investment opportunities. We add cash flow to this specification, and estimate the augmented model separately for R&D participation and spending. We find that R&D spending is sensitive to cash-flow fluctuations, conditional on firm fundamentals. We also find that the cash-flow sensitivity of R&D varies across firms depending on ownership. We conclude that credit market imperfections pose a constraint for R&D in Chinese industry.

In sum, this thesis attempts to study issues related to team cooperation and firm performance. The findings are expected to contribute to the discussion of accommodating contractual and production constraints of firms.

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Paper I

Cooperation in teams: The role of identity, punishment and endowment distribution

Qian Weng[*], Fredrik Carlsson[†]

Abstract

Common identity and peer punishment have been identified as crucial means to reduce free riding and to promote cooperation in teams. This paper examines the relative importance of these two mechanisms under two income distributions in team cooperation. In a repeated public good experiment, conditions vary among different combinations of homogeneous or heterogeneous endowment, strong or weak identity, and absence or presence of peer punishment. We find that without punishment, strong identity can counteract the negative impact of endowment heterogeneity on cooperation. Moreover, punishment increases cooperation irrespective of income distribution. However, the impact of punishment under strong identity depends on the relative strengths of the identity-building activity and the effectiveness of punishment. Furthermore, we find no evidence of stronger punishment in teams with a strong identity. These findings provide important implications for management policy makers in organizations: implementing *ex ante* income heterogeneity within teams should be done with caution, and the decision of whether identity or punishment is a more effective norm enforcement mechanism in teams is rather sensitive to their interaction and relative strengths.

Keywords: Endowment distribution; identity; punishment; cooperation; public goods experiments

JEL classification: C92; D63; H41; M54

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Acknowledgements: We thank the co-editor Tim Cason, two anonymous reviewers, Maria Bigoni, Martin Dufwenberg, Haoran He, Martin Kocher, Peter Martinsson, Matthew Rabin, Amrish Patel, Matthias Sutter, Måns Söderbom, and seminar and conference participants at the University of Gothenburg, University of International Business and Economics, Renmin University of China, the 2012 Asia-Pacific ESA Conference in Xiamen, and the 2012 International ESA Conference in New York for helpful discussions and comments. We are grateful to Xiujuan Zhang and Pengyuan Pei for assistance in conducting the experiment. Financial support from Formas through the COMMONS program and from the Jan Wallander and Tom Hedelius Foundation is gratefully acknowledged.

1. Introduction

Teams have been increasingly viewed as an important way to enhance the efficiency of organizations and firms. One common underlying philosophy of successful teams is to foster cooperation among their members (Che and Yoo, 2001). However, organizations face several challenges to efficient teamwork. The benefits of working as a team may be undercut by the incentives to free ride, which cannot be completely controlled through formal contracts if compensation is based on team output rather than personal input (Alchian and Demsetz, 1972). Experiments have shown that cooperation typically cannot be sustained by intrinsic altruistic motives alone (e.g., Andreoni, 1995; Fischbacher et al., 2001; Fischbacher and Gächter, 2010). Rather, (centrally) building a common identity among employees and allowing (decentralized) mutual monitoring and sanctioning of team members have been considered effective attempts to discipline free riding and to promote cooperation in teamwork settings. Social identity theory (Tajfel and Turner, 1979, 1985) has received growing interest in the organizational literature (see, e.g., Akerlof and Kranton, 2000, 2005, 2008). A number of experiments have shown that salient identification with an organization or a team can increase cooperation (e.g., Eckel and Grossman, 2005; McLeish and Oxoby, 2011).[1] Punishment, in terms of both pecuniary consequences such as reduced salaries and non-pecuniary ones such as social pressure and disapproval, has also been shown to be an important means to increase cooperation (Fehr and Gächter, 2000b, Masclet et al., 2003; Kandel and Lazear, 1992; Mas and Moretti, 2009).[2]

An additional aspect of teams is that they are often composed of individuals who are unequal in productivity, ability, and motivation. Payments tend to be differentiated partly to induce greater individual effort and partly to incentivize employees contributing to the team output to stay away from distinct outside options (Balafoutas et al., 2013). Previous public goods experiments investigating the role of income distribution (in terms of homogeneous or heterogeneous endowment) in cooperation have shown mixed results: Cherry et al. (2005) report a negative effect of heterogeneity on aggregate cooperation, Chan et al. (1996), Visser and Burns (2006), and Prediger (2011) find the opposite, and Hofmeyr et al. (2007) find no significant difference. However, when it comes to individual behavior in unequal income

[1] A closely related strand of literature focusing on identity conflict between two groups in general find favoritism toward ingroup members and discrimination against outgroup ones in terms of cooperation (e.g., Charness et al., 2007; McLeish and Oxoby, 2007), coordination (e.g., Chen and Chen, 2011; Chen et al., 2014), social preferences (e.g., Chen and Li, 2009), and norm enforcement (e.g., Ruffle and Sosis, 2006; Bernhard et al., 2006; Goette et al., 2006; Goette et al., 2012a; Goette et al., 2012b).

[2] However, some other studies question the beneficial effects of punishment (Egas and Riedl, 2008; Houser et al., 2008; Abbink et al., 2010), and some even find anti-social punishment directed at relatively cooperative people (e.g., Herrmann et al., 2008; Nikiforakis, 2008; Cinyabuguma et al., 2006).

teams, low-income people are ubiquitously found to cooperate relatively more than their high-income counterparts (e.g., Buckley and Croson, 2006; van Dijk et al., 2002). Some studies further explore whether the power of punishment in norm enforcement in symmetric settings can carry over to asymmetric settings, and obtain an affirmative answer that punishment in heterogeneous populations shows similar or even higher efficacy (e.g., Nikiforakis et al., 2010; Visser and Burns, 2006; Prediger, 2011).[3] Nikiforakis et al. (2012) and Reuben and Riedl (2013) look particularly at the normative rules underlying contributions to public goods in homogeneous and heterogeneous groups as well as the punishment behavior intended to enforce the rules. As these papers suggest, heterogeneous income matters for cooperation for reasons such as disagreements in fairness principles of equality, equity and efficiency that often stipulate different normative rules individuals consider as appropriate for behavior, and self-serving selection of the principles that hinders the emergence and enforcement of a specific rule governing cooperation.

In this paper we study the three dimensions affecting team cooperation: identity, punishment, and income distribution. While identity and punishment in isolation have been shown to increase cooperation, the potential interaction and relative importance of these two means have not, to the best of our knowledge, been investigated. Clearly, when deciding on team incentives and organization, the relative importance and interaction between identity and punishment is central. In addition, there are only a few studies looking at the impact of identity on punishment behavior, but the results are inconclusive.[4] Chen and Li (2009) find that individuals are less likely to punish an ingroup member for misbehavior, whereas McLeish and Oxoby (2007) find that unfair offers to ingroup members incur greater use of costly punishment than those to outgroup members. This paper will thus provide additional evidence on this issue.

Moreover, although the effect of income distribution on team cooperation both in the absence and presence of punishment has been investigated, whether and how income distribution affects the role of identity has not. One implication from social identity theory is that once an individual has gone through a cognitive change and emotional investment process to categorize herself as part of a unit with shared goals, values, and norms, her behavior tends to conform to the norms of that unit, which could lead to a higher degree of

[3] Apart from endowment heterogeneity, heterogeneity can also be represented by different marginal benefit from a public good (e.g., Isaac and Walker, 1988; Fisher et al., 1995; Carpenter et al., 2009; Reuben and Riedl, 2009), or different fixed lump-sum payments such as show-up fees (e.g., Anderson et al., 2008).

[4] Besides punishment extended by the same agents playing the previous game, punishment can also take the form of third-party punishment (e.g., Bernhard et al., 2006; Goette et al., 2006; Goette et al., 2012a; Goette et al., 2012b).

team cohesion and more effective teamwork (Lembke and Wilson, 1998). Thus, an additional goal of this paper is to demonstrate whether the disagreements and self-serving biases in normative rules governing cooperation in heterogeneous income teams can be ameliorated or even resolved by building a strong identity such that a contribution norm can be agreed upon and enforced.

We use laboratory experiments to examine the interactive effects of identity and punishment and of identity and income distribution on team cooperation, as well as the interactive effect of identity and income distribution on punishment behavior. We induce a strong common identity via a face-to-face identity-building activity involving all subjects in one session; this activity is absent if identity is weak. We use a repeated linear public good game to elicit contributions for measuring cooperation. We distinguish two team endowment distribution environments in the public good game: in one, endowment is homogeneously distributed among team members; in the other, each member is given a different endowment according to their productivity ranking within the team, yet the total team endowment is the same as that of the homogeneous endowment teams. Productivity ranking is determined by the performance in a quiz. To compare the difference in behavior without and with punishment, we add a second sub-stage in half of the treatments where subjects are given the opportunity to punish other team members.

We find that at the team level, when punishment is not possible, endowment heterogeneity negatively affects cooperation, yet strong identity can counteract this negative impact. However, strong identity does not increase cooperation more in heterogeneous than in homogeneous teams. The introduction of punishment successfully raises and sustains cooperation in both homogeneous and heterogeneous teams and under both weak and strong identities. With punishment, cooperation is greater under strong identity in homogeneous than in heterogeneous teams, and so is the punishment inflicted. However, strong identity fails to further enhance cooperation or pushes punishment in either endowment distribution. Nor does strong identity increase cooperation more with punishment than without. Within the heterogeneous teams, lower endowment individuals always show the greater degree of cooperation relative to endowment, and punish as intensively as higher endowment individuals. Strong identity does not play a part in either contribution or punishment behavior.

Our findings, in particular that punishment is more important than identity may raise the question of to what extent this is specific to our experimental design. In order to investigate this, we conduct additional treatments where we strengthen identity by establishing it via online communication to help team members who will subsequently play the public good game, and weaken punishment effectiveness by making it more costly to the punishers. We keep the endowment homogeneous in all the additional treatments. While most of our previous findings hold, some do not. Punishment fails to enhance cooperation in presence of strong identity, and punishment is lower when identity is strong. These results suggest that the interactive effect of identity and punishment indeed depends on the relative strengths of the identity-building activity and the cost of punishment.

2. Experimental design

The experiment uses a 2×2×2 design. In one dimension, we vary the endowment distribution by giving subjects in a team the same or different endowment in order to create homogeneous or heterogeneous teams. In the second, we make the strength of identity strong or weak by conducting or not conducting an identity-building activity. The third dimension concerns whether or not subjects have the opportunity to punish other team members. This generates eight different combinations of conditions, each of which is a treatment of the experiment as summarized in Table 1. The experiment is conducted in three stages. The first stage is an identity-building stage. The second stage is an endowment-determination stage. The third stage is a repeated linear public good game.

<Table 1 about here>

The identity-building stage was included only in the four treatments with strong identity. A "human knot" game was played with all subjects in one session in another room before they entered the laboratory. Subjects stood shoulder to shoulder, in a circle, facing each other. First they were asked to form a knot by lifting both hands and reaching across the circle to hold the hands of two other subjects who were not standing directly beside them, left hand to left hand and right hand to right hand. After ensuring that a knot had been constructed, subjects were asked to untangle the knot to form one or a couple of circles without crossing arms anymore. They were not allowed to let go of any hands in the process. Anyone who let go of a hand was required to immediately grab the same hand again. The game lasted for approximately ten minutes regardless of whether or not the knot was successfully untangled. The reason for choosing such an identity-building activity was that it is a typical activity conducted in orientation or training programs in real-world organizations to promote mutual understanding, raise common objectives, and yield organizational belongingness among new members or members from different departments. Communication was allowed during the course of the game. The experimenters observed that the game sparked extensive communication among team members. After finishing the identity-building activity, the subjects were led to the laboratory. In the four treatments with weak identity, subjects entered the laboratory directly once everybody had arrived, yet they did have a chance to meet each other while waiting for the experiment to start.

The rest of the experiment was conducted in the laboratory, where subjects were first seated in partitioned computer terminals and then given written instructions while the experimenter read the instructions aloud. At the second stage, subjects individually solved a six-minute quiz consisting of 20 general knowledge questions. The quiz performance determined the endowment levels of subjects in the heterogeneous teams for the public good game. That is, the more questions that were answered correctly, the higher the endowment level. The quiz was used to create feelings of entitlement over the endowment (see, e.g., Hoffman and Spitzer, 1985; Gächter and Riedl, 2005) and to justify the fairness of inequalities within the heterogeneous teams. To enable comparison across treatments, this stage was also conducted in the homogeneous endowment treatments, where the endowment levels were however not affected by the quiz performance.

At the third stage, 24 subjects in one session were randomly assigned to six teams of four members and each team played a public good game framed as a team production problem for 10 periods. The reason for using partner rather than stranger matching was that we wanted to mimic the situation where people usually worked in relatively fixed teams and interacted repeatedly over a period of time.[5] The subjects knew that their teams consisted of themselves and three other individuals, whereas their identities were kept anonymous throughout the experiment.

At the beginning of each period, each subject was endowed with a fixed amount of experimental currency units (ECUs), E_i . They decided simultaneously and without communication how to allocate the endowment between individual and team work (i.e., the public good). By freely choosing an amount to contribute to the team work, c_i, where $0 \leq c_i \leq E_i$, the remaining endowment, $E_i - c_i$, was automatically considered the allocation to the individual work. Each ECU that a subject kept for individual work generated one ECU for herself, whereas the payoff from the team work was 50% of the team's total contribution. That is, the marginal per capita return (MPCR) from a contribution to the public good was equal to 0.5. In the heterogeneous teams, members were endowed with 80, 60, 40, and 20 ECUs, respectively, according to their quiz performance ranking within a team. In the

[5] See Botelho et al. (2009) for a critical review of the experimental literature on partner and stranger matching. The authors further compare behavior under random strangers and perfect strangers matching (where subjects meet only once) in a public good experiment, and find a significantly lower proportion of subjects contributing in a random strangers than in a perfect strangers protocol.

homogeneous teams, each member was endowed with 50 ECUs. Subject i's period payoff was given by

$$\pi_i^c = (E_i - c_i) + 0.5 \sum_{h=1}^{4} c_h \tag{1}$$

In the treatments with punishment, a second sub-stage was added. Subjects were informed of the other team members' proportion of endowment contributed, i.e., contribution rate, and were given the opportunity to punish each other.[6] To punish, member i could assign punishment points to member j within the same team, p_{ij}, $i \neq j$. The punishment decisions were made simultaneously and without communication. However, punishment points were not costless. Each assigned punishment point cost the punished member 3 ECUs and the punishing member 1 ECU. Hence, subject i's payoff at the end of the period was given by

$$\pi_i^p = \pi_i^c - \sum_{\substack{j=1 \\ j\neq i}}^{4} p_{ij} - 3\sum_{\substack{j=1 \\ j\neq i}}^{4} p_{ji} \tag{2}$$

Equation (2) implies that a subject could have a negative payoff in a given period. To reduce the probability of this, we constrained the income reduction associated with received punishment to not exceed the income from the contribution sub-stage, i.e., $3\sum_{\substack{j=1 \\ j\neq i}}^{4} p_{ji} \leq \pi_i^c$. In addition, a subject could at most distribute 25 points to each other team member, i.e., $p_{ij} \leq 25, j = 1,2,3,4, j \neq i$. Despite the restrictions, negative payoff could still occur in some extreme cases where subjects had little income from the contribution sub-stage, attracted considerable punishment, and also decided to punish heavily. Negative period payoff occurred in three out of 1,920 possible cases (192 subjects × 10 periods); these losses were covered by cumulative payments from previous periods. As is common in public goods

[6] We reveal relative contribution rather than absolute contribution amount to preserve the anonymity of endowment levels and to prevent individual reputation building. We are aware of the possible different impacts posed by different feedback formats on cooperation and efficacy of punishment as pointed out by Nikiforakis (2010). The author considers three feedback formats – subjects receive information about each team member's contribution, earnings, or both contribution and earnings before making punishment decisions – and finds that earnings feedback leads to significantly less cooperation and lower efficiency than contribution feedback. Nevertheless, this paper follows the most common format used in public goods experiments with peer punishment to adopt the contribution feedback. A potential drawback is that a relative contribution norm is exogenously imposed. Brekke et al. (2012) compare the cooperation effect of three ways of framing the decision variable in a multi-period threshold public good experiment with unequally endowed participants: absolute contributions, contributions relative to endowments, and amounts of endowments kept (i.e., in terms of the effects of contributions on final payoffs). They find no significant difference in absolute contribution amounts between the absolute and relative framings for both high and low endowment subjects at conventional levels. Their finding to some extent mitigates the norm imposing concern in our experiment. Moreover, we are aware of the different views on fair contribution rules. See Reuben and Riedl (2013) and Brekke et al. (2012) for detailed discussions.

experiments with punishment, each subject was also given a one-off lump-sum payment of 50 ECUs to pay for any eventual loss that might be incurred during the experiment. In our experiment, however, nobody incurred such a loss.

The endowment distribution, the payoff functions, the duration of the experiment (10 periods), and the instructions were common knowledge to all participants in each treatment. Before the commencement of actual decision making, the subjects were required to answer control questions to ensure that they had understood the features of the game correctly. In the treatment without punishment, at the end of each period the subjects were informed of their team's total contribution, their own income, and the contribution rates of other team members in the current period. In the treatments with punishment, at the end of each period the subjects were reminded of the income from the contribution sub-stage and the associated cost of the punishment points they had assigned. They were also informed of the punishment they received in total, the associated income reduction, as well as their final income from that period as given by Equation (2). To prevent the possibility of individual reputation formation, each of the four subjects in a team was randomly assigned an identification number from 1 to 4 to identify her actions in a given period and these numbers were randomly shuffled across periods.

The experiment was conducted using z-Tree (Fischbacher, 2007) in the experimental laboratory at Beijing Normal University in May and June 2011. This university is located in the center of Beijing and has approximately 20,000 full-time students. The subjects were recruited via announcements on a bulletin board system and bulletin boards in teaching and accommodation buildings at the university. In total, we had observations from 384 subjects[7], 48 for each treatment. All subjects were allowed to participate in only one session, and they did not know about any treatments other than the one in which they participated. To control for experimenter effect, the same two individuals, who were unknown to the participants, ran all sessions. To keep the outcome of the experiment anonymous, subjects were informed at the beginning that they would be paid confidentially and individually in another room and that they would leave the laboratory successively so that they would not meet and communicate with other subjects after completing the session. The final earnings from the experiment totaled the sum of the period payoffs at an exchange rate of 1 ECU to 0.1 Chinese yuan (CNY) plus a show-up fee of 10 CNY. The experiment lasted an average of about 76 (104) minutes in the treatments without (with) punishment, including above-described stages and a

[7] All subjects were Chinese citizens and university students with various academic majors.

post-experimental survey covering questions on demographics, academic background, past donation behavior, and perceptions about their team in the experiment. The subjects on average earned 80.9 (94.6) CNY[8] in the treatments without (with) punishment, including the show-up fee in all treatments and the lump-sum payment in the treatments with punishment.

3. Behavioral hypotheses

This section develops behavioral hypotheses on how income distribution and identity strength affect cooperation and punishment behavior based on theory and existing empirical evidence. Assuming that all people are rational and self-interested exclusively in their material payoffs, the standard economic model predicts that people will not contribute anything in a linear public good game, irrespective of the income distribution, salience of identity or punishment opportunities. However, there is considerable experimental evidence that such a model fails to predict actual behavior under many circumstances, suggesting that people are motivated by other-regarding preferences and that concerns for fairness and reciprocity cannot be overlooked in social interactions.

3.1 Contributions when punishment is not possible

It has been well documented in the social psychology and economics literature that a salient common organizational or team identity has a positive impact on pro-social behavior. In particular, it has been found that a strong identity can reduce free riding in teams with homogeneous endowments (see, e.g., Eckel and Grossman, 2005). We expect that the positive effect of a common identity on contributions carries over to a heterogeneous endowment setting. A strong common identity is likely to ameliorate the disagreements and self-serving biases in the selection of normative rules underlying contribution behavior by heterogeneously endowed subjects. We hence propose the following hypothesis.

Hypothesis 1.1: *Team average contribution rate and contribution rate at each endowment level will be higher in heterogeneous teams with strong identity (Hetero-Strong-NoPunish) than in heterogeneous teams with weak identity (Hetero-Weak-NoPunish) when there is no punishment.*

Given that strong identity is expected to increase contribution rates in both homogeneous and heterogeneous teams, a related question is if the effect of identity is greater under one of these conditions. Although existing theory or evidence cannot provide any comparable

[8] The average exchange rate in May and June 2011 was 1 USD = 6.48 CNY. The average hourly wage for university students in Beijing at the time of the experiment was approximately 50 CNY.

results, we can reason as follows. When a strong identity is built, it is plausible that the commonality induced would exert a symmetric positive impact on average contributions in homogeneous and heterogeneous teams, since the average endowment is the same across these two types of teams. It is also likely that the effect of identity is similar across subjects with different endowment levels in heterogeneous teams. At the same time, the potential envy from lower endowment subjects to higher endowment teammates in heterogeneous teams could be reduced, which would further increase relative contributions from lower endowment subjects. For example, Chen and Li (2009) show that participants show a 93% decrease in envy when matched with an ingroup member than with an outgroup member. Combining these two effects, we formulate the following hypothesis.

Hypothesis 1.2: *A strong identity increases team average contribution rates more in heterogeneous teams (Hetero-Strong-NoPunish - Hetero-Weak-NoPunish) than in homogeneous teams (Homo-Strong-NoPunish - Homo-Weak-NoPunish) when there is no punishment.*

In heterogeneous teams, the question is as well if low and high endowment subjects contribute the same (in absolute or relative terms) or not. A number of studies have found that individuals with low endowments contribute more relative to endowment than their high-endowment counterparts (Cherry et al., 2005; Buckley and Croson, 2006). This suggests that people are not sufficiently inequity averse (Fehr and Schmidt, 1999; Buckley and Croson, 2006). Rather, they are motivated by normative rules in a self-serving manner that yields them the greatest earnings (Nikiforakis et al., 2012). We predict that this pattern will hold or even magnify when a strong identity is induced due to the reduced envy from lower endowment subjects to higher endowment teammates.

Hypothesis 1.3: *In heterogeneous teams, subjects with lower endowment will give more in relative terms than subjects with higher endowment when identity is strong and there is no punishment (Hetero-Strong-NoPunish).*

3.2 Contributions when punishment is possible

A well-established finding from repeated public goods experiments is that the existence of peer punishment increases and sustains cooperation. Inequity-averse subjects who cooperate could be sufficiently upset by the payoff inequality so that they are willing to sanction the free riders even at their own cost (Fehr and Schmidt, 1999). Free riders on the other hand could perceive the threat of punishment to be credible and thus would tend to cooperate (Fehr and Gächter, 2000a). The efficacy of punishment has also been shown to be able to extend to the heterogeneous endowment settings (e.g., Visser and Burns, 2006; Prediger, 2011; Reuben and Riedl, 2013). These findings are obtained without an occurrence of strong identity. What if identity is strong? The answer depends on the relative strengths of identity and punishment on contributions, and the potential interaction between the two. If strong identity increases contribution rates substantially, there will be little room left for an additional effect of introducing punishment. Vice versa, if the existence of punishment opportunities increases contribution rates substantially, there will be little effect of identity on contribution behavior. At the same time, there could be reinforcement between the two. In particular, identity could affect punishment behavior. As we argue in the next section, we expect punishment of non-cooperative behavior to increase with a strong identity. We also predict contribution rates to increase with the introduction of punishment even when identity is strong since the low contributor is likely to raise her contribution to deter punishment. Our hypotheses are that both punishment and strong identity affect contribution rates even in the presence of each other, thus

Hypothesis 2.1: *The introduction of peer punishment will increase team average contribution rates in both homogeneous (Homo-Strong-NoPunish vs. Homo-Strong-Punish) and heterogeneous teams (Hetero-Strong-NoPunish vs. Hetero-Strong-Punish) even with the presence of strong identity.*

Hypothesis 2.2: *Team average contribution rates in teams with strong identity will be higher than in teams with weak identity even with the presence of peer punishment irrespective of endowment distribution (Homo-Strong-Punish vs. Homo-Weak-Punish, Hetero-Strong-Punish vs. Hetero-Weak-Punish).*

Given that we expect strong identity to increase contribution rates both with and without punishment, and that identity and punishment tend to reinforce each other, we also hypothesize that

Hypothesis 2.3: *A strong identity increases average contribution rates more with punishment than without punishment irrespective of endowment distribution ((Homo-Strong-Punish - Homo-Weak-Punish) vs. (Homo-Strong-NoPunish - Homo-Weak-NoPunish), (Hetero-Strong-Punish - Hetero-Weak-Punish) vs. (Hetero-Strong-NoPunish - Hetero-Weak-NoPunish)).*

What about the behavior of subjects with different endowments in heterogeneous teams? We have reasoned that within heterogeneous teams people are motivated by normative rules in a self-serving manner that yields them the greatest earnings when there is strong identity but no punishment. Conditional on the reinforcement between identity and punishment, we would expect that the pattern of individual contributions in heterogeneous teams in the absence of punishment carries over to the setting in the presence of punishment.

Hypothesis 2.4: *In heterogeneous teams, subjects with lower endowment will give more in relative terms than subjects with higher endowment when identity is strong and there is punishment (Hetero-Strong-Punish).*

3.3 Punishment behavior

Previous studies have shown that a substantial fraction of subjects are willing to engage in costly punishment of free riders (e.g., Fehr and Gächter, 2000b; Nikiforakis and Normann, 2008; Anderson and Putterman, 2006; Carpenter, 2007). Negative emotions toward free riders triggered by payoff inequality (i.e., inequity aversion) is the main motive behind this altruistic punishment (Fehr and Gächter, 2002; Fuster and Meier, 2010). How will punishment behavior change when a strong identity is induced? Chen and Li (2009) find that individuals are more forgiving to ingroup members for misbehavior, whereas McLeish and Oxoby (2007) find that unfair offers to ingroup members incur greater use of punishment than those to outgroup members. While the existing findings are contradictory, we expect the latter in our experiment. First, the proposer-responder game McLeish and Oxoby (2007) used may well translate into the public good game we conducted: the allocation of endowment by the proposer at the first stage and the punishment assignment by the responder at the second stage in the proposer-responder game are simply replaced by actions from every team member in the public good game. Second, the sanctioning mechanism in McLeish and Oxoby (2007) applies to our experiment as well. Contribution rates lower than the other team members' average contribution rate violate the implicit contribution norm associated with the strong common identity. Under such circumstances, the team members are more likely to punish and to punish more severely the low contributor than in the absence of a strong identity. Hence, a strong identity can help ensure punishment to be pro-social (Goette and Meier, 2011), and we expect the intensity of punishment to increase with identity strength.

Hypothesis 3.1: *Punishment will be stronger in teams with strong identity than in teams with weak identity irrespective of endowment distribution (Homo-Strong-Punish vs. Homo-Weak-Punish, Hetero-Strong-Punish vs. Hetero-Weak-Punish).*

4. Results

In this section, we analyze the impact of endowment distribution and identity strength on contributions to the public good when punishment is absent and present, and on punishment behavior.

4.1 Contributions when punishment is not possible

Figure 1 depicts the evolution of average contribution rates over the 10 periods for all treatments. For the four treatments without punishment, average contributions start from 30% to 50% of subjects' endowment. This is consistent with previous experimental findings. The average contribution rates all rise in the early periods and then decline, although the peaks appear at different points in time and the rates of change differ across treatments. As the experiment progresses, average contribution rate in the *Hetero-Weak* treatment becomes substantially lower than those of the other three treatments without punishment.

<Figure 1 about here>

Table 2 reports the average contribution rates over all 10 periods depending on treatment (first row) and endowment level (last four rows). Throughout the paper, for team average, the unit of observation is team mean over all periods; for subject average, the unit of observation is subject mean over all periods. *High, Second, Third,* and *Low* refer to endowment levels with 80, 60, 40, and 20 ECUs, respectively. In the four treatments without punishment, team average contribution rates in *Homo-Weak, Homo-Strong,* and *Hetero-Strong* are at least 50% higher than that in the *Hetero-Weak* treatment (left panel first row).

<Table 2 about here>

Since individual cross-period differences and the data structure are not taken into consideration in the summary statistics, we now turn to a statistical analysis by regressing individual contribution rate on treatment variables of the experiment.[9] Since contribution rates range between zero and one in each period, i.e., truncated from both above and below, and contribution decisions within teams are interdependent across periods, we estimate a subject random effects double-censored tobit model with standard errors clustered at the team level. We construct one dummy variable for each endowment distribution and identity strength combination, i.e., *Hetero-Weak, Homo-Weak, Hetero-Strong*, and *Homo-Strong,* equal to one if the observation comes from the respective treatment and zero otherwise. *Period* dummies are also included to control for time order effects. To investigate how contribution rates differ

[9] We have also conducted non-parametric tests and obtained qualitatively similar results as those from the regressions.

among subjects with different endowment levels and identity strengths in the heterogeneous teams, we use one separate binary dummy variable for each endowment and identity combination, i.e., *Weak-High*, *Weak-Second*, *Weak-Third*, *Weak-Low*, *Strong-High*, *Strong-Second*, *Strong-Third*, and *Strong-Low*. *Hetero-Weak* and *Weak-Low* are excluded from the regressions as the reference groups.

Table 3 presents the regression results. Models (1) and (2) are estimated for the four treatments without punishment. Model (1) includes both homogeneous and heterogeneous teams to investigate the aggregate treatment effect, and model (2) includes only heterogeneous teams to study the endowment effect. The topmost panel reports the average marginal effects of the independent variables.[10] In model (1), when identity is weak, homogeneous teams on average contribute 13.2 percentage points more than heterogeneous teams. This significant difference is in line with the finding in Cherry et al. (2005). It might be explained by the perceived unfairness of endowment heterogeneity, which reduces the possibility for a team contribution norm to emerge. When identity becomes strong, the significant difference between homogeneous and heterogeneous teams disappears, which suggests that building a strong identity can counteract the negative impact of endowment heterogeneity on contributions (bottom panel (i)). The bridging of the difference is because strong identity significantly and substantially increases contribution rates in heterogeneous teams (14.8 percentage points) but it does not have a significant effect on contributions in homogeneous teams (bottom panel (ii)). Consequently, Hypothesis 1.1 on the positive effect of identity on contribution rates for heterogeneous teams is supported. There are two possible interpretations for the null result for homogeneous teams: one is that our identity manipulation is not salient enough to exert a significant effect on homogeneous teams (see, e.g., Eckel and Grossman, 2005; Charness et al., 2007); the other is that contribution rates are already high under weak identity, and therefore the impact of a strong identity is weakened. Which interpretation is more appropriate will be discussed in Section 5. Although the increase in contribution rates due to strong identity is greater in heterogeneous than in homogeneous teams, the difference is not statistically significant at conventional levels (linear combination of the model marginal effects ((Homo-Strong-NoPunish - Homo-Weak-NoPunish) - (Hetero-

[10] Using McDonald and Moffitt (1980) decomposition, the marginal effect of contribution rates, $\left(\frac{c}{E}\right)_{i,t}$, is calculated as

$$\frac{\partial E(\left(\frac{c}{E}\right)_i|\mathbf{x})}{\partial x_j} = \frac{\partial \Pr\left(0<\left(\frac{c}{E}\right)_i<1|\mathbf{x}\right)}{\partial x_j} \cdot E\left(\left(\frac{c}{E}\right)_i \middle| \mathbf{x}, 0 < \left(\frac{c}{E}\right)_i < 1\right) + \Pr\left(0 < \left(\frac{c}{E}\right)_i < 1|\mathbf{x}\right) \cdot \frac{\partial E(\left(\frac{c}{E}\right)_i|\mathbf{x},0<\left(\frac{c}{E}\right)_i<1)}{\partial x_j} + \frac{\partial \Pr(\left(\frac{c}{E}\right)_i=1|\mathbf{x})}{\partial x_j} \cdot 1.$$

Strong-NoPunish - Hetero-Weak-NoPunish)) is -0.103, and the standard error is 0.087). Therefore, Hypothesis 1.2 is rejected.

<Table 3 about here>

When breaking heterogeneous teams down to various endowment levels (model (2)), we observe that the marginal effects of the endowment level dummies under weak identity are negative and statistically significant only except *Weak-Third*, indicating that low endowment subjects on average always contribute the largest proportion of endowment compared to their team members with higher endowments under weak identity.[11] This result is in line with previous findings (e.g., Buckley and Croson, 2006; Prediger, 2011). In addition, we also find that low endowment subjects contribute relatively more in the *Hetero-Strong* treatment (bottom panel (iii)-(v)).[12] Thus, we cannot reject Hypothesis 1.3. Investigating the effect of identity for each endowment level, we see that the increase in contribution rates when endowment decreases is the same under weak and strong identities (bottom panel (vi)-(viii)). This suggests that the effect of identity is similar across subjects with different endowment levels. Hence, we reject Hypothesis 1.1 on the positive effect of identity on contribution rates at each endowment level.

4.2 Contributions when punishment is possible

In this section, we examine whether and how contribution behavior changes when peer punishment is introduced. Comparing team average contribution rates in each column between the left and right panel of Table 2 (first row), we find that contribution rates are drastically and significantly higher in the treatments with punishment for all endowment distribution and identity strength combinations (Mann-Whitney U test, *p*-value=0.024 for *Homo-Weak*; *p*-value=0.002 for *Hetero-Weak*; *p*-value=0.002 for *Homo-Strong*; *p*-value=0.043 for *Hetero-Strong*). Consequently, we find strong support for Hypothesis 2.1 that punishment increases contribution rates in both endowment distributions under strong

[11] However, it should be noted that the pattern is different if we look at absolute contribution amounts: higher endowment subjects always contribute a greater absolute amount.

[12] We believe that it is the endowments rather than using quiz performance to determine endowments that cause the effects. First, the general knowledge quiz consists of questions from ten different fields, including astronomy and navigation, geography and biology, science and technology. The coverage of questions should not favor subjects with certain knowledge structure or social preference. Second, we have compared the team average number of correct quiz answers between the heterogeneous endowment treatments and between subject average number of correct quiz answers at each endowment level, and find no significant difference in any pairs (Mann-Whitney U test, p-value<0.1). Third, we have also tested the equality of age, gender, major (natural science or social science) and degree (bachelor or master degree) of the subjects of any two endowment levels within each heterogeneous endowment treatment, and in general find support for the null hypothesis in these general knowledge related characteristics (Wilcoxon signed-rank test, p-value<0.1).

identity. It should be noted already here that later on we show that this result is not necessarily robust to the identity-building activity and the effectiveness of punishment. The same pattern can be found for subjects at the same endowment level when we compare the last four entries of column (2) with (6) and (4) with (8) (Mann-Whitney U test, all p-values<0.1). However, the magnitude of the increase varies considerably across treatments and endowment levels. The strong effect of punishment is not unique to our experiment. Other studies using partner matching with similar MPCR and punishment effectiveness parameter as ours obtain a similar increase in contribution rates when punishment is introduced (e.g., Herrmann et al., 2008; Reuben and Riedl, 2013). As shown in Figure 1, average contribution rates in the treatments with punishment are all at a higher level after a similar starting point as in the treatments without punishment, and overall appear to be increasing over time. The evolution of contribution rates follows a similar pattern among the four treatments with punishment except *Homo-Strong*, which outstands the others from the beginning of the experiment. The divergence between treatments with and without punishment over time confirms the general finding from the existing literature that the presence of punishment opportunities is effective in improving and sustaining cooperation. However, the average contribution rates do not reach the maximum possible level in any of the four treatments with punishment. Full contributions account for 40%, 35%, 47%, and 33% of the total observations in *Homo-Weak*, *Hetero-Weak*, *Homo-Strong*, and *Hetero-Strong*, respectively, suggesting that the contribution "ceiling" is not reached by the majority in any of these treatments.

Models (3) and (4) in Table 3 present the regression results for the four treatments with punishment. In model (3), there is only one important and statistically significant difference among the treatments: under strong identity team average contribution rates are higher in homogeneous teams than in heterogeneous teams (bottom panel (i)). This is an interesting but unexpected result, in particular since we find that without punishment strong identity removes the contribution difference between homogeneous and heterogeneous teams. This contradiction may be interpreted by the different reinforcing effects between punishment and identity on relative contributions in homogeneous and heterogeneous teams: punishment of non-cooperative behavior under strong identity tends to be more severe in homogeneous than in heterogeneous teams, which will be discussed in the next section, and as a consequence contributions in the following periods will respond and rise more in homogeneous teams. That the other treatment effects are statistically insignificant indicates that we can reject Hypothesis 2.2 that contribution rates are higher under strong identity than under weak identity when there is punishment (marginal effect of *Hetero-Strong* and bottom panel (ii)).[13] From this it also follows that we can reject Hypothesis 2.3 that a strong identity increases average contribution rates more with punishment than without (*p*-value for the cross-treatment tests ((Homo-Strong-Punish - Homo-Weak-Punish) - (Homo-Strong-NoPunish - Homo-Weak-NoPunish)) is 0.595, and *p*-value for ((Hetero-Strong-Punish - Hetero-Weak-Punish) - (Hetero-Strong-NoPunish - Hetero-Weak-NoPunish)) is 0.155)[14]. One possible explanation for why strong identity does not further raise contributions in either endowment distribution may be that peer punishment alone is effective enough to push contribution rates to a high level and a strong common identity will not exert any further influence. This finding suggests that under this experimental design, peer punishment dominates common identity when both are viable in the effect on cooperation enhancement.

Regarding various endowment levels within heterogeneous teams (model (4)), we find that low endowment subjects on average always contribute a significantly greater proportion of the endowment than subjects with higher endowments, under both weak and strong identities (marginal effects of *Weak-High*, *Weak-Second*, and *Weak-Third*, and bottom panel (iii)-(v), except (v) where the difference is insignificant at conventional levels).[15] These results could hence be interpreted by similar motives as those underlying behavior in heterogeneous teams without punishment, and Hypothesis 2.4 is supported. If we compare contribution rates between the weak and strong identity for each endowment level in relation to the *Low* endowment, we see that again there are not statistically significant differences (bottom panel (vi)-(viii)).

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[13] The finding of only one statistically significant difference in contribution rates among the four treatments with punishment may raise a concern that subjects contribute a high share anyway due to the presence of punishment and do not respond to different endowment distributions and identity strengths adequately well. Besides the proportion of full contributions in each treatment with punishment, we also look at a less restrictive concept of the "ceiling", which is an arbitrarily high contribution rate but not 1. To test the presence of such a "ceiling effect" in contribution rates, we split the observations in the treatments with punishment into two subsamples – one with team average contribution rate above the median of each treatment and one below. The average contribution rate in the above median subsample is 0.89, 0.88, 0.93, and 0.86 for the *Homo-Weak*, *Hetero-Weak*, *Homo-Strong*, and *Hetero-Strong* treatments, respectively. These are rather high rates. We also rerun model (3) of Table 3 for each subsample separately. We find that in the below median subsample, there are no significant treatment effects, whereas in the above median subsample the team average contribution rate in the *Homo-Strong* treatment is significantly higher than that in the *Hetero-Strong* and *Homo-Weak* treatments at conventional levels. This suggests that subjects in the above median subsample respond to the treatments and do not contribute anyway at a high level.

[14] For single parameter tests, we calculate $z = \frac{\alpha_j - \tilde{\alpha}_j}{\sqrt{\Sigma_{jj} + \tilde{\Sigma}_{jj}}}$, where α_j and $\tilde{\alpha}_j$ are the two parameters of interest from the two regressions, and Σ_{jj} and $\tilde{\Sigma}_{jj}$ are the corresponding main diagonal elements in the variance-covariance matrix. Since the two parameters come from two separate regressions, their covariance by construction is zero. Z follows a standard normal distribution under the null of equality. We report two-sided *p*-values.

[15] Absolute contribution amounts are also always higher from higher endowment subjects.

4.3 Punishment behavior

We now turn to the analysis of punishment behavior. Table 4 reports the average number of punishment points assigned by subject *i* to *j* in the same team depending on treatment and endowment level. The first row shows that the average number of punishment points allocated is around 0.5 out of a maximum of 25 in all four treatments. Punishment occurs in 1,071 out of 5,760 possible cases, and boils down to 22% of 1,440 possible cases in *Homo-Weak*, 17% in *Hetero-Weak*, 19% in *Homo-Strong*, and 16% in *Hetero-Strong*. The last four entries in columns (2) and (4) demonstrate that there are some variations in punishment assignment across endowment levels within heterogeneous teams. Friedman two-way analysis of variance by ranks tests reject the null hypothesis that punishment points assigned by subjects of different endowment levels are from the same population under either identity strength (*p*-values<0.01).

<Table 4 about here>

Some regularities regarding punishment behavior have been identified from previous public goods experiments (see, e.g., Fehr and Gächter, 2000b; Carpenter and Matthews, 2009; Nikiforakis et al., 2010). In particular, punishment is mostly directed toward team members contributing less than the team average, and the severity of punishment increases with the difference between the contributions of the target and of the team average. In order to investigate this, we conduct a regression analysis of punishment assignment behavior. To account for the large number of zero punishment and a handful of full punishment as well as the interdependence of punishment decisions across periods among team members, we again apply the random effects double-censored tobit model with standard errors clustered at the team level. In addition to the treatment variables and period dummies, we include the following three independent variables in some of the regressions to capture the regularities in punishment behavior: others' average contribution rate, absolute negative deviation, and positive deviation. *Others' average contribution rate* is the average value of the team members' contribution rates of subject *j* (i.e., $\sum_{h\neq j}\left(\frac{c}{E}\right)_{h,t}/3$), excluding that of subject *j*. *Absolute negative deviation* is the absolute value of the deviation of subject *j*'s contribution rate from the others' average in case her own contribution is below the average (i.e., $\max\{0, \frac{\sum_{h\neq j}\left(\frac{c}{E}\right)_{h,t}}{3} - \left(\frac{c}{E}\right)_{j,t}\}$). This variable is zero if the subject's own contribution rate is equal or above the others' average. *Positive deviation* (i.e., $\max\{0, \left(\frac{c}{E}\right)_{j,t} - (\sum_{h\neq j}\left(\frac{c}{E}\right)_{h,t})/3\}$) is constructed analogously. [16]

Table 5 reports the regression results. Models (1) and (2) are estimated using both homogeneous and heterogeneous teams, whereas models (3) and (4) are estimated only using heterogeneous teams. Models (1) and (3) only include treatment variables, whereas models (2) and (4) also account for the punishment regularities. The topmost panel reports the average marginal effects of the independent variables.[17] The results in model (1) indicate that punishment does not vary with identity strength (marginal effect of *Hetero-Strong* and bottom panel (ii)). Thus, we find no support for Hypothesis 3.1 that a strong identity increases punishment. Our result is at odds with the findings from both Chen and Li (2009) and McLeish and Oxoby (2007), indicating that negative reciprocity is not affected by identity strength in our setting. Furthermore, homogeneous teams punish more severely than heterogeneous teams under weak identity but not under strong identity (marginal effect of *Homo-Weak* and bottom panel (i)). In model (2), when punishment regularities are accounted for, the difference between homogeneous and heterogeneous teams under strong identity also becomes statistically significant. This is consistent with our finding in contribution behavior. The more vehement punishment in homogeneous teams suggests that negative emotions toward low contributors triggered by payoff inequity aversion are stronger when endowments are equal. The upward change in marginal effects and significance shows that the effect of endowment homogeneity on punishment is underestimated without controlling for punishment regularities. The three regularity variables are all statistically significant with expected signs. The negative marginal effect of *Others' average contribution rate* indicates that less punishment is used when a high common team contribution standard has already been established. The positive marginal effect of *Absolute negative deviation* and negative marginal effect of *Positive deviation* show that the extent of punishment increases (decreases)

[16] We are aware of other possible punishment regularities within one's own team such as that based on individual contribution comparison between the punisher and the target. That is, individuals often punish team members who contribute proportionally less than they do. Although we choose to follow the literature and use the most commonly assumed punishment regularities since Fehr and Gächter (2000b) as based on team average contribution comparison, qualitatively similar results are obtained when we instead control for *individual absolute negative deviation* (i.e., $\max\{0, \left(\frac{c}{E}\right)_{i,t} - \left(\frac{c}{E}\right)_{j,t}\}$) and *individual positive deviation* (i.e., $\max\{0, \left(\frac{c}{E}\right)_{j,t} - \left(\frac{c}{E}\right)_{i,t}\}$).

[17] Using McDonald and Moffitt (1980) decomposition, the marginal effect of punishment, $p_{ij,t}$, is calculated as

$$\frac{\partial E(p_i|\mathbf{x})}{\partial x_j} = \frac{\partial \Pr(0 < p_i < 25|\mathbf{x})}{\partial x_j} \cdot E(p_i|\mathbf{x}, 0 < p_i < 25) + \Pr(0 < p_i < 25|\mathbf{x}) \cdot \frac{\partial E(p_i|\mathbf{x}, 0 < p_i < 25)}{\partial x_j} + \frac{\partial \Pr(p_i = 25|\mathbf{x})}{\partial x_j} \cdot 25$$

with the size of absolute negative (positive) deviation of the target's from the others' average contribution rate.

<Table 5 about here>

The patterns in punishment behavior discussed above are at an aggregate level for all four treatments with punishment. In order to check whether these patterns are common across treatments, we examine them separately for each treatment. Table 6 reports the regression results. Following Goette et al. (2012b), we test the equality of marginal effects across treatments in the bottom panel using two-sided z-tests for single parameter comparison and χ^2-tests for parameter vector comparison.[18] In all treatments, the marginal effect of *Absolute negative deviation* is positive and statistically significant, i.e., the more an individual's contribution rate falls below the others' average, the more she gets punished. The tests comparing two marginal effects show no significant difference across treatments (bottom panel (ii)). *Others' average contribution rate* exerts a negative and statistically significant effect only in the *Homo-Weak* and *Hetero-Strong* treatments. However, the marginal effects do not differ between any of the treatments (bottom panel (i)). In contrast, *Positive deviation* has a significantly negative impact only in the *Homo-Strong* treatment, but the marginal effects do not differ between any of the treatments (bottom panel (ii)). Finally, as expected, for all joint response tests (bottom panel (iv)), we fail to find any significant differences between treatments.

<Table 6 about here>

Models (3) and (4) of Table 5 present the regression results on punishment assignment by subjects with different endowment levels in the heterogeneous teams. In model (3), without punishment regularities, we find no evidence of any differences between endowment levels (marginal effects of *Weak-High*, *Weak-Second*, and *Weak-Third* and bottom panel (iii)-(v)). These results are in line with those in Visser and Burns (2006) and Prediger (2011). Thus, punishment does not decrease with the relative cost of sanctioning, which contrasts the results in Anderson and Putterman (2006) and Nikiforakis and Normann (2008), but is rather income inelastic, which is consistent with the findings in Carpenter (2007). In addition, comparing punishment between weak and strong identity for each endowment level in relation to the *Low* endowment, we find that there are no significant differences (bottom panel (vi)-(viii)). When punishment regularities are accounted for (model (4)), third endowment subjects with weak

[18] For single parameter tests, please refer to footnote 14. For parameter vector tests, we calculate the analogous test statistic $\chi^2 = (\boldsymbol{\beta} - \widetilde{\boldsymbol{\beta}})'(\boldsymbol{\Sigma} + \widetilde{\boldsymbol{\Sigma}})^{-1}(\boldsymbol{\beta} - \widetilde{\boldsymbol{\beta}})$, where $\boldsymbol{\beta}$ is a column vector. χ^2 follows a Chi-squared distribution with *k* degrees of freedom, where *k* is the number of variables in $\boldsymbol{\beta}$.

identity and second endowment subjects with strong identity punish significantly more than their low endowment teammates but only at the 10% level. Punishment assignment responds to *Others' average contribution rate* and to *Absolute negative deviation* in a similar fashion as that in the pooled sample with both homogeneous and heterogeneous teams. However, *Positive deviation* does not have a significant impact on the size of punishment in heterogeneous teams, which is consistent with the results in Table 6.

The final issue we investigate is to what extent the role of the punishment regularities depends on the endowment level of the *target*. We test this by interacting the three variables *Others' average contribution rate*, *Absolute negative deviation*, and *Positive deviation* with three dummy variables for the endowment level of the target. The reference group is that the target has *Low* endowment. Results are presented in Table 7.

<Table 7 about here>

A few of the interaction terms are statistically significant. To begin with, the influence of *Others' average contribution rate* on punishment is the strongest if the endowment level of the target subject is low or third. This is revealed by the positive sign of the interaction terms for the target with high and second endowments. This suggests that a punisher is less likely to be influenced by the overall contribution rate when deciding how much to punish a higher endowment target. Regarding the interaction terms for *Absolute negative deviation* and *Positive deviation*, only one of the terms is statistically significant and only at the 10% level. This indicates that punishment on the deviations from the average contribution rate does not depend on the endowment of the target.

5. Are the findings robust?

Our findings, in particular that punishment is more important than identity, of course raise the question of to what extent they are specific to our experimental design. In order to investigate this, we conducted four additional treatments, where we strengthened identity and weakened punishment effectiveness. In all the treatments the endowment is homogenous in order to keep the amount of sessions at a reasonable level. The new identity-building activity involved computerized team communication and was conducted after the endowment-determination stage. Subjects were randomly assigned to teams of four members and solved a second quiz of four questions similar to those used to determine endowments. They were given 2.5 minutes to answer each question and the opportunity to discuss the question with other members of their own teams via an online chat program. Participation in the discussion was voluntary. All subjects submitted their answers individually without a requirement to conform to a team answer. No reward was attached to correct answers or identical answers from all team members. The same four subjects of a team would subsequently play the public goods game. We believe that the strength of identity induced by the online chat is elevated from that induced by the "human knot" game, because the feeling of generalized reciprocity (e.g., Yamagishi and Kiyonari, 2000) is created over the same small group of people, and the discrepancy between the number of people who share a common goal and help each other and the number of people who interact in the public goods game is removed.

We also changed the effectiveness of punishment to make it more costly to the punishers: each punishment point now cost the punished member 2 ECUs and the punishing member 1 ECU; previously it was 3 to 1. The new treatments were conducted at Beijing Normal University as well in December 2013. All conditions remained identical to those in the original experiments, including number of subjects in each treatment, subject recruitment procedure, and experiment implementation process.

5.1 Contribution behavior

Table 8 reports the average contribution rates for the four new treatments. Compared to those in the original homogeneous treatments, average contribution rates are higher in the two new treatments without punishment and lower in the two new treatments with punishment.

<Table 8 about here>

In order to gauge the relative strengths of our two identity-building activities and two sets of punishment effectiveness parameters on promoting cooperation, we estimate one regression model for the four new treatments and one for the four original homogenous treatments. We again construct one dummy variable for each identity and punishment combination. The weak identity with no punishment is used as the reference group and omitted from the regressions. Table 9 reports the regression results from these two tobit models. It is clear that some of our previous findings are robust, whereas some are not. To begin with, when there is no punishment, in the new enhanced identity treatment contributions are not higher than those in the treatment with weak identity (marginal effect of *Strong-NoPunish*). This is consistent with our previous finding. Thus, even a stronger identity-building activity fails to increase contributions in homogenous teams. We stated two possible interpretations for the null result in Section 4.1: one is that our identity manipulation is not salient enough to exert a significant effect on homogeneous teams; the other is that contribution rates are already high under weak identity, and therefore the impact of a strong identity is weakened. The failure of a stronger identity manipulation in increasing contributions in homogenous teams suggests that the second argument is more plausible. These findings complement the literature of induced identity by showing that not only the salience of identity matters for its effect on cooperation, but also the initial level of cooperation needs to be sufficiently low. In addition, with a more costly punishment in the new treatments, contributions still increase when identity is weak compared to the case of no punishment (marginal effect of *Weak-Punish*). However, what differs from our original results is that punishment fails to enhance contributions in presence of strong identity (third panel (ii)). Therefore, these new results suggest that the interactive effect of identity and punishment indeed depends on the relative strengths of the identity-building activity and the cost of punishment. Do note that compared with the previous treatments, there are two things that are different: identity is stronger and punishment is less effective.

<Table 9 about here>

At the bottom of Table 9 we make a comparison of marginal effects across the original and new treatments. Since contribution behavior in the baseline treatments (*Homo-Weak-NoPunish*) is not statistically significantly different between original and new treatments, we can make a direct comparison between them. [19] First of all, without punishment there is no statistically significant difference between the impacts of the "human knot" game and the online chat (bottom panel (iii)). Second, with weak identity, the effect of punishment does not vary with the effectiveness of punishment (bottom panel (iv)). Thus, even if there are some differences in the strengths of identity and punishment, we fail to find any significant differences in contribution behavior. However, when both identity and punishment mechanisms are adopted, online chat is equivalent to punishment effectiveness of 2 to 1 in terms of the effect on contribution promotion, whereas "human knot" game is not as effective as punishment of 1 to 3. Moreover, given that identity is strong, punishment parameter of 3 to 1 exceeds 2 to 1 in stimulating contributions (bottom panel (vi)).

5.2 Punishment behavior

The next step is to unravel the effect of the new identity-building activity on punishment assignment. Table 8 also reports the average number of punishment points assigned for the four new treatments. In relation to those in the original homogeneous treatments, punishment is higher in the new treatment under weak identity, but is lower in the new treatment under strong identity. Table 10 reports the regression results for the two new treatments with

[19] We have compared contribution rates in these two baseline treatments using both Mann-Whitney U test and regression and obtained consistent result of statistical equality.

punishment and the two original homogeneous treatments with punishment. In the new treatments, we find that subjects with strong identity punish significantly less than subjects with weak identity (marginal effect of *Strong-Punish*). This result holds when punishment regularities are controlled for in model (2). Hence, Hypothesis 3.1 that a strong identity increases punishment is again rejected; on the contrary we find that punishment is lower when identity is strong. In the original treatments we find no significant difference between weak and strong identity. However, while the marginal effect of strong identity in the new treatments is three times as large as that in the original treatments, the large standard errors lead to no rejection to the equality of the two marginal effects (bottom panel (i) and (ii)).[20]

<Table 10 about here>

6. Conclusions

How to foster cooperation in organizations when free-riding incentives prevail and individual members are diverse in for example ability and motivation is an important economic problem. In this paper, we have investigated the relative importance of common identity and peer punishment under homogeneous and heterogeneous income distributions in contribution rates to a team public good. There are three key findings. First, when punishment is not possible, endowment heterogeneity negatively affects cooperation, yet strong identity can counteract this negative impact. However, strong identity does not increase cooperation in homogeneous teams, nor increase cooperation more in heterogeneous than in homogeneous teams. Second, the introduction of punishment successfully raises and sustains cooperation in both homogeneous and heterogeneous teams when identity is weak. Under strong identity, the effect of punishment depends on the effectiveness of punishment and the strength of the identity-building activity. In the original strong identity treatments we find that punishment increases cooperation even under strong identity for both income distributions. However, when introducing another stronger identity-building activity and a less effective punishment in the robustness test, we find that punishment does not further increase cooperation. Moreover, with punishment, cooperation is greater under strong identity in homogeneous than in heterogeneous teams, and so is the punishment inflicted. However, strong identity fails to further enhance cooperation or to push punishment in either endowment distribution. Third, the interaction between the new punishment level and identity suggests that if anything punishment is less fierce in teams with strong identity.

[20] We have compared punishment assignment in the two baseline treatments (*Homo-Weak-Punish*) using both Mann-Whitney U tests and regression and obtained consistent result of statistical equality.

Our findings provide some important implications for our understanding of how teams can be organized, for instance in the workplace, in order to induce higher cooperation. First, management policy makers should be precautious in implementing *ex ante* income heterogeneity within teams. It leads to lower cooperation than does an *ex ante* equal income scheme when neither building a common identity nor peer punishment is viable. Although there is not significantly distinguishable difference from homogeneous income teams any more in terms of cooperation when a common identity is induced, some cost incurred in changing employees’ identities is not avoidable. Second, when both identity building and peer punishment are available, it is not clear what the relative effects of these two are, and what the implications of implementing both at the same time are. Our initial evidence suggests that punishment is more effective than establishing a common identity. However, when we weaken the effectiveness of punishment and strengthen identity, this difference disappears. The changes in punishment effectiveness and identity-building activity are not dramatic, and in isolation their effects on cooperation are not affected compared to the original measures, but the interactive effect between them is affected. Consequently, which of identity and punishment could be considered a more effective norm enforcement mechanism in teams is rather sensitive to their relative strengths. Finally, our finding regarding punishment and identity is interesting, since it suggest that if anything punishment is less prevalent in groups with strong identity.

This study should be viewed as a first step toward considering the interactive effects of income distribution, identity, and punishment on cooperation. A natural extension would be to conduct the same experiment with real employees and real tasks in real-world workplaces to test the external validity of our results. Moreover, it would be interesting to use natural identities within existing social groups or primed natural social identities, such as gender, ethnicity, and different household registration types to study the same issues.

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Table 1. Experimental treatments

Treatment	Endowment distribution	Identity	Punishment
Homo-Weak-NoPunish	Homogeneous	Weak	No
Hetero-Weak-NoPunish	Heterogeneous	Weak	No
Homo-Strong-NoPunish	Homogeneous	Strong	No
Hetero-Strong-NoPunish	Heterogeneous	Strong	No
Homo-Weak-Punish	Homogeneous	Weak	Yes
Hetero-Weak-Punish	Heterogeneous	Weak	Yes
Homo-Strong-Punish	Homogeneous	Strong	Yes
Hetero-Strong-Punish	Heterogeneous	Strong	Yes

Table 2. Average contribution rates across treatments

	Without punishment				With punishment			
	Homo-Weak	Hetero-Weak	Homo-Strong	Hetero-Strong	Homo-Weak	Hetero-Weak	Homo-Strong	Hetero-Strong
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average	0.46	0.31	0.50	0.46	0.69	0.67	0.79	0.67
	(0.22)	(0.16)	(0.16)	(0.22)	(0.25)	(0.25)	(0.17)	(0.25)
High		0.27		0.38		0.65		0.63
		(0.21)		(0.26)		(0.27)		(0.26)
Second		0.25		0.42		0.63		0.61
		(0.14)		(0.27)		(0.27)		(0.30)
Third		0.32		0.46		0.68		0.72
		(0.20)		(0.24)		(0.27)		(0.26)
Low		0.39		0.59		0.74		0.73
		(0.29)		(0.26)		(0.27)		(0.28)

Notes: The table reports the average contribution rates depending on treatment (first row) and endowment level (last four rows). Standard deviations are in parentheses.

Table 3. Determinants of contribution rates

Dependent variable: contribution rate of subject i in period t, $\left(\frac{c}{E}\right)_{i,t}$				
	Without punishment		With punishment	
	Homo & Hetero (1)	Hetero only (2)	Homo & Hetero (3)	Hetero only (4)
Homo-Weak	0.132**		0.034	
	(0.061)		(0.071)	
Hetero-Strong	0.148**		0.011	
	(0.063)		(0.072)	
Homo-Strong	0.176***		0.125**	
	(0.054)		(0.063)	
Weak-High		-0.141**		-0.090**
		(0.064)		(0.041)
Weak-Second		-0.166**		-0.116***
		(0.074)		(0.023)
Weak-Third		-0.086		-0.056***
		(0.070)		(0.021)
Strong-High		-0.027		-0.115
		(0.095)		(0.072)
Strong-Second		0.004		-0.113
		(0.099)		(0.086)
Strong-Third		0.037		-0.027
		(0.094)		(0.075)
Strong-Low		0.173*		0.033
		(0.099)		(0.083)
Observations	1920	960	1920	960
Wald χ^2	120.24***	186.30***	84.18***	93.85***
Log-likelihood	-748.10	-344.08	-683.29	-346.40
Left / right censored observations	262 / 185	145 / 93	37 / 746	27 / 325
Linear combination of the model marginal effects:				
(i) (Homo-Strong) - (Hetero-Strong)	0.028		0.114*	
	(0.062)		(0.064)	
(ii) (Homo-Strong) - (Homo-Weak)	0.045		0.091	
	(0.059)		(0.064)	
(iii) (Strong-High) - (Strong-Low)		-0.200***		-0.148***
		(0.050)		(0.038)
(iv) (Strong-Second) - (Strong-Low)		-0.169***		-0.146***
		(0.050)		(0.050)
(v) (Strong-Third) - (Strong-Low)		-0.136***		-0.061
		(0.046)		(0.058)
(vi) (Strong-High - Strong-Low) - (Weak-High - Weak-Low)		-0.059		-0.058
		(0.081)		(0.056)
(vii) (Strong-Second - Strong-Low) - (Weak-Second - Weak-Low)		-0.004		-0.030
		(0.093)		(0.055)
(viii) (Strong-Third - Strong-Low) - (Weak-Third - Weak-Low)		-0.049		-0.005
		(0.085)		(0.062)

Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. Models (1) and (2) are estimated for the treatments without punishment, and models (3) and (4) with punishment. Models (1) and (3) are run on both homogeneous and heterogeneous treatments, whereas models (2) and (4) are run on heterogeneous treatments only. Entries in the topmost panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. The bottom panel shows the linear combination of the model marginal effects. Standard errors are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 4. Average number of punishment points assigned across treatments

	Homo-Weak	Hetero-Weak	Homo-Strong	Hetero-Strong
	(1)	(2)	(3)	(4)
Average	0.53	0.47	0.46	0.36
	(0.36)	(0.44)	(0.32)	(0.41)
High		0.68		0.30
		(1.06)		(0.34)
Second		0.33		0.57
		(0.24)		(0.80)
Third		0.46		0.37
		(0.50)		(0.69)
Low		0.41		0.20
		(0.67)		(0.19)

Note: The table reports the average punishment points assigned by subject i to j depending on treatment (first row) and endowment level (last four rows). Standard deviations are in parentheses.

Table 5. Determinants of punishment

Dependent variable: punishment points assigned from subject i to j in period t, $p_{ij,t}$				
	Homo & Hetero		Hetero only	
	(1)	(2)	(3)	(4)
Homo-Weak	0.202*	0.205**		
	(0.122)	(0.088)		
Hetero-Strong	-0.038	-0.058		
	(0.111)	(0.072)		
Homo-Strong	0.090	0.171		
	(0.132)	(0.109)		
Weak-High			0.176	0.263
			(0.157)	(0.168)
Weak-Second			0.070	0.145
			(0.176)	(0.170)
Weak-Third			0.148	0.185*
			(0.230)	(0.112)
Strong-High			0.008	0.069
			(0.170)	(0.140)
Strong-Second			0.284	0.359*
			(0.251)	(0.198)
Strong-Third			0.086	0.049
			(0.181)	(0.133)
Strong-Low			-0.092	-0.085
			(0.158)	(0.127)
Others' average contribution rate		-0.586***		-0.557***
		(0.160)		(0.206)
Absolute negative deviation		2.589***		2.334***
		(0.200)		(0.254)
Positive deviation		-0.402*		-0.231
		(0.224)		(0.240)
Observations	5760	5760	2880	2880
Wald χ^2	71.59***	432.09***	60.53***	377.70***
Log-likelihood	-4414.68	-3792.35	-1971.61	-1699.95
Left / right censored observations	4689 / 2		2406 / 1	
Linear combination of the model marginal effects:				
(i) (Homo-Strong) - (Hetero-Strong)	0.127	0.230**		
	(0.121)	(0.104)		
(ii) (Homo-Strong) - (Homo-Weak)	-0.112	-0.033		
	(0.137)	(0.119)		
(iii) (Strong-High) - (Strong-Low)			0.100	0.153
			(0.185)	(0.146)
(iv) (Strong-Second) - (Strong-Low)			0.377	0.444*
			(0.304)	(0.228)
(v) (Strong-Third) - (Strong-Low)			0.178	0.133
			(0.222)	(0.124)
(vi) (Strong-High - Strong-Low) -			-0.076	-0.110
(Weak-High - Weak-Low)			(0.229)	(0.205)
(vii) (Strong-Second - Strong-Low) -			0.307	0.299
(Weak-Second - Weak-Low)			(0.366)	(0.298)
(viii) (Strong-Third - Strong-Low) -			0.031	-0.052
(Weak-Third - Weak-Low)			(0.399)	(0.167)

Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. Models (1) and (2) are estimated on both homogeneous and heterogeneous treatments, whereas models (3) and (4) on heterogeneous treatments only. Models (1) and (3) only include treatment variables, whereas models (2) and (4) also include punishment regularity variables. Entries in the topmost panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. The bottom panel shows the linear combination of the model marginal effects. Standard errors are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 6. Response to punishment regularities by treatment

Dependent variable: punishment points assigned from subject *i* to *j* in period *t*, $p_{ij,t}$				
	Homo-Weak (1)	Hetero-Weak (2)	Homo-Strong (3)	Hetero-Strong (4)
Other's average contribution rate (β_1)	-0.512*	-0.400	-0.736	-0.727*
	(0.265)	(0.304)	(0.643)	(0.377)
Absolute negative deviation (β_2)	2.715***	2.695***	2.850***	2.090***
	(0.343)	(0.454)	(0.525)	(0.504)
Positive deviation (β_3)	-0.402	-0.114	-1.383**	-0.313
	(0.426)	(0.361)	(0.609)	(0.330)
Observations	1440	1440	1440	1440
Wald χ^2	351.76***	339.79***	343.74***	962.57***
Log-likelihood	-1088.80	-904.75	-970.99	-786.86
Left / right censored observations	1120 / 0	1196 / 0	1163 / 1	1210 / 1
Tests across treatments (p-value):				
	Homo-Weak = Hetero-Weak	Homo-Strong = Hetero-Strong	Homo-Weak = Homo-Strong	Hetero-Weak = Hetero-Strong
(i) Test that β_1 differs	0.781	0.991	0.747	0.499
(ii) Test that β_2 differs	0.973	0.297	0.829	0.373
(iii) Test that β_3 differs	0.606	0.123	0.187	0.683
(iv) Test that β_1, β_2, and β_3 differ	0.963	0.105	0.580	0.506

Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. Each model is estimated for one treatment with the treatment name specified in the column heading. Entries in the topmost panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. The bottom panel shows two-sided *p*-values for the cross-treatment tests. Standard errors are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 7. Punishment depending on endowment level of the target

Dependent variable: punishment points assigned from subject *i* to *j* in period *t*, $p_{ij,t}$	
Weak-High	0.316*
	(0.181)
Weak-Second	0.173
	(0.172)
Weak-Third	0.200*
	(0.118)
Strong-High	0.111
	(0.144)
Strong-Second	0.383**
	(0.195)
Strong-Third	0.059
	(0.133)
Strong-Low	-0.079
	(0.115)
Other's average contribution rate	-0.754***
	(0.231)
Other's average contribution rate × target endowment high	0.247**
	(0.106)
Other's average contribution rate × target endowment second	0.251**
	(0.098)
Other's average contribution rate × target endowment third	0.075
	(0.091)
Absolute negative deviation	2.124***
	(0.323)
Absolute negative deviation × target endowment high	0.245
	(0.431)
Absolute negative deviation × target endowment second	0.022
	(0.434)
Absolute negative deviation × target endowment third	0.322
	(0.351)
Positive deviation	-0.167
	(0.344)
Positive deviation × target endowment high	-0.231
	(0.789)
Positive deviation × target endowment second	-0.980*
	(0.584)
Positive deviation × target endowment third	0.109
	(0.332)
Observations	2880
Wald χ^2	553.22***
Log-likelihood	-1690.10
Left / right censored observations	2406 / 1

Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. This model is estimated on Hetero-Weak-Punish and Hetero-Strong-Punish treatments. Entries in the top panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. Standard errors are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 8. Average contribution rates and punishment points across new treatments

Without punishment		With punishment			
Contribution rates		Contribution rates		Punishment	
Homo-Weak	Homo-Strong	Homo-Weak	Homo-Strong	Homo-Weak	Homo-Strong
(1)	(2)	(3)	(4)	(5)	(6)
0.52	0.61	0.65	0.62	0.60	0.42
(0.24)	(0.21)	(0.29)	(0.20)	(0.45)	(0.60)

Notes: The table reports the average contribution rates for the four new treatments. For treatments with punishment it also reports the average punishment points assigned by subject *i* to *j*. Standard deviations are in parentheses.

Table 9. Determinants of contribution rates in homogeneous treatments: original treatments and new treatments

Dependent variable: contribution rate of subject *i* in period *t*, $\left(\frac{c}{E}\right)_{i,t}$		
	New treatments (1)	Original treatments (2)
Strong-NoPunish (γ_1)	0.092	0.043
	(0.071)	(0.058)
Weak-Punish (γ_2)	0.147*	0.259***
	(0.079)	(0.070)
Strong-Punish	0.104	0.353***
	(0.070)	(0.061)
Observations	1920	1920
Wald χ^2	51.30***	73.90***
Log-likelihood	-1027.99	-865.67
Left /right censored observations	99 / 578	127 / 513
Linear combination of the model marginal effects:		
(i) (Strong-Punish) - (Weak-Punish) (γ_3)	-0.043	0.094
	(0.081)	(0.066)
(ii) (Strong-Punish) - (Strong-NoPunish) (γ_4)	0.012	0.311***
	(0.071)	(0.056)
Tests across treatments (p-value):		
(iii) Test that γ_1 differs	0.587	
(iv) Test that γ_2 differs	0.287	
(v) Test that γ_3 differs	0.190	
(vi) Test that γ_4 differs	0.001	

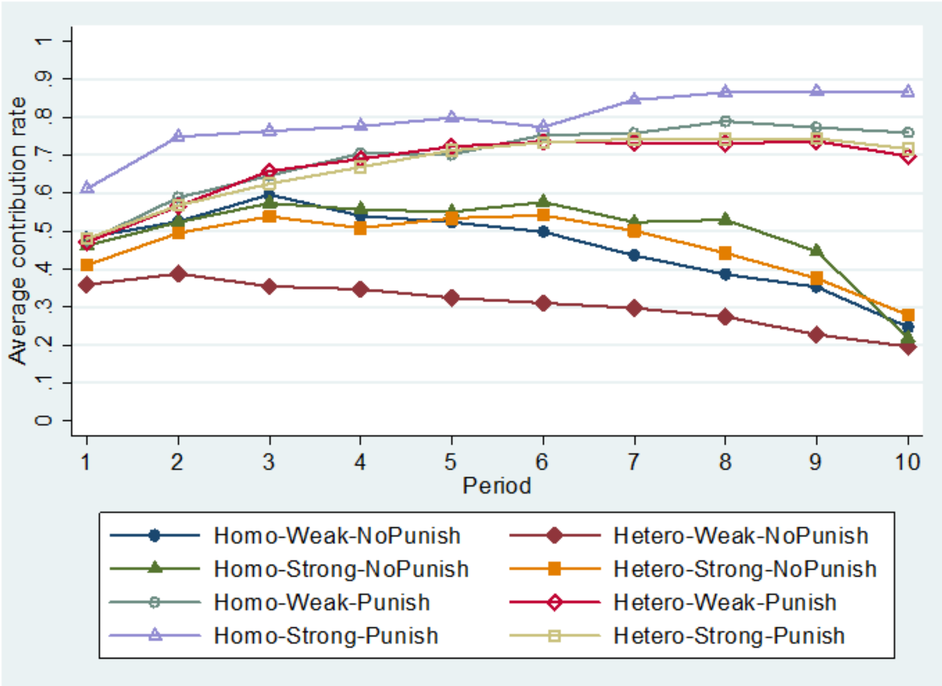
Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. Models (1) and (2) are estimated on the new and original homogeneous treatments, respectively. Entries in the topmost panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. The third panel shows the linear combination of the model marginal effects. The bottom panel shows two-sided *p*-values for the cross-treatment tests. Standard errors are in parentheses. *** indicates significance at the 1% level, * at the 10% level.

Table 10. The interaction between identity and punishment: original treatments and new treatments

Dependent variable: punishment points assigned from subject *i* to *j* in period *t*, $p_{ij,t}$	New treatments		Original treatments	
	(1)	(2)	(3)	(4)
Strong-Punish (δ_1)	-0.327*	-0.318*	-0.101	-0.031
	(0.184)	(0.179)	(0.136)	(0.109)
Others' average contribution rate		-0.807**		-0.597**
		(0.356)		(0.274)
Absolute negative deviation		3.421***		2.813***
		(0.957)		(0.582)
Positive deviation		-0.706**		-0.632
		(0.330)		(0.399)
Observations	2880	2880	2880	2880
Wald χ^2	65.24***	410.56***	40.84***	267.93***
Log-likelihood	-1901.55	-1594.98	-2436.49	-2082.99
Left / right censored observations	2484 / 5		2283 / 1	
Tests across treatments (p-value):				
(i) Test that δ_1 differs for models without punishment regularities	0.323			
(ii) Test that δ_1 differs for models with punishment regularities	0.170			

Notes: The table reports the regression results for a tobit model with both upper and lower censoring and subject random effects clustering standard errors at the team level. Models (1) and (2) are estimated on the new treatments, whereas models (3) and (4) are estimated on the original homogeneous treatments. Models (1) and (3) only include treatment variables, whereas models (2) and (4) also include punishment regularity variables. Entries in the topmost panel are the average marginal effects of the independent variables. Period dummies are controlled for in the regressions, but the results are not shown here. The bottom panel shows two-sided *p*-values for the cross-treatment tests. Standard errors are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, * at the 10% level.

Figure 1. Evolution of average contribution rates across treatments



Appendix A. Instructions

Here we provide a sample copy of the experimenter's instructions we used in our Hetero-Strong-Punish treatment. The instructions for the other treatments were adapted accordingly. The instructions were originally written in Chinese. The first part of the experiment is conducted without using computers in an activity room. Instructions are read by an experimenter to the participants. After this part, participants are led to the laboratory, and the remaining parts are conducted using computers. The instructions are read aloud by an experimenter as the participants follow along on their own copies.

In the Activity Room

Hello, everyone! You are now taking part in an economic experiment. During the experiment, all of you will be asked to do some activities and make some decisions. You can earn money by making these decisions. The amount of money you earn will depend on the decisions you make and on the decisions that other participants make.

The experiment has three parts and 24 participants. We will first play a game here, and then go to the laboratory to conduct the rest of the experiment using computers. The experiment will in total last for approximately 110 minutes.

The game we will play is called the "human knot". The rules are as follows: Everyone please stand shoulder to shoulder, facing each other in a circle. First, please lift your left hand and reach across the ring to take the hand of someone standing on the other side. Next, please lift your right hand and reach across the ring to take the hand of another person standing on the other side. Please make sure that you are not holding hands with someone standing directly beside you, and that you are not holding two hands with the same person. Ok, you have formed a knot. Now let's try to untangle the knot to form one or a couple of circles of people without letting go of any hand. If you let go of a hand, please grab that hand again immediately. You will have 10 minutes to do the untangling. You are free to discuss how to untangle the knot.

Next we will conduct the experiment in the laboratory. Please take all your belongings with you and go to the laboratory with me.

In the Laboratory

The rest of the experiment is computerized. It consists of two parts. The instructions you have now are for the first part. I will read the instructions aloud, and you can follow along on your copies. **All your decisions and answers to questions will remain confidential and anonymous**.

It is prohibited to communicate in any way with the other participants during the experiment. If you violate this rule, you will be dismissed from the experiment and denied all payments. If you have any questions during the experiment, please raise your hand and the experimenters will come to help you.

During the experiment we will not speak in terms of Renminbi (RMB), but of experimental currency units (ECUs). At the end of the experiment, the total amount of ECUs you have earned will be converted to RMB at the following rate:

1 ECU = 0.1 yuan RMB

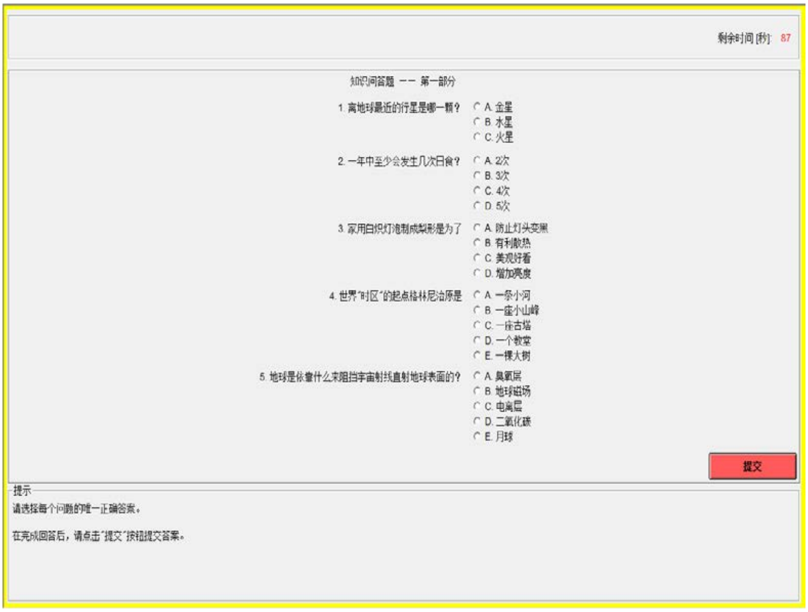
Each participant will receive a lump-sum payment of **50 ECUs** at the beginning of the experiment in addition to the show-up fee of 10 yuan RMB. This one-off payment will be used to pay for eventual losses during the experiment. **However, you can always avoid losses with certainty through your own decisions**. At the end of the experiment, your entire earnings from the experiment plus the remaining lump-sum payment and the show-up fee will be immediately paid to you **in cash in private in another room**.

The first part

In the first part of the experiment, you will be asked to complete a quiz individually. You are given 6 minutes to answer 20 general knowledge questions. For each question we will provide 3, 4 or 5 response alternatives, but **only one** of them is correct. The number of correctly answered questions will affect your status in the next part of the experiment.

Each screen will display five questions. In the top right corner of your screen you can see how much time remains for you to answer the questions on the current screen. You may change your answers as many times as you want; your final decision must be made before the time displays 0 seconds by clicking the “Submit” button. Once you have done this, your answers can no longer be changed. You may leave the answer blank for any question; the response will then be considered a wrong answer. Even if you do not answer any questions on a screen, please still click the “Submit” button to show that you have finished. If you finish before the time is up, please wait for the other participants to answer the questions. After all participants have submitted their responses, the next screen of questions will appear automatically. Please raise your hand if you have any questions.

Quiz screen



The second part

The second part of the experiment consists of 10 separate periods, and each period consists of two stages. Four participants in this room will be randomly assigned to a team. **The composition of the teams will stay the same throughout the experiment.** It is not possible to identify each other. The total income from the experiment will equal the sum of the period income.

<u>The first stage</u>

At the beginning of each period, each member of your team will receive a **different** amount of ECUs according to the quiz performance, from here on referred to as the **endowment**. The team member within your team obtained the most correct answers will receive the highest endowment, the one obtained the second-most correct answers will receive the second-highest endowment, and so on. Equal numbers of correct answers will be resolved by a random draw of the computer. Thus, there is always a strict ranking of endowments within your four-person team. The four endowment levels are **80, 60, 40 and 20 ECUs**. For example, if your quiz performance is ranked the third in your team, your endowment will be 40 ECUs. Endowments of your team members are hence 20, 60 and 80 ECUs, respectively. Your actual endowment level will be shown on the screen when you start this part of the experiment, and this level will be kept unchanged for all 10 periods.

At the first stage, you and your fellow team members are asked to allocate the endowment between two activities - **individual work** and **team work**. In particular, your task is to decide how much of your endowment to allocate to the individual work and to the team work, respectively. You (and the other members of your team) can allocate any proportion of the endowment to the individual work or the team work. At the beginning of each period, the following input screen at the first stage will appear:

Input screen at the first stage

The period number appears in the top left corner of the screen. In the top right corner, you can see how much time remains for you to make your allocation decision. You will have 90 seconds in the first two periods and 60 seconds in the remaining periods. You make your decision by typing an integer number between 0 and your endowment as your allocation to the team work. The remaining endowment will automatically be considered your allocation to the individual work. You can revise your decision as many times as you want, but your final decision must be made before the time displays 0 seconds by clicking the "Submit" button. Once you have done this, your decision can no longer be revised. If you finish before the time is up, please wait for other team members to make the decision.

Your income at the first stage of each period consists of two parts:

(1) Your income from the individual work. The individual work yields 1 ECU for each ECU you allocated.

(2) Your income from the team work. Your earning (and everyone else's in your team) is equal to 0.5 times the total allocation by all members of the team to the team work.

Your income at the first stage of a period = 1 × (allocation to the individual work) + 0.5 × (team total allocation to the team work)

Each team member's income from the team work is calculated in the same way. This means that each team member receives the same income from the team work. Suppose that the sum of the allocation to the team work from all team members is 60 ECUs. In this case, each member of the team receives an income from the team work of 0.5×60=30 ECUs.

After all members of your team have made their decision, the following screen will show you the total amount of endowment allocated by all four team members to the team work as well as your income at the first stage for the period. In the first two periods you will have 45 seconds and in the remaining periods 30 seconds to view this income screen. If you finish before the time is up, please click the "Continue" button.

Income screen at the first stage

The second stage

At the second stage, you will be informed about how much each of the other team members allocated to the team work. At this stage you can **reduce** the income of each other team member by assigning **deduction points**, or you can leave the income of each team member **unchanged**. The other team members can also reduce **your** income if they wish to. This can be seen from the input screen at the second stage:

Input screen at the second stage

This screen shows how much each team member allocated to the team work as a percentage of his/her endowment in the first stage of the period; that is, the allocation rate. At the beginning of each period, each team member will be randomly assigned a number from 1 to 4 as his/her identification number. Your allocation rate will be shown under the text “You”. Those of the other team members will be displayed under the corresponding identification numbers. Although the team composition stays fixed, the identification numbers are **changed randomly in each period**. Hence, the same identification number may represent a different member for each period.

Your task now is to decide whether, and if so, how many deduction points to assign to **each** of the other three team members. Each point you assign will cost you **1 ECU**, and will reduce the income from the first stage of the member you assign the point to by **3 ECUs**. You can **assign between 0 and 25 points to each other team member.** You must enter an integer number for each of them. If you do not wish to change the income of a specific team member, you must enter 0.

Suppose that you assign 5 points to one team member. This costs you 5 ECUs and reduces that member’s income by 15 ECUs. If you assign 8 points to another member, this costs you an additional 8 ECUs and reduces that member’s income by 24 ECUs. If you give the last team member 0 points, this has no cost for you and will not change that member's income either. In this case your total costs of distributing points will be 13 ECUs (5+8+0), and you will reduce in total 39 ECUs of income from the first stage of all your team members.

Whether and by how much your income from the first stage is reduced also depends on the total points you receive. If you receive 4, 7 and 0 points from the other three team members, respectively, your income will be reduced by 33 ECUs (3× (4+7+0)).

Your final income from the two stages of a period consists of three parts:

(1)Your income from the first stage;

(2) Income reduction due to the total deduction points you have received in the period;

(3) Income reduction due to the total deduction points you have assigned in the period, that is, sum of the assigned deduction points.

The final income from the two stages is therefore calculated as follows:

Final income of a period at the end of the second stage

= (income from the first stage)	(1)
- 3 × (total deduction points you have received)	(2)
- (total deduction points you have assigned)	(3)

If (1) + (2) is greater than or equal to 0, final income of a period is calculated as above;

If (1) + (2) is smaller than 0, final income of a period = **0** –total deduction points you have assigned

If any team member receives points that reduce income more than what he/she earned from the first stage, his/ her income will be reduced to zero. Please note that one's income at the end of the second stage can be negative if the costs of the assigned points exceed the income from the first stage minus the income reduction by the received deduction points.

For your decision you have 180 seconds in the first two periods and 120 seconds in the remaining periods. You can move from one input field to the other by pressing the Tab key (→|) or by using the mouse.

After all members of your team have made their decision, the following screen will show you the deduction decision and final income for the period. In the first two periods you will have 45 seconds and in the remaining periods 30 seconds to view this income screen.

Income screen at the end of the second screen

Do you have any questions?

The decision making is over now. Please remain seated, and complete a survey that is shown on your screen in a moment.

Control questions:

Before making your actual decision, please first answer all control questions. They serve as a test of your understanding of payoff calculations. There is no time limit on answering the control questions.

1. Suppose that you have an endowment of 40 ECUs, and the other team members have an endowment of 20, 60 and 80 ECUs, respectively. The other three team members together allocate a total of 40 ECUs to the team work. What is:
   a. Your income at the first stage of the period if you allocate 0 ECUs to the team work? ……….
   b. Your income at the first stage of the period if you allocate 10 ECUs to the team work? ……….

2. Suppose that you have an endowment of 40 ECUs, and the other team members have an endowment of 20, 60 and 80 ECUs, respectively. You allocate 18 ECUs to the team work. What is:
   a. Your income at the first stage of the period if the other team members together allocate a further total of 16 ECUs to the team work? ……….
   b. Your income at the first stage of the period if the other team members together allocate a further total of 52 ECUs to the team work? ……….

3. Suppose that your income from the first stage is 60 ECUs. What is your income at the end of the period if
   a. You receive a total of 10 deduction points, but do not assign any yourself? ……….
   b. You receive a total of 10 deduction points, and assign a total of 7 points yourself? ………..…

Appendix B. Post-Experiment Survey

Please answer the following survey questions. All your answers will remain confidential and anonymous. (*Summary statistics are in italics in parentheses.*)

1. What is your age? _____ *(Mean 21.5, Std Dev 2.3, Median 21, Min 17, Max 33)*
2. What is your gender?
   (a) Female *(69.1%)*
   (b) Male *(30.9%)*
3. What is your ethnic group?
   (a) Han *(89.4%)*
   (b) Zhuang *(1.2%)*
   (c) Man *(2.4%)*
   (d) Hui *(2.3%)*
   (e) Miao *(0.4%)*
   (f) Weiwu'er *(0.7%)*
   (g) Tujia *(0.7%)*
   (h) Yi *(0.0%)*
   (i) Menggu *(0.7%)*
   (j) Zang *(0.3%)*
   (k) Other, please specify _____ *(1.9%)*
4. Which kind of household registration did you hold before enrolling into university?
   (a) Rural *(43.2%)*
   (b) Urban *(56.3%)*
   (c) No household registration *(0.5%)*
5. What was your permanent home address before enrolling into university?
   Province (City) _____ City (District) _____ County _____ *(Subjects are from all 31 provinces of mainland China, plus Taiwan)*
6. How many biological siblings do you have excluding yourself (if you are the single child, please write 0)? _____ *(0 siblings 46.5%, 1-2 48.6%, 3 or more 4.9%)*
   If you have any biological siblings, please specify your order in the siblings _____
   (a) First *(41.2%)*
   (b) Second *(42.2%)*
   (c) Third *(12.0%)*
   (d) Fourth *(2.9%)*

(e) Fifth *(1.3%)*

(f) Sixth *(0.3%)*

7. How many siblings, half-blood siblings, cousins have you been living with for more than six months of a year (including six months) before enrolling into university (if none, please write 0)? _____ *(0 siblings 42.2%, 1-2 40.5%, 3 or more 17.3%)*

8. Have you been to a boarding high school?

   (a) Yes *(63.4%)*

   (b) No *(36.6%)*

9. Please choose in which of the following categories that your family (with which you lived before enrolling into university) current monthly before-tax total income falls into? _____

<400	401-1000	1001-2000	2001-3000	3001-4000	4001-6000	6001-8000	8001-10000	10001-20000	20001-30000	30001-40000	> 40001
1.7%	*6.4%*	*14.2%*	*14.1%*	*14.2%*	*20.5%*	*9.4%*	*8.3%*	*7.1%*	*2.3%*	*0.9%*	*0.9%*

10. What is your major?

    School/Institute/Center___________ Department___________ Major___________

11. Are you an undergraduate or graduate student?

    (a) Vocational degree student *(2.1%)*

    (b) Bachelor student *(63.9%)*

    (c) Master student *(33.8%)*

    (d) PhD student *(0.2%)*

    (e) Post-doctoral student *(0.0%)*

12. Which year are you in your program? _____ *(Mean 2.0, Std Dev 1.0, Median 2, Min 1, Max 5)*

13. Are you a member of the Communist Party?

    (a) Yes *(28.8%)*

    (b) No *(71.2%)*

14. Are you a member of any civic voluntary association (e.g. political, interest groups, sports, culture, nonprofit, etc.)?

    (a) Yes. *(46.5%)* Please specify the full name of all associations that you are a member of, with a comma between the names _____

    (b) No *(53.5%)*

15. Have you ever participated in any economics experimental studies before?
    (a) Yes. *(25.7%)* Please specify the number of times _____ *(Mean 1.3, Std Dev 0.6, Median 1, Min 1, Max 5)*
    (b) No *(74.3%)*
16. Have you ever participated in any psychology experimental studies before?
    (a) Yes. *(62.8%)* Please specify the number of times_____ *(Mean 3.1, Std Dev 2.9, Median 2, Min 1, Max 30)*
    (b) No *(37.2%)*
17. How many other participants in the session do you know from before (if none, please write 0)? _____ *(0 other participants 71.7%, 1-2 27.4%, 3 or more 0.9%)*
18. In the past twelve months, have you donated money or goods to or done volunteer work for charities or other nonprofit organizations?
    (a) Yes. *(71.2%)* Please specify the total amount ¥_____ *(Mean 140.9, Std Dev 162.7, Median 100, Min 0, Max 1050)* and/or the number of hours _____ *(Mean 47.8, Std Dev 86.0, Median 20, Min 0, Max 720)*
    (b) No *(28.8%)*
19. On a scale from 0 (least) to 10 (most), please rate how closely attached you felt to your own team throughout the experiment. _____ *(Mean 5.6, Std Dev 3.2, Median 6, Min 0, Max 10)*

Least										Most
0	1	2	3	4	5	6	7	8	9	10

20. **(For strong identity treatments only)** On a scale from 0 (least) to 10 (most), please rate how much you think the “human knot” game / the second quiz where you can get help from or offer help to other members in your own team helped enhance the sense of being in a team. _____ *(Mean 6.2, Std Dev 3.0, Median 7, Min 0, Max 10)*

Least										Most
0	1	2	3	4	5	6	7	8	9	10

Paper II

Session size and its effect on identity building: Evidence from a public good experiment

Qian Weng*

Abstract

The effect of session size has largely been ignored in experimental studies, despite the possibility that it may affect people's perception of the strength of the potential link between them and consequently the strategies used in the interactions. This paper investigates how the effect of an induced common identity on individual cooperative behavior differs depending on session size in a repeated public good experiment with constant group size and partner matching. We find that induced identity significantly enhances cooperation only when the session size is small and only in the initial period. In all other periods, induced identity does not have a significant effect on cooperation in either small or large sessions. The same null effect of identity in small and large sessions suggests that session size is not a confounding factor of identity in repeated interaction settings.

Keywords: Session size; identity building; public goods experiments; China

JEL Classification: C92; H41

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Acknowledgements: I thank Fredrik Carlsson, Haoran He, Martin Kocher, Matthias Sutter, Måns Söderbom, Marie-Claire Villeval, and participants at the 2012 Asia-Pacific ESA Conference in Xiamen and the 2012 International ESA Conference in New York for helpful discussions and comments. I am grateful to Xiujuan Zhang for assistance in conducting the experiment. Financial support from Formas through the COMMONS program and from the Jan Wallander and Tom Hedelius Foundation is gratefully acknowledged.

1. Introduction

According to social identity theory (Tajfel and Turner, 1979; 1985), social identity describes the aspects of an individual's self-concept derived from perceived membership in social groups. Once a person identifies herself as part of a group, her attitudes, values, and norms may be shaped by the group, and her behavior hence conforms to the stereotypes associated with the group's identity. Before it was systematically introduced into economic analysis by Akerlof and Kranton (2000), identity had already been recognized as a central concept to understand phenomena in social psychology, sociology, anthropology, and political science. Economic experiments studying the effects of identity on human decision making employ three design methods, i.e., using natural identities within existing social groups (e.g., Bernhard et al., 2006; Goette et al., 2006; Goette et al., 2012), priming natural social identities (e.g., Afridi et al., 2012; Benjamin et al., 2010; Chen et al., 2014), and inducing artificial group identities. A number of economic experiments using induced identities have shown that individual behavior is affected by group identity, and the extent of the effect depends on the salience of identity.[1] However, to our best knowledge, no previous study has considered the potential interaction between induced identity and the number of subjects in an experimental session, i.e., session size, which may also affect the salience of identity. In this paper, we use a laboratory experiment to investigate whether session size influences the effect of induced identity on individual cooperative behavior.

Broadly speaking, there are two common approaches to building and enhancing group identity in the existing experimental economics literature. One adapts the "minimal group paradigm" from social psychology to distinguish the identity between ingroup (with whom people identify) and outgroup (with whom people do not identify) members. Typically, two distinct group identities are first induced by randomly assigning all subjects in an experimental session to two non-overlapping groups based on some trivial tasks such as stating preferences for artwork by two different artists (e.g., Chen and Li, 2009; Chakravarty and Fonseca, 2010) or no task at all (e.g., Chen and Chen, 2011; Morita and Servátka, 2011).

[1] A variety of games have been played to study the effect of induced identity on different individual behavior. See, e.g., Eckel and Grossman (2005), Charness et al. (2007), Smith (2011), Chakravarty and Fonseca (2010), Drouvelis and Nosenzo (2013) on cooperation; McLeish and Oxoby (2007) on cooperation and punishment; Chen and Chen (2011) on coordination; Hargreaves Heap and Zizzo (2009) on trust; Chen and Li (2009) on social preferences; Sutter (2009) on individual and team decision making; Eberlein and Walkowitz (2008) on promotion; Morita and Servátka (2011) on relation-specific investment; and Riener and Schacht (2011) on a market setting.

Group identities are then enhanced within each identity group by various means.[2] After identities have been induced (and enhanced), a game, e.g., a public good game, prisoner's dilemma game, or trust game, is played, where a pair or group of subjects from the ingroup and/or outgroup interact. The number of subjects in a game-playing pair or group is generally smaller than the number of subjects who have the same group identity, and the pairs or groups are often re-matched across periods in multiple period games. Experiments using this approach generally find ingroup favoritism and outgroup discrimination when the group identity is salient.

However, in this approach, the number of subjects in a session is usually not controlled. The number can vary across experiments or across sessions in the same experiment depending partly on the number of people who showed up. No matter how the two identity groups are partitioned, the difference in the total number of subjects in a session and consequently the number of subjects in each identity group may affect people's perception of the ingroup/outgroup and of the potential interactions that will occur. Increasing the number of subjects in each identity group tends to reduce the strength of group identity by making subjects feel less connected to the ingroup, which may change people's perception of the strategies employed by their counterparts and consequently their strategies played in subsequent interactions.

The other identity-building approach forms a group membership without introducing an identity contrast or in fact even without the existence of an outgroup. The main difference from the previous approach is that group identity is built and enhanced only among the subjects (e.g., 3 to 5 people) who are randomly assigned to a group and will later interact in various games. Group composition always remains fixed throughout the experiment. Studies using this method of group identity building show that a salient group membership strongly affects individual behavior in both strategic (e.g., Eckel and Grossman, 2005) and non-strategic (e.g., Sutter, 2009) decision-making situations. Session size, however, may not matter much in this approach, since the same small fixed group of people share a common identity and play the games.

The aim of the present paper is to examine how session size may influence the effect of induced identity on individual cooperative behavior. We conduct a repeated-play linear

[2] Identity-strengthening activities include completion of a group task with own identity group members through either face-to-face communication (e.g., McLeish and Oxoby, 2007; Smith, 2011) or online chatting (e.g., Chen and Li, 2009; Chakravarty and Fonseca, 2010; Chen and Chen, 2011), presence of own group members as audience when an individual makes the decision, or payoff sharing among group members (e.g., Charness et al., 2007).

public good experiment, prior to which we manufacture the strength of identity between strong and weak depending on whether subjects participate in an identity-building activity or not, and vary the session size between small and large (with 8 and 24 subjects, respectively). Our identity-building activity combines the features of the above-described two approaches: all participants in one session play a face-to-face “human knot” game to induce one common identity, and then they are randomly assigned to fixed groups of four to interact in the public good game.[3] Our activity hence adopts the merit of the identity-building approach where no outgroup is needed for creation of an identity conflict,[4] and furthermore controls for the potential interactive effect of session size on identity. The same identity-building activity is used by Weng and Carlsson (2014), who study how induced identity together with endowment distribution and peer punishment interactively affects individual cooperative behavior.

Given the design of our identity-building activity, we expect identity to have a positive impact on individual cooperation, and this positive impact to decrease with session size. A task conducted with all participants in a session like ours where participants share a common goal and help each other to achieve the goal likely renders a better feeling of connection, and they will as a result cooperate more. Increasing the number of participants in such a task may tend to make them consider those who are not spatially close or physically connected an outgroup and hence weaken the influence of the common identity on cooperation. The importance of session size for the effect of identity on cooperation also has real-world implications. Participants in an experimental session can be viewed as representing the total sum of workers in a firm. Hence, session size captures firm size in terms of employment. Building a common identity of the workers is one way to urge the sense of firm spirit and loyalty, which helps reduce shirking and pursue the firm goal. When the identity is built at the firm level, and the intervention activity and other conditions are kept identical, the effect of the identity tends to be greater for small than for large firms. This may be because in smaller firms workers have more chances of interacting with others even if they belong to different task performing groups.

[3] Eight is used as the small session size because it is the minimum number of participants that allows for anonymous and random group assignment to fixed groups of four subjects. Twenty-four is chosen as the large session size given that the capacity of the laboratory where the experiment took place is 25. These two numbers also represent the lower and upper bounds of session size in many of the public goods experiments that we are aware of.

[4] Chen and Li (2009) investigate the extent to which the presence of an outgroup affects behavior and find no significant difference from no outgroup.

Some psychological experiments have studied the interactive effect of group size[5] and induced identity in social dilemmas, and have confirmed the existence of such an effect. For example, Brewer and Kramer (1986) find that in a small-group public good game (i.e., 8 people), individuals for whom a collective identity is made salient keep less for themselves compared to individuals with an individual-level identity, yet this outcome is reversed in a large-group condition (i.e., 32 people). De Cremer and Leonardelli (2003) on the other hand demonstrate that when social constraints that promote cooperation, such as accountability, personal identifiability and felt responsibility, are absent, members of small groups (i.e., 4 people) are more likely to contribute to a public good than members of large groups (i.e., 8 people) when the psychological need to belong to a group[6] is low, whereas the opposite is true when need to belong is high.

A related series of experiments have tested the direct effects of group size on public goods provision. A well-grounded conjecture is that a group's ability to provide the optimal level of a public good is inversely correlated with group size (e.g., Olson, 1965; Buchanan, 1968). The basis for this conjecture is that increasing group size tends to diminish the marginal per capita return (MPCR) from a contribution to an "impure" public good to all consumers (Isaac and Walker, 1988), and to make people feel less efficacious (Kerr, 1989), less identifiable and differentiable (Hamburger et al., 1975), and less responsible for the pursuit of group welfare (Stroebe and Frey, 1982). The empirical test results of the inverse relationship between group size and cooperation depend on whether the influences of variation in the MPCR and of a pure change in the number of group members are separated. Isaac and Walker (1988) and Isaac et al. (1994) examine the efficiency of public goods provision in groups of size 4, 10, 40 and 100, and find that the above conjecture is supported in the smaller groups (i.e., 4 and 10 people) if increases in group size generate a smaller MPCR, whereas holding MPCR constant, mean percentage of contributions is greater in larger groups (i.e., 40 and 100 people) than in smaller groups when the MPCR is low, and there is no discernible difference when the MPCR is high. This paper hence also tries to see whether there is any pure effect of session size, as an analogue to group size, on public goods contributions, while keeping MPCR constant.

[5] Group size is equivalent to session size when there is only one group in a session.

[6] According to the authors, psychological need to belong to a group is reflected in people's desire to form and maintain social relationships with others. It is measured using a Need to Belong Scale (Leary et al., 2001), which includes 10 items rated on a 5-point scale with 1 indicating "not at all characteristic of me" and 5 indicating "extremely characteristic of me".

We find that induced identity significantly enhances cooperation only when session size is small and only in the initial period. In all other periods, induced identity does not have a significant effect on cooperation in either small or large sessions. The null result could arise from the relatively low strength of identity rooted in the cultural setting in China where the experiment took place. The same null effect of identity in small and large sessions suggests that session size is not a confounding factor of identity in repeated interaction settings.

The remainder of the paper is organized as follows. Section 2 describes the experimental design, section 3 presents the results and discussions, and section 4 concludes the paper.

2. Experimental design

The experiment uses a 2×2 design. One dimension is to vary session size with either 8 or 24 subjects to establish a small or large session. The other is to manufacture the strength of identity to be strong or weak by conducting an identity-building activity or not. This generates four different combinations of conditions, each of which is a treatment of the experiment as summarized in Table 1.

<Table 1 about here>

The experiment was conducted in two stages. The first was an identity-building stage, which was only implemented in the two treatments with strong identity, i.e., Small-Strong and Large-Strong. A "human knot" game was played with all subjects in one session in another room before they entered the laboratory. Subjects stood shoulder to shoulder, in a circle, facing each other. They were first asked to form a knot by lifting both hands and reaching across the circle to hold the hands of two other subjects who were not standing directly beside them, left hand to left hand and right hand to right hand. After ensuring that a knot had been constructed, subjects were then asked to untangle the knot to form one or a couple of circles without crossing arms anymore. They were not allowed to let go of any hands in the process. Anyone who let go of a hand was required to immediately grab the same hand again. The game lasted for approximately ten minutes. The reason for choosing such an identity-building activity was that it fits the aim of the exercise, and also that it is a typical activity undertaken in orientation and training programs in real-world organizations. Communication was allowed during the course of the game. The experimenters observed that the communication closely surrounded the game. After finishing the identity-building activity, the subjects were led to the laboratory. In the two treatments with weak identity, i.e., Small-Weak and Large-Weak, subjects entered the laboratory directly once all 8 or 24 of them had arrived, yet they did have a chance to meet each other while waiting for the experiment to start.

The second stage was a decision-making stage, which was conducted in the laboratory in all four treatments. Subjects were seated in partitioned computer terminals and were then given written instructions while the experimenter read the instructions aloud. They first individually solved a quiz consisting of 20 general knowledge questions. The quiz was used only to legitimize the receipt of the endowment (see, e.g., Hoffman and Spitzer, 1985; Gächter and Riedl, 2005), but the quiz performance did not affect the endowment level in the public good game that followed. Then the 8 or 24 subjects in one session were randomly assigned to groups of four members and each group played a public good game framed as a team production problem for 10 periods. The subjects knew that their groups consisted of themselves and three other individuals, whereas their identities were kept anonymous throughout the experiment.

At the beginning of each period, each subject was endowed with 50 experimental currency units (ECUs). They decided simultaneously and without communication how to allocate the endowment between individual and team work (i.e., the public good). By freely choosing an amount to contribute to the team work, c_i, where $0 \leq c_i \leq 50$, the remaining endowment, $50 - c_i$ was automatically considered the allocation to the individual work. Each ECU that a subject kept for individual work generated one ECU for herself, whereas the payoff from the team work was 50% of the group's total contribution. That is, the MPCR from a contribution to the public good was equal to 0.5. The period payoff for subject i was hence given by $\pi_i = (50 - c_i) + 0.5 \sum_{j=1}^{4} c_j$.

The payoff function, the duration of the experiment (10 periods), and the instructions were common knowledge to all participants in each treatment. Before the commencement of actual decision making, the subjects were required to answer control questions to ensure that they had understood the features of the game correctly. At the end of each period, the subjects were informed of their group's total contribution, their own earnings, and the contributions of other group members in the current period. To prevent the possibility of individual reputation formation, each of the four subjects in a group was randomly assigned an identification number from 1 to 4 to identify her actions in a given period and these numbers were randomly shuffled across periods.

The experiment was conducted using z-Tree (Fischbacher, 2007) in the experimental laboratory at Beijing Normal University in May and June 2011. This university is located in the center of Beijing and has approximately 20,000 full-time students. The subjects were recruited via announcements on a bulletin board system and bulletin boards in teaching and accommodation buildings at the university. In total, we had observations from 192 subjects[7], 48 for each treatment. All subjects were allowed to participate in only one session, and they did not know about any treatments other than the one in which they participated. To control for experimenter effect, the same two individuals, who were unknown to the participants, ran all sessions. To keep the outcome of the experiment anonymous, subjects were informed at the beginning that they would be paid confidentially and individually in another room and that they would leave the laboratory successively so that they would not meet and communicate with other subjects after completing the session. The final earnings from the experiment totaled the sum of the period payoffs at an exchange rate of 1 ECU to 0.1 Chinese Yuan (CNY) plus a show-up fee of 10 CNY. The experiment lasted an average of about 63 minutes, including above-described stages and a post-experimental survey covering questions on demographics, academic background, past donation behavior, and perceptions about their group in the experiment. The subjects on average earned 84.5 CNY[8] including the show-up fee.

3. Results and discussions

The impact of session size and identity on average contributions over time can be identified in Figure 1. Average contributions start at similar levels in the Small-Weak, Large-Weak, and Large-Strong treatments, ranging from 45% to 48% of the total endowment. They follow each other closely in the first five periods, and then contributions in the Large-Strong treatment start exceeding those in the other two treatments until the ninth period. The Small-Strong treatment displays the highest contributions during the entire course of the experiment except in the sixth period. Moreover, average contributions in all treatments rise in the early periods and then decline, although the peaks appear at different points in time and the rates of change differ across treatments.

<Figure 1 about here>

Table 2 reports, in the left panel, the cumulative period average contributions across treatments and, in the right panel, *p*-values of the pair-wise treatment comparisons using Mann-Whitney U tests on the null hypotheses that average contributions are equal in two

[7] All subjects were Chinese citizens and university students, but with various academic majors.

[8] The average exchange rate in May and June 2011 was 1 USD = 6.48 CNY. The average hourly wage for university students in Beijing at the time of the experiment was approximately 50 CNY.

different treatments. The unit of observation is subject for period 1 and group average for the relevant cumulative periods.[9] As shown in the left panel, average contributions in the Small-Weak, Large-Weak, and Large-Strong treatments do not differ much in any entries, and they are all lower than the contributions in the Small-Strong treatment. The non-parametric test results in the right panel confirm the general pattern. We find that there exists no statistically significant difference in contributions between small and large sessions over the entire course of the experiment, regardless of the strength of identity (*p*-value > 0.1 for all entries of columns (5) and (6)). This corresponds to the finding from the group size literature of no pure group size effect when the MPCR is held constant. Strong identity significantly raises contributions in small sessions in the first period (*p*-value = 0.083 in the first entry of column (7)), whereas this effect fades from the second period onwards (*p*-value > 0.1 for the rest of the entries in column (7)). This could be because identity built on a small group of people has an impact on behavior when individuals meet initially, but this effect is increasingly dominated by other factors in repeated interactions, such as group norm adherence. However, identity fails to exert any effect in large sessions over the entire course of the experiment (*p*-value > 0.1 for all entries of column (8)). Our results suggest that the effect of induced identity on cooperation is stronger in small than in large sessions, which is in line with the finding from existing experiments. Studies that show a strong effect of identity usually have a small number of people who share the same identity. For example, Smith (2011) and Drouvelis and Nosenzo (2013) explicitly write that there are 12 and 18 subjects, respectively, in one session of their experiments, and 6 in each identity group. Chen and Li (2009) on average have 16 subjects in one session, and 6 and 10[10] in each identity type. The small number of subjects guarantees the successful enhancement of identity.

<Table 2 about here>

To control for subjects' individual cross-period contribution differences and the interaction of group members across periods, we estimate a random effects generalized least squares (GLS) model with robust standard errors clustered at the group level to analyze the interplay between session size and identity again. Table 3 presents the regression results. We use the following independent variables: *Small* is a dummy variable taking the value of one if

[9] Since subjects in a group interact for the first time in period 1, the contribution from each subject is an independent decision in this period. From period 2 onwards, a subject's contribution decision may also be affected by her and other group members' behavior in the previous period(s). This history dependency makes individual contributions no longer independent. Therefore, group average contribution, which takes account of this dependency within a group and is still independent across groups, is the appropriate unit of observation.

[10] In the post-experimental survey, Chen and Li (2009) report the proportion of subjects belonging to the Klee group being 40% and Kandinsky group being 60%.

the observation comes from small sessions and zero otherwise; *Strong* is a dummy variable equal to one if the observation comes from the strong identity treatments and zero otherwise; and *Small×Strong* is their interaction term. Period dummies are also included to control for time order effects. In order to test whether strong identity significantly increases contributions in small sessions in the initial period as found in the non-parametric test, regression (2) introduces interaction terms between *Period 1*, *Small*, *Strong* and *Small×Strong.* The regression results are fully consistent with the non-parametric test results: average contributions over the entire course of the experiment are similar between any two session size and identity strength combinations (column (1) coefficients on *Small*, *Strong*, and bottom panel (i)-(ii)); and contribution is significantly higher in small sessions when identity is strong than weak in the first period (column (2) panel (iii)).

<Table 3 about here>

A concern may be raised that our results are driven by the possibility that identity is stronger in small than in large sessions in the two strong identity treatments because the "human knot" is easier to untangle with fewer participants. However, we believe that the effect of identity comes from the action of participating in the task *per se*, not from the success of accomplishing the task. On the one hand, we controlled for the length of the game in each session to be approximately ten minutes and terminated it regardless of whether or not the knot was successfully untangled when it was time. On the other hand, we witnessed the entire course of the game and sensed no dramatic distinction in the process and procedure of solving the task between small and large sessions. This anecdotal evidence could at least to some extent relieve this concern.

Our results hence convey an important message to the literature studying the effect of induced identity on individual behavior. In a repeated interaction setting, the effect of induced identity on individual behavior does not differ depending on the number of people with whom a manufactured identity is shared. Consequently, variation in experimental session size does not generally affect subjects' perception of group membership or their behavior. However, on the other hand, the effect of identity does vary between small and large number of people who share the identity in the initial interaction, which implies that session size should be particularly controlled in one-shot interactions.

It is also worth noting that our results lend support to a general finding in the induced identity literature that the extent to which induced identity affects individual behavior depends on the salience of identity (see, e.g., Eckel and Grossman, 2005; Charness et al., 2007). Our finding that identity does not significantly affect individual cooperative behavior, regardless of experimental session size, except in the first period in small sessions may be explained by the relatively low strength of identity even in our strong identity treatments. This low strength could be rooted in the Chinese culture. Since Chinese people tend to be more conservative and connotative compared to westerners, it may take longer for them to get acquainted and identified with one another, which may be beyond the timeframe of an experiment. Weng and Carlsson (2014) induce identity by allowing communication in solving a group task via an online chat program in public good game playing groups with Chinese university students, and again fail to find any significant effect of identity, whereas such method is effective among university students in the U.S. (Chen and Li, 2009) and New Zealand (Morita and Servátka, 2011).

4. Conclusions

In previous studies on the impact of group identity where the identity has been induced in all subjects in an experimental session, the effect of session size has largely been ignored. Since interactions often take place between/among some of the subjects, variations in the total number of subjects may affect their perception of the extent of the interactions and consequently the results of the interactions. The present paper investigates how the effect of induced identity on individual cooperative behavior differs depending on session size in a repeated public good experiment. We find that induced identity significantly enhances cooperation only when session size is small and only in the initial period. That the difference in the effect of identity in small and large sessions disappears already in the second period suggests that the role of session size may become dominated by other factors, and that session size does not confound the effect of identity in repeated interaction settings.

Our study attempts to raise attention to controlling session size in laboratory experiments which involve activities conducted with all subjects in a session. The activities include not only identity building but also others that could affect people’s perception in a similar manner. A natural extension is to use another identity-building activity or method to test the robustness of our findings. It would also be interesting to consider a broader range of session size variations in different games to identify the potential thresholds to behavioral differences.

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Table 1. Summary of the experimental design

Treatments	Session size	Identity
Small-Weak	8	Weak
Large-Weak	24	Weak
Small-Strong	8	Strong
Large-Strong	24	Strong

Notes: "Small-Weak" refers to the small session/weak identity treatment; "Large-Weak" refers to the large session/weak identity treatment; "Small-Strong" refers to the small session/strong identity treatment; "Large-Strong" refers to the large session/strong identity treatment.

Table 2. Cumulative period average contributions across treatments

Period	Treatment average contributions				*P*-values from Mann-Whitney U tests			
	Small-Weak	Large-Weak	Small-Strong	Large-Strong	Small-Weak = Large-Weak	Small-Strong = Large-Strong	Small-Weak = Small-Strong	Large-Weak = Large-Strong
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	22.40	24.13	27.67	23.08	0.616	0.129	0.083	0.764
1-2	23.79	25.18	29.13	24.65	0.729	0.214	0.149	0.954
1-3	24.85	26.72	29.77	26.00	0.751	0.387	0.248	0.908
1-4	25.48	26.79	29.86	26.47	0.931	0.419	0.341	0.954
1-5	25.90	26.66	29.90	26.69	0.840	0.564	0.341	0.863
1-6	25.61	26.37	29.59	27.04	0.931	0.603	0.371	0.773
1-7	25.55	25.71	29.35	26.91	0.885	0.729	0.453	0.817
1-8	25.00	24.91	29.06	26.86	0.954	0.773	0.419	0.686
1-9	24.26	24.10	28.48	26.35	0.954	0.863	0.470	0.644
1-10	23.19	22.93	27.13	24.81	0.954	0.817	0.583	0.644

Notes: The left panel reports the cumulative period average contributions across treatments, starting from period 1 only, to first two periods, to all ten periods. The right panel reports the *p*-values of the pair-wise treatment comparisons using Mann-Whitney U tests.

Table 3. Determinants of contributions

Dependent variable: contribution of subject *i* in period *t*, $c_{i,t}$		
	(1)	(2)
Small	0.265	0.486
	(4.339)	(4.677)
Strong	1.883	2.208
	(3.789)	(4.087)
Small×Strong	2.056	1.583
	(5.946)	(6.355)
Period 1×Small		-2.215
		(3.871)
Period 1×Strong		-3.250
		(3.688)
Period 1×Small×Strong		4.729
		(5.196)
Period 1	11.359***	12.910***
	(1.620)	(3.344)
Period 2	14.094***	14.094***
	(1.459)	(1.461)
Period 3	16.182***	16.182***
	(1.426)	(1.427)
Period 4	15.141***	15.141***
	(1.476)	(1.477)
Period 5	14.865***	14.865***
	(1.469)	(1.470)
Period 6	13.521***	13.521***
	(1.539)	(1.540)
Period 7	12.297***	12.297***
	(1.339)	(1.340)
Period 8	10.531***	10.531***
	(1.469)	(1.470)
Period 9	7.557***	7.557***
	(1.092)	(1.093)
Constant	11.370***	11.215***
	(3.264)	(3.458)
Observations	1920	1920
Wald Chi2	194.59***	204.13***
Linear combination of the model coefficients:		
(i) Small + Small×Strong	2.321	
	(4.065)	
(ii) Strong + Small×Strong	3.940	
	(4.582)	
(iii) Strong + Small×Strong + Period 1×Strong + Period 1×Small×Strong		5.271*
		(3.045)

Notes: Table reports the regression results for random effects GLS model with robust standard errors clustered at the group level. Standard errors are in parentheses. The bottom panel shows the Wald test results of linear hypotheses about the model coefficients. Period 10 is used as the base period and omitted from the regression. *** indicates significance at the 1% level, * at the 10% level.

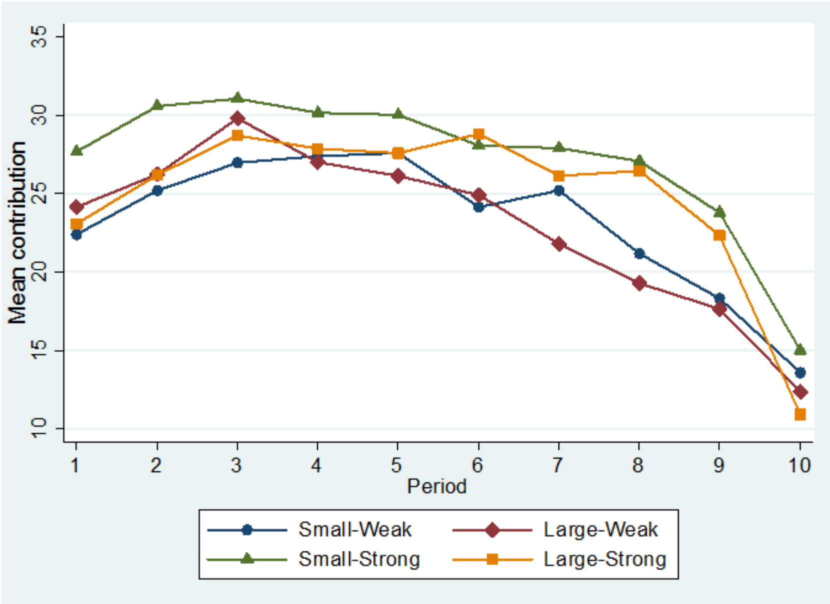


Figure 1. Evolution of average contributions across treatments

Appendix A. Instructions

Here we provide a sample copy of the experimenter's instructions we used in our Large-Strong treatment. The instructions for the other treatments were adapted accordingly. The instructions were originally written in Chinese. The first part of the experiment is conducted without using computers in an activity room. Instructions are read by an experimenter to the participants. After this part, participants are led to the laboratory, and the remaining part is conducted using computers. The instructions are read aloud by an experimenter as the participants follow along on their own copies.

In the Activity Room

Hello, everyone! You are now taking part in an economic experiment. During the experiment, all of you will be asked to do some activities and make some decisions. You can earn money by making these decisions. The amount of money you earn will depend on the decisions you make and on the decisions that other participants make.

The experiment has two parts and 24 participants. We will first play a game here, and then go to the laboratory to conduct the second part using computers. The experiment will in total last for approximately 65 minutes.

The game we will play is called the "human knot." The rules are as follows: Everyone please stand shoulder to shoulder, facing each other in a circle. First, please lift your left hand and reach across the ring to take the hand of someone standing on the other side. Next, please lift your right hand and reach across the ring to take the hand of another person standing on the other side. Please make sure that you are not holding hands with someone standing directly beside you, and that you are not holding two hands with the same person. Ok, you have formed a knot. Now let's try to untangle the knot to form one or a couple of circles of people without letting go of any hand. If you let go of a hand, please grab that hand again immediately. You will have 10 minutes to do the untangling. You are free to discuss how to untangle the knot.

Next we will conduct the experiment in the laboratory. Please take all your belongings with you and go to the laboratory with me.

In the Laboratory

The rest of the experiment is computerized. It consists of two parts. The instructions you have now are for the first part. I will read the instructions aloud, and you can follow along on your copies. **All your decisions and answers to questions will remain confidential and anonymous**.

It is prohibited to communicate in any way with the other participants during the experiment. If you violate this rule, you will be dismissed from the experiment and denied all payments. If you have any questions during the experiment, please raise your hand and the experimenters will come to help you.

During the experiment we will not speak in terms of Renminbi (RMB), but of experimental currency units (ECUs). At the end of the experiment, the total amount of ECUs you have earned will be converted to RMB at the following rate:

1 ECU = 0.1 yuan RMB

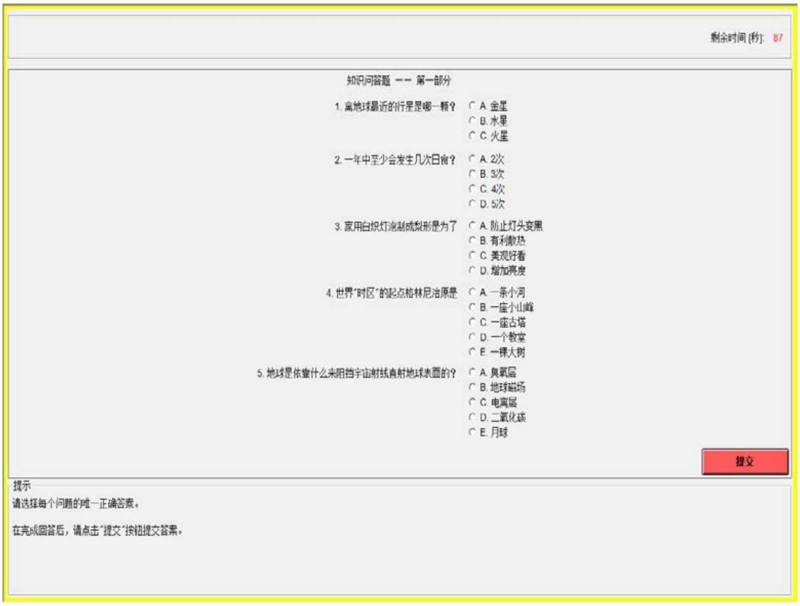
Your entire earnings from the experiment plus the show-up fee of 10 yuan RMB will be immediately paid to you **in cash in private in another room**.

The first part

In the first part of the experiment, you will be asked to complete a quiz individually. You are given 6 minutes to answer 20 general knowledge questions. For each question we will provide 3, 4, or 5 response alternatives, but **only one** of them is correct.

Each screen will display five questions. In the top right corner of your screen you can see how much time remains for you to answer the questions on the current screen. You may change your answers as many times as you want; your final decision must be made before the time displays 0 seconds by clicking the “Submit” button. Once you have done this, your answers can no longer be changed. You may leave the answer blank for any question; the response will then be considered a wrong answer. Even if you do not answer any questions on a screen, please still click the “Submit” button to show that you have finished. If you finish before the time is up, please wait for the other participants to answer the questions. After all participants have submitted their responses, the next screen of questions will appear automatically. Please raise your hand if you have any questions.

Quiz screen



The second part

The second part of the experiment consists of 10 separate periods. Four participants in this room will be randomly assigned to a team. **The composition of the teams will stay the same throughout the experiment.** It is not possible to identify each other. The total income from the experiment will equal the sum of the period income.

At the beginning of each period, each member of your team will receive **50 ECUs**, from here on referred to as the **endowment**. You and your fellow team members are asked to allocate the endowment between two activities - **individual work** and **team work**. In particular, your task is to decide how much of your endowment to allocate to the individual work and to the team work, respectively. You (and the other members of your team) can allocate any proportion of the endowment to the individual work or the team work. At the beginning of each period, the following input screen will appear:

Input screen

The period number appears in the top left corner of the screen. In the top right corner, you can see how much time remains for you to make your allocation decision. You will have 90 seconds in the first two periods and 60 seconds in the remaining periods. You make your decision by typing an integer number between 0 and 50 as your allocation to the team work. The remaining endowment will automatically be considered your allocation to the individual work. You can revise your decision as many times as you want, but your final decision must be made before the time displays 0 seconds by clicking the “Submit” button. Once you have done this, your decision can no longer be revised. If you finish before the time is up, please wait for other team members to make the decision.

Your income at the end of each period consists of two parts:

(1)Your income from the individual work. The individual work yields 1 ECU for each ECU you allocated.

(2)Your income from the team work. Your earning (and everyone else’s in your team) is equal to 0.5 times the total allocation by all members of the team to the team work.

Your income of a period = 1 × (allocation to the individual work) + 0.5 × (team total allocation to the team work)

Each team member's income from the team work is calculated in the same way. This means that each team member receives the same income from the team work. Suppose that the sum of the allocation to the team work from all team members is 60 ECUs. In this case, each member of the team receives an income from the team work of 0.5×60=30 ECUs.

After all members of your team have made their decision, the following screen will show you the total amount of endowment allocated by all four team members to the team work as well as your income for the period. In the first two periods you will have 45 seconds and in the remaining periods 30 seconds to view this income screen. If you finish before the time is up, please click the "Continue" button.

Income screen

Next, the information screen will appear. It shows how much each team member allocated to the team work as a percentage of his/her endowment in the period; that is, the allocation rate. At the beginning of each period, each team member will be randomly assigned a number from 1 to 4 as his/her identification number. Your allocation rate will be shown under the text "You." Those of the other team members will be displayed under the corresponding identification numbers. Although the team composition stays fixed, the identification numbers are **changed randomly in each period**. Hence, the same identification number may represent a different member for each period. You will have 45 seconds in the first two periods and 30 seconds in the remaining periods to view this screen. Do you have any questions?

Information screen

The decision making is over now. Please remain seated, and complete a survey that is shown on your screen in a moment.

Control questions:

Before making your actual decision, please first answer all control questions. They serve as a test of your understanding of payoff calculations. There is no time limit on answering the control questions.

1. Each team member has an endowment of 50 ECUs. The other three team members together allocate a total of 40 ECUs to the team work. What is:
   a. Your income at the end of the period if you allocate 0 ECUs to the team work? ……….
   b. Your income at the end of the period if you allocate 10 ECUs to the team work? ……….

2. Each team member has an endowment of 50 ECUs. You allocate 18 ECUs to the team work. What is:
   a. Your income at the end of the period if the other team members together allocate a further total of 16 ECUs to the team work? ……….
   b. Your income at the end of the period if the other team members together allocate a further total of 52 ECUs to the team work? ……….

Appendix B. Post-Experiment Survey

Please answer the following survey questions. All your answers will remain confidential and anonymous. (*Summary statistics are in italics in parentheses.*)

1. What is your age? _____ *(Mean 21.7, Std Dev 2.2, Median 21.5, Min 17, Max 33)*
2. What is your gender?
   (a) Female *(73.4%)*
   (b) Male *(26.6%)*
3. What is your ethnic group?
   (a) Han *(85.9%)*
   (b) Zhuang *(0.5%)*
   (c) Man *(3.7%)*
   (d) Hui *(3.1%)*
   (e) Miao *(0.5%)*
   (f) Weiwu'er *(1.0%)*
   (g) Tujia *(1.0%)*
   (h) Yi *(0.5%)*
   (i) Menggu *(0.0%)*
   (j) Zang *(0.5%)*
   (k) Other, please specify _____ *(3.1%)*
4. Which kind of household registration did you hold before enrolling into university?
   (a) Rural *(46.3%)*
   (b) Urban *(53.7%)*
   (c) No household registration *(0.5%)*
5. What was your permanent home address before enrolling into university?
   Province (City) _____ City (District) _____ County _____ *(Subjects are from 30 provinces of mainland China, excluding Shanghai)*
6. How many biological siblings do you have excluding yourself (if you are the single child, please write 0)? _____ *(0 siblings 40.1%, 1-2 53.6%, 3 or more 6.3%)*
   If you have any biological siblings, please specify your order in the siblings _____
   (a) First *(47.0%)*
   (b) Second *(33.9%)*
   (c) Third *(13.0%)*
   (d) Fourth *(3.5%)*

(e) Fifth *(2.6%)*

(f) Sixth *(0.0%)*

7. How many siblings, half-blood siblings, cousins have you been living with for more than six months of a year (including six months) before enrolling into university (if none, please write 0)? _____ *(0 siblings 42.7%, 1-2 40.6%, 3 or more 16.7%)*
8. Have you been to a boarding high school?

(a) Yes *(60.4%)*

(b) No *(39.6%)*

9. Please choose in which of the following categories that your family (with which you lived before enrolling into university) current monthly before-tax total income falls into? _____

<400	401-1000	1001-2000	2001-3000	3001-4000	4001-6000	6001-8000	8001-10000	10001-20000	20001-30000	30001-40000	> 40001
2.6%	*8.9%*	*17.7%*	*14.6%*	*15.6%*	*17.7%*	*8.8%*	*6.8%*	*4.7%*	*1.0%*	*1.6%*	*0.0%*

10. What is your major?

School/Institute/Center____________ Department____________ Major____________

11. Are you an undergraduate or graduate student?

(a) Vocational degree student *(1.0%)*

(b) Bachelor student *(71.4%)*

(c) Master student *(27.6%)*

(d) PhD student *(0.0%)*

(e) Post-doctoral student *(0.0%)*

12. Which year are you in your program? _____ *(Mean 2.1, Std Dev 1.1, Median 2, Min 1, Max 5)*
13. Are you a member of the Communist Party?

(a) Yes *(26.6%)*

(b) No *(73.4%)*

14. Are you a member of any civic voluntary association (e.g. political, interest groups, sports, culture, nonprofit, etc.)?

(a) Yes. *(44.8%)* Please specify the full name of all associations that you are a member of, with a comma between the names _____

(b) No *(55.2%)*

15. Have you ever participated in any economics experimental studies before?
    (a) Yes. *(19.3%)* Please specify the number of times _____ *(Mean 1.1, Std Dev 0.4, Median 1, Min 1, Max 3)*
    (b) No *(81.5%)*
16. Have you ever participated in any psychology experimental studies before?
    (a) Yes. *(66.1%)* Please specify the number of times_____ *(Mean 3.1, Std Dev 3.3, Median 2, Min 1, Max 30)*
    (b) No *(33.9%)*
17. How many other participants in the session do you know from before (if none, please write 0)? _____ *(0 other participants 78.7%, 1-2 20.8%, 3 or more 0.5%)*
18. In the past twelve months, have you donated money or goods to or done volunteer work for charities or other nonprofit organizations?
    (a) Yes. *(75.5%)* Please specify the total amount ¥_____ *(Mean 145.2, Std Dev 194.1, Median 100, Min 0, Max 1200)* and/or the number of hours _____ *(Mean 40.5, Std Dev 74.3, Median 15, Min 0, Max 500)*
    (b) No *(24.5%)*
19. On a scale from 0 (least) to 10 (most), please rate how closely attached you felt to your own team throughout the experiment. _____ *(Mean 4.3, Std Dev 3.0, Median 4, Min 0, Max 10)*

Least										Most
0	1	2	3	4	5	6	7	8	9	10

20. **(For strong identity treatments only)** On a scale from 0 (least) to 10 (most), please rate how much you think the "human knot" game helped enhance the sense of being in a team. _____ *(Mean 5.8, Std Dev 3.0, Median 6, Min 0, Max 10)*

Least										Most
0	1	2	3	4	5	6	7	8	9	10

Paper III

China Economic Review 23 (2012) 801–818

Contents lists available at SciVerse ScienceDirect

China Economic Review

Multi-product firms, product mix changes and upgrading: Evidence from China's state-owned forest areas

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ARTICLE INFO

Article history:
Received 10 September 2011
Received in revised form 11 February 2012
Accepted 6 April 2012
Available online 13 April 2012

JEL classification:
D22
E23
L11
O14

Keywords:
Multi-product firms
Product mix changes
Product upgrading
Firm characteristics
China's state-owned forest areas

ABSTRACT

Product selection matters for a firm's productivity and long-run growth. Recent theoretical and empirical studies indicate that an important margin of adjustment to policy reforms is the reallocation of output within firms through changes in product mix decisions. This paper examines the frequency, pervasiveness and determinants of product-switching and upgrading activities in firms located in China's state-owned forest areas during a period of gradual institutional and managerial reforms (2004–2008). We find that changes to the product mix are pervasive and characterized by adding or churning products rather than only shedding products. Moreover, changes in firms' product mix have made a significant contribution to the aggregate output growth during our sample period. We also find that firms with different characteristics, human capital and market conditions differ in their propensity to diversify and upgrade product mix.

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1. Introduction

A rapidly growing literature indicates that what a country makes matters for its growth. In the endogenous growth models, such as those in Aghion and Howitt (1998) and Barro and Sala-i-Martin (2003), long-run growth tends to depend on economic structure and the rate at which it is being transformed. These models suggest that specializing in the production of some products is more growth promoting than specializing in others. Hausmann, Hwang, and Rodrik (2007) construct a quantitative index that ranks traded goods in terms of their implied productivity, and show that countries that latch on to higher productivity goods will perform better subsequently. UNIDO (2009) also finds that there is a strong and positive relationship between the sophistication level of a country's industrial production structure (in terms of technology, organizational quality, design and logistics) and its subsequent growth.

As this literature suggests, an important channel for fostering economic growth is to move up the product sophistication ladder by altering the production structure to products that embody high productivity and generate positive learning spillovers to the rest of the economy. However, product switching may be costly. Production of a new good requires investment, the costs of which are borne by the pioneer entrepreneur in full whereas the gains may not be fully appropriated. This occurs in both

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doi:10.1016/j.chieco.2012.04.002

technology innovation and importation processes. Hence, if the inducements such as investment subsidies or anti-competition policies to discover costs in new activities are inadequate, product switching may not happen and the investment already made may well be sunk (Acemoglu, Aghion, & Zilibotti, 2006; Hausmann & Rodrik, 2003). Besides, unfavorable institutions and regulations on input and/or output markets tend to retard product switching due to the associated high sunk costs (Goldberg, Khandelwal, Pavcnik, & Topalova, 2010). Under such circumstances, economic growth is likely to be slowed down.

The link between a country's product sophistication and economic growth applies at the industry and firm level too (UNIDO, 2009). However, there are still few studies on the characteristics and product mix decisions of multi-product firms from developing country settings. The present paper examines patterns of product selection, switching and upgrading, and the determinants of the changes at the firm level. First, it analyzes how firms located in China's state-owned forest areas adjust product lines over a period during which gradual institutional and managerial reforms occurred. Whether a reform can induce a reallocation of resources within industries that will render gains in aggregate output is a core issue for assessing the effect of the reform. Until quite recently, research into industry dynamics has addressed this issue by focusing exclusively on firm entry and exit where each firm is treated as producing a single product, and the adjustments of extensive margins undertaken by multi-product firms through adding and dropping products are ignored (Bernard, Redding, & Schott, 2010). Some recent papers empirically examine the contribution of firms' product mix changes to the changes in firms' output over time and find it significant (e.g., see Bernard et al. (2010) for the US, Goldberg et al. (2010) for India and Navarro (2008) for Chile).

The second question this paper seeks to address is how firm-level characteristics drive the decision of a continuing firm to alter and upgrade the product mix under the institutional and managerial reforms. We model both product growth rate and the probability of a continuing firm to change product mix against three sets of variables—firm characteristics (ownership, firm age, size, technology level measured by research and development (R&D) intensity and computerization level, productivity level, and product scope), human capital (age, experience, education and political connections of the manager, and education of workers) and market environment variables (credit constraints and perceived raw material supply constraints measured by perceived wood, energy, and other raw material supply constraints). In order to investigate the drivers of upward moves of the product portfolio in the productivity hierarchy, we model the likelihood that a continuing firm will upgrade its product structure as a function of the same variables. An increase in the firm's detrended overall productivity associated with the whole product bundle computed as a firm-level analogue to the index in Hausmann et al. (2007) is used as the measure for product upgrading.

The analysis is based on a unique firm-level panel dataset for the years 2004 and 2008 coming from surveys conducted in China's state-owned forest areas. China's state-owned forests account for 42% of the country's total forest area, 68% of total timber volume, and almost all of the nation's natural forest resources. They mainly locate in the upper reaches of large river basins and mountainous regions, and provide various forest-related products and important environmental services (Xu, Tao, & Amacher, 2004). While historically having contributed enormously to China's economic development, these areas have relapsed into the problem of "two crises"—ecological degradation and economic loss-making. In order to alleviate this problem, the government has implemented a series of gradual institutional and managerial reforms in recent years that altered the conditions in which the firms operated. While all firms used to be state- or collective-owned workshops of state forest bureaus (SFBs) which are the key economic and political actors in the state-owned forest areas, some of the firms have been privatized, and restructuring of the remaining ones is still ongoing. These areas hence provide an interesting case and an attractive setting. In addition, this dataset contains very detailed product information, not available in most other Chinese dataset, which allows our investigation on product switching and output growth. Moreover, firms in the forest areas usually engage in activities that do not require massive sunk cost investment in new state-of-the-art technology, which implies product switching is not prohibitively expensive and may happen.

We find that there is considerable variation in the value-added associated with different products. Within the same industry multi-product firms in our sample are larger, more productive and more likely to export than single-product firms. In addition, product mix changes are frequent in our sample. Such changes are characterized by adding or churning products rather than only shedding products, and multi-product firms are more likely to change product mix than single-product firms, especially through product churning. Moreover, changes in firms' product mix have made a significant contribution to the aggregate output growth during our sample period.

The econometric results further indicate that some firms are more prone to diversify and upgrade their product mix than others. Firms that are older, have an R&D department, produce a single product, have a lower proportion of workers with college degree or above, have separate manager and Communist Party leader, and face wood supply constraint in 2004 have higher product growth rate between 2004 and 2008. Firms that are less computerized, produce multiple products, have a manager with college degree or above, and have less difficulty in accessing external finance are more likely to change their product mix. Moreover, firms that are less productive, whose manager has no experience of working in governmental organizations but works concurrently as the Party leader, and that are not confronted with constraints in either external finance or energy supply tend to have higher probability to upgrade product portfolio subsequently. These results hold when we control for attrition also.

The remainder of the paper is structured as follows. Section 2 reviews the literature on firm-product level heterogeneity, and the link between productivity of a country's industrial production structure and growth. Section 3 introduces the background of China's state-owned forest areas and ongoing reforms, and describes the data. Section 4 documents the firm-product level patterns. Section 5 presents the nature of product mix changes between the sample years. Section 6 discusses the econometric models and reports the results. Section 7 concludes with a brief discussion on policy implications.

2. Literature review

This paper relates primarily to two strands of a rapidly growing literature. One studies patterns of heterogeneity observed at firm-product level to understand how firms respond to changes in their economic environment. The other examines the link between productivity of a country's industrial production or export structure and growth.

Developments in the first strand of literature have been stimulated by the need to ameliorate the drawbacks in the previous research in industry dynamics, where studies focus almost exclusively on the contribution of firm entry and exit to resource reallocation, treat each firm as producing a single product and ignore the adjustments of the extensive margins undertaken by multi-product firms through adding and dropping products in response to policy reforms (Bernard et al., 2010). The analysis on multi-product firms' product mix decisions is intriguing since the intra-firm resource reallocation can potentially be a significant source of productivity increase at the firm level (Aw & Lee, 2009).

Bernard et al. (2010), Goldberg et al. (2010) and Navarro (2008) document patterns of firm characteristics and product mix changes for the US, Indian and Chilean manufacturing firms over the period of 1987–1997, 1989–2003 and 1996–2003 respectively.[2] Though differences in their product classifications and design of firm-level surveys make it difficult to compare results related to firm and product characteristics across countries, some similar patterns are observed. One common finding is that multi-product firms are stronger performers: multi-product firms are larger in terms of output,[3] more productive and more likely to export than single-product firms. In addition, they all find that product switching is a very common activity: 54% and 28% of surviving firms alter their product mix every five years in the US and Indian firms, and three quarters of Chilean firms change product composition in the sample period. Furthermore, changes in firms' product mix have made a considerable contribution to aggregate output growth: it accounts for 25% and 55% of the net increase in Indian and Chilean manufacturing output during the sample period, respectively. These findings stress the importance of product-switching activities for output growth and justify the focus on firms' product margin in empirical work (Goldberg et al., 2010; Navarro, 2008).

This firm-product level heterogeneity is usually related to international trade liberalization in this strand of literature. While differing in their assumptions regarding firm-product characteristics and dynamics, recent theoretical models of multi-product firms all predict that the range of products within a firm (i.e. firm scope) is an important margin of adjustment in response to trade policy changes (see Bernard, Redding, & Schott, 2009; Eckel & Neary, 2010; Nocke & Yeaple, 2006). A common approach in this literature is to treat product switching as a selection process based on the efficiency (trade costs) of the products. Firms drop their least efficient products, hence reduce scope, and concentrate resources on their core competence. Some empirical analyses provide support for the theoretical predictions. Iacovone and Javorcik (2010) find that fringe products are more likely to be shed than core products in Mexican manufacturing firms during the period of 1994-2003 after the implementation of the North American Free Trade Agreement. Aw and Lee (2009) document trends of specialization in the Taiwanese electronics sector during the 1990s under the circumstances of increased foreign competition.

Relocation of firms across industries or product lines is also empirically relevant in industry dynamics (Plehn-Dujowich, 2009). Dunne, Klimek, and Roberts (2005) study plant exit patterns in seven industries in the US using Census of Manufactures data for the period from 1963 to 1997. They distinguish two modes of exit: a plant exits the market by entirely shutting down its operation, or the plant remains open but shifts its production toward other products. Averaging across all industries and census intervals, product-line shifts in ongoing plants account for 22% of all exits, while plant closures account for the remaining 78%. When identifying the factors influencing the choice between the modes of exit, Dunne et al. (2005) find that larger and more productive firms are more likely to exit by changing their product lines. On the other hand, market demand has no effect on the decision of a firm to shift out of an industry versus shutdown.

The emerging literature focusing on the link between productivity of a country's industrial production or export structure and growth originates from the work of Hausmann et al. (2007). The principal message conveyed is that what countries produce matters. While the argument that specializing in the production of some products is more growth promoting than specializing in others is not new, Hausmann et al. (2007) establish a quantitative index by which learning-by-doing effects—a cornerstone in endogenous growth models—can be empirically verified. They first rank traded goods in terms of their implied income or productivity, constructed as the weighted average of per-capita GDPs of the countries exporting a particular product (which they call PRODY). They then construct the income or productivity level corresponding to a country's export basket as a measure of that country's specialization pattern (which they call EXPY), by calculating the export-weighted average of all the PRODYs for that country.[4] This approach attempts to classify products according to the outcomes of structural change they embody rather than the process technology they use (UNIDO, 2009). They find that after controlling for standard covariates countries that specialize in producing and exporting more sophisticated products, those that are primarily manufactured and exported by countries at higher income levels, tend to grow faster subsequently. Two prominent examples are China and India, whose industrial productivity levels are much higher than what would be predicted based on their income levels. The economic mechanism behind this link is that growth is a result of transferring resources from lower-productivity goods to higher productivity goods identified by the entrepreneurial "cost discovery" process that generates positive knowledge spillovers from the pioneer entrepreneur into new activities to emulators. Since the positive externalities imply that investment levels in "cost discovery" among private economic

[2] The unit of observation for Navarro (2008) is plant rather than firm.
[3] Bernard et al. (2010) and Navarro (2008) also report that multi-product firms are larger in terms of employment.
[4] Hausmann et al. (2007) focus on exports rather than on production partly because they have more detailed data on exports.

agents are sub-optimal, Hausmann et al. (2007) suggest government-led industrial policies to promote entrepreneurship and investment into new activities. UNIDO (2009) provides support to the aforementioned positive relationship.

3. Data

3.1. Background of China's state-owned forest areas and its reforms

Accounting for 42% of China's total forest area, 68% of total timber volume and almost all of the nation's natural forest resources (Xu et al., 2004), China's state-owned forest areas are an important part of the forest sector.[5] The formation of state-owned forest areas dates back to the early 1950s, when the vast natural forests mainly in northeastern and southwestern China were decreed to be owned by the state. SFBs, which are actually state-owned enterprises, serve as the key economic and political actors in the state-owned forest areas, with timber logging and transportation, wood processing and silviculture as three primary business sections. [6] They were set up in the 1950s and 1960s by the government to harvest the nationalized natural forests for industrial use. There are 135 such SFBs in China,[7] each of which administers hundreds of thousands of hectares of forest area, and employed up to a total of one million people throughout the 1980s and 1990s (China Forestry Statistical Yearbook, 1987–2000). These SFBs as part of the state-owned enterprise system, were also responsible for providing social services for the communities where they located, many of which came into existence due to the establishment of the bureaus (Bennett, Jiang, & Xu, 2008).

To facilitate wood processing and related product manufacturing, the SFBs set up thousands of smaller mills, which located in geographical vicinity and were often part of the so-called integrated forestry system. Although a majority of them produce wood related products, there are also a host of mills operating in other sectors, such as food and beverage manufacturing, or providing ancillary services to the processing mills, such as machine manufacturing and maintenance. In the planned economy era, the SFBs were both owners and managers, and were the only legal agents to deal with the state over taxation and profit-contracting and with external economic agents (Zhang, 2000). The mills acted only as workshops of the bureaus with all land, capital and other material inputs supplied through budgetary channels, and all profits required to be remitted to the bureaus.

Up through the late-1980s to mid-1990s, the operating expenses and social welfare responsibilities of the bureaus could generally be covered by the revenues generated from timber production and processing from natural forests, despite in many cases via unsustainable harvesting practices (Bennett et al., 2008). However, like other sectors in the planned economy, most SFBs suffered from low efficiency, overstaffing and weak competitiveness and up to the 1990s most of them run into net losses. The state forest sector relapsed into the problem of “two crises”—ecological degradation and economic loss-making. Hence since the mid-1990s the attempts to restructuring the processing section have never ceased. In general, the reforms have followed more or less the same course as in other state-owned industrial sectors (Zhang, 2000), but at a lower rate. They have focused primarily on the implementation of “managerial responsibility systems” and on the transformation of organizational models, and then switched to privatization.

“Managerial responsibility systems” were introduced to depoliticize the mills. Under these systems, managers were delegated autonomy to make many decisions, and both managers and workers were given financial incentives—primarily bonuses—contingent on mill performance which was measured by the sum of turned-in taxes and profits to the SFB. In addition, new managers were not exclusively appointed by the SFBs anymore, but through auctioning-off to select competent candidates. The mills became independent cost accounting units, which was a step toward the modern form of firm management. Manifold organizational reform was also widely implemented, including multi-mill corporation formation, joint-stock reform, contracting management, lease management, etc. (Li & Zhang, 2000). All these arrangements reflected the attempts to maximize the value of the processing business section and to align the interests of the managers and workers with those of the owners.

However, the agency problem was still prevalent and the residual claim of rights was unclear in the state-owned mills. A gradual process of privatization was hence initiated in the late 1990s, partly evoked by the introduction of the Natural Forest Protection Program (NFPP) due to the severe floods in 1998, which called for a logging reduction in state-owned forests and exacerbated the situation of mills whose raw material was mainly bought from local SFBs. Marketizing the mills and removing the political influence of the SFBs were the main policy changes purporting to alleviate the “two crises”. The privatization process is still ongoing.

3.2. Data collection

This study uses combined panel data on firms and SFBs located in China's Northeast-Inner Mongolia state-owned forest area, collected in face-to-face interviews with firms' management and SFBs' officials in 2005 and 2009 by the Environmental Economics Program in China. The survey area covers Heilongjiang and Jilin provinces and Inner Mongolia Autonomous Region, and the dataset includes information for 2004 and 2008.

The sampling frame for the SFBs and firms is as follows. The forests in this area are, based on geographical locations, under the jurisdiction of seven regional SFBs and managed by 84 subordinated SFBs. The survey covered all seven regional SFBs. At each

[5] The other part of China's forest sector is collective forest areas.

[6] In China's state-owned forest areas, besides the administrative functions, SFBs operate as corporate enterprises. Their enterprise feature mainly embodies timber production and processing for revenue. This differs from the role of forest bureaus in collective forest areas whose sole responsibility is regional forest resource administration.

[7] There are 20 other SFBs in China's state-owned forest areas operating only for afforestation and reforestation.

level the samples were randomly selected to guarantee representativeness. In each regional SFB, the subordinated SFBs were stratified into three groups by the size of the forest area administered, and one was randomly selected from each group.[8] Ten firms were then randomly selected from each of the chosen SFBs. In total 206 firms were finally included in the survey.[9] Since 32 firms did not provide detailed product information or data on other major variables, they are excluded from our analysis. As a follow-up survey, the 2009 survey tracked the same SFBs and firms that were interviewed in 2005 and no new entrants were taken into consideration. Systematic reasons (e.g. shutdown, merger and acquisition, temporary suspension of production) and random dropouts (e.g. non-reachable, decline to answer, missing values in major variables) rendered a reduction in the number of firms to 97 in the 2008 data.[10]

While the sample size is small, the information collected is rather rich. At the SFB level, it contains information on SFBs' forest resource, production and sales, financial status, employment, leadership and ongoing projects. At the firm[11] level, the questionnaire consists of two parts. One part, designed to be answered by the firm manager, asks questions about the firm's basic characteristics, ownership structure and privatization process, histories of manager turnover, managerial arrangements, and contractual relations with the SFBs. The other part, directed to the accountant, covers details about the firm's major financial sheets and use of inputs (capital, workers and wage bills, material and energy). The survey also records detailed information on each firm's product list including names, production and sales prices, quantities and thereby values. In addition, general information on product market and raw material market environments is also collected. Hence, this dataset is well suited to study how firms in the state-owned forest areas adjust their product lines over time and how their choices may be related to the firm-level characteristics.

3.3. Product classification

While our sample firms are located in forest areas, they do not exclusively produce wood related products. The reporting of products by our sample firms is not governed by any particular product classification. Since the names of products reported by the firms could differ in aggregation or the way firms called them, we standardize the product names and define product, industry and sector according to two national standards. One is China's Industrial Classification for National Economic Activities (2002), henceforth ICNEA, which categorizes economic activities in China into four levels, using English alphabets, two-, three- and four-digit codes respectively.[12] The other is China's Products Classification for Statistical Use (2010), henceforth CPC, which classifies products to a more disaggregated level. CPC uses a five-level coding system, with two-, four-, six-, eight- and ten-digit codes. ICNEA and CPC are harmonized at the two- and four-digit code levels.[13] We map all reported product names into six-, eight- or ten-digit CPC codes and take this as the definition of a "product".[14] We refer to the three-digit ICNEA categories as "industries" and two-digit ICNEA categories as "sectors". There are a total of 90 products linked to 26 industries across 17 sectors in our data.

Table 1 reports the distribution of industries and products by sector in the 2004 and 2008 pooled sample. The number of products by sector is highly heterogeneous. The number of products ranges from one in seven sectors to 47 in the Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products sector (ICNEA 20), henceforth wood processing. Similarly, the average number of products per industry within sectors ranges from one in ten sectors to 16 in wood processing. As observed in the table, 71.9% of the sample firms operate in the wood processing sector. Comparing the distributions of industries and products by sector between pooled all firms and pooled continuing firms,[15] the patterns are similar. However, in the latter sample the total number of products reduces to 74 related to 19 industries and 14 sectors, and the share of firms operating in wood processing sector falls to 70.6% (results not shown). For continuing firms the number of products and industries increases from 62 to 66, and from 17 to 18, respectively, between 2004 and 2008. In addition, the share of firms operating in wood processing sector drops from 72.2% to 69.1%.

An example of the mapping hierarchy of sectors, industries and products is given in Table A1 in the Appendix A. The table reports two industries within the wood processing sector (ICNEA 20): Processing of sawnwood and wood chips (ICNEA 201), which contains 17 products, and Manufacture of panel board (ICNEA 202), which contains 10 products. As with all classifications, the degree of detail varies across industries and sectors. Even so, we refer to firms producing only one product by our definition as single-product firms and multi-product firms otherwise. A complete list of sector, industry and product classification is available in an Online Appendix.[16]

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[8] To account for the fact that the number of SFBs under the jurisdiction of Yichun regional SFB in Heilongjiang Province doubled that in other six regional SFBs, one more set of sample SFBs was selected. Consequently, fifteen, six and three SFBs were selected from Heilongjiang, Jilin and Inner Mongolia, respectively.

[9] According to the sampling frame, 240 firms were supposed to be interviewed. However, due to the limited number of firms in some SFBs, not up to ten firms could be reached in all SFBs. In such cases, all entities were interviewed.

[10] Systematic reasons account for 56% of the observation reduction and random dropouts for the remaining44%.

[11] The unit of observation in our sample is firm. It is rarely the case that a firm has more than one plant in our sample area.

[12] ICNEA is comparable to the UNSD: 1989, International Standard Industrial Classification of All Economic Activities, NEQ.

[13] At the four-digit level, ICNEA and CPC assign the same code to most, but not all economic activities. However, this does not matter for our analysis, since we do not use the four-digit codes as our classification for product, industry or sector.

[14] Eight-digit codes are our primary standard of classification. Two products are classified at the ten-digit level. Since for some products six-digit codes that are the most disaggregated level in CPC are not disaggregated enough for our analysis, we create the eight-digit codes by ourselves. This applies to eight products.

[15] Number of observations for the pooled all firm sample is 271, 174 for year 2004 and 97 for year 2008. Number of observations for the continuing firm sample is 194, 97 firms for each year.

[16] The web address is http://www.economics.handels.gu.se/english/staff/phd_candidates/qian_weng/.

Table 1
Sectors, industries and products.

ICNEA	Sector	Products (1)	Industries (2)	Products per industry (3)	Share of firms (4)
2	Forestry	2	2	1.00	0.006
3	Husbandry	2	2	1.00	0.011
13	Processing of food from agricultural products	3	1	3.00	0.029
14	Manufacture of food	1	1	1.00	0.001
15	Manufacture of beverages	7	2	3.50	0.038
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	47	3	15.67	0.719
21	Manufacture of furniture	10	2	5.00	0.082
22	Manufacture of paper and paper products	3	2	1.50	0.015
24	Manufacture of articles for culture, education and sport activities	1	1	1.00	0.010
26	Manufacture of raw chemical materials and chemical products	1	1	1.00	0.002
27	Manufacture of medicines	4	1	4.00	0.021
31	Manufacture of non-metallic mineral products	3	3	1.00	0.018
35	Manufacture of general purpose machinery	1	1	1.00	0.007
37	Manufacture of transport equipment	1	1	1.00	0.007
41	Manufacture of measuring instruments and machinery for cultural activity and office work	1	1	1.00	0.006
42	Manufacture of artwork and other manufacturing	2	1	2.00	0.020
58	Storage services	1	1	1.00	0.007
	Total	90	26	3.46	1

Notes: Table reports the distribution of industries and products by sector. Column (1) reports the number of products by sector. Column (2) reports the number of industries within each sector. Column (3) is the first column divided by the second column. Column (4) reports the share of firms producing in each sector. If a firm produces products in multiple sectors, the share in each sector the firm produces is calculated as the number of the product(s) in that sector to the total number of products the firm produces.
Data are for the 2004 and 2008 pooled sample and the number of observations is 271.

4. Firm-product level patterns

The overall aims of this paper are to document how firms in China's state-owned forest areas adjust their product lines over a period of institutional and managerial reforms and to identify firm-level characteristics that may affect product switching and upgrading. In this section, we portray product level value-added, and compare single- and multi- product firms in terms of their economic significance and main firm characteristics.

First of all, we investigate how products differ in terms of their value-added. This is done by estimating a log-form value-added Cobb–Douglas production function with product dummies as follows:

$$lnvalueadded_{it} = \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \sum_j \theta_j P_{ij} + \alpha_t \mathrm{year}_t + \varepsilon_{it} \tag{1}$$

where $valueadded_{it}$ is firm i's value-added level in year t measured as total sales revenue[17] minus the value of total material inputs (i.e. sum of the non-labor expenses on raw materials and energy), L_{it} is firm i's labor in year t measured by number of workers, K_{it} is firm i's capital in year t measured by the net value of fixed assets, P_{ij} is firm i's product dummy for product j, and $year_t$ is the year dummy. The product dummy is equal to one over the number of product(s) for each product that firm i produces and zero otherwise. The time dimension of the product dummies is suppressed since we assume that the value-added associated with each product (θ_j) is prevailing during the whole sample period. Value-added and capital in 2008 are converted to 2004 constant values using different price indices as deflators to capture the real value changes.[18] The estimated coefficients $\hat{\theta}$s hence indicate differences in the value-added level associated with different products, conditional on the other explanatory variables in the model. Table 2 presents the estimation results of Eq. (1) by ordinary least squares (OLS). The Wald test result of the coefficient estimates associated with the product dummies indicates that the products are jointly significant at less than 1% level. The standard deviation of these estimates is around 2, implying that there is a wide dispersion of the product-specific value-added. This result suggests that product selection does matter for the value-added level for a firm as a whole.

[17] We focus on revenue-based measures of productivity rather than quantity-based measures because data on physical units of quantity are not available for all products and physical units of output are not comparable across firms for many products, e.g. wooden furniture. We are fully aware of the possible problems of revenue-based productivity measures as pointed out by Foster, Haltiwanger, and Syverson (2008) and Katayama, Lu, and Tybout (2009). It is somewhat soothing that Foster et al. (2008) find a highly positive correlation between revenue- and quantity-based measures of productivity for a sample of 11 homogenous products using the US Census of Manufactures data.

[18] Different variables in 2008 are adjusted by different price deflators to the 2004 price level. Sales revenue is deflated primarily by sectoral *producer price indices for manufactured goods*, together with *producer price index* for sector Forestry (ICNEA 2) and Husbandry (ICNEA 3), and country-level *retail price index* for sector Storage services (ICNEA 58). Capital is deflated by provincial *price indices for investment in fixed assets*. Material input is deflated by *purchasing price indices for timber and pulp paper sector*. The reason for choosing this price index is that timber and related stuff is the main material for our sample firms. Energy input is deflated by country-level *purchasing price indices for fuel and power*. All the price indices are obtained from China Statistical Yearbook (2006–2009) and based upon authors' calculation.

Table 2
Product-specific value-added.

	Ln(value-added)	
Ln(employment)	0.744	(0.109)***
Ln(capital)	0.189	(0.063)***
Product dummy	Yes	
Year dummy	Yes	
Observations	271	
R-squared	0.71	
Wald test for joint significance of product dummies (P value)	0.000	
Standard deviation of product-specific value-added estimates	1.994	

Notes: Table presents the regression result of Eq. (1). Coefficient on the constant is not reported. Data are for the 2004 and 2008 pooled sample. Robust standard errors in parentheses. *** indicates statistical significance at 1% level.

We then explore the relative economic significance of single- and multi-product firms in China's state-owned forest areas. Table 3 reports the average breakdown of single- and multi-product firms in terms of number and aggregate output (i.e. total sales), and also the average number of products, industries and sectors multi-product firms produce across 2004 and 2008. As indicated in the table, multi-product firms account for 47% of the firms and 50% of the aggregate output. They are relatively more important, but not as dominant as found in the US (Bernard et al., 2010) and Indian (Goldberg et al., 2010) cases.[19] Multi-industry and multi-sector firms exert similar influence, responsible for 34% and 9% of the firms and 43% and 25% of the output, respectively. Column (3) of Table 3 reveals that multi-product firms on average manufacture 2.76 products, that multi-industry firms on average operate in 2.25 industries and that multi-sector firms on average are present in 2.08 sectors.

Table 4 compares the characteristics of single- and multi-product firms in the 2004 and 2008 pooled sample. Each cell reports a separate OLS regression coefficient (standard error in parenthesis) of the (natural logarithm of) firm characteristics (except probability of export which is a binary dummy) on a dummy variable equal to one if the firm produces more than one product (i.e. multiple products, column (1)), operates in more than one industry (column (2)), and operates in more than one sector (column (3)), respectively, with industry and year fixed effects controlled. As reported in the table, multi-product firms in our sample are significantly larger than single-product firms within an industry in terms of output (0.751 log points), employment (0.569 log points) and capital (0.753 log points).[20 21] Multi-product firms are also more likely to export and have higher revenue-based total factor productivity (TFP)[22] and labor productivity[23] than single-product firms in the same industry, though the differences are statistically insignificant. This is in general consistent with the cross-section evidence reported by Bernard et al. (2010) and Goldberg et al. (2010). Similar patterns are discovered with respect to firms producing in multiple industries and sectors, except that the differential in probability to export turns out to be marginally significant.

The model presented in Bernard et al. (2009) predicts that firms possess "core competencies", implying that firms should have highly skewed distribution of output towards products for which they have particular expertise. We find support for this prediction in our data that the distribution of output across products within the firms is uneven and firms possess a "core competent" product, as shown in Table 5. The average share of the "core competent" product ranges from 73% to 46% in total output in firms that produce from 2 to 6 products. These results are comparable to what Bernard et al. (2010), Goldberg et al. (2010) and Navarro (2008) find for the US, Indian and Chilean manufacturing firms, respectively.

[19] Though it is nice to link our results to the findings from other studies in the literature, we have to admit that comparisons between our study and other studies must be conducted with great caution since the sample coverage, size and economic environments in which the firms operate differ tremendously.

[20] The Average size of the firms, measured by output, employment and capital across the two years, is 10,385 thousand CNY (1 USD = 6.32 CNY in January 2012), 160 employees and 6001 thousand CNY, respectively. The standard deviation is 24,237 thousand CNY, 362 employees and 17,790 thousand CNY, respectively, indicating that the range of firms covered in this dataset is large. Firms range in size from 6 to 192,314 thousand CNY in output, from 2 to 4992 in employees, and from 2 to 176,300 thousand CNY in capital.

[21] At first glance it seems to be contradictory with the finding from Table 3 that single- and multi-product firms are similar across size. When comparing the distribution of size (output, employment and capital) between single- and multi-product firms, we find that the means are very similar, whereas the median of multi-product firms is twice as large as that of single-product firms. Therefore, the similarity across size can be explained as driven by some exceptionally large single-product firms.

[22] Revenue-based TFP is measured as the residual of the log-form Cobb–Douglas production function

$$\mathrm{TFP}_{it} = \ln Y_{it} - \alpha_L \ln L_{it} - \alpha_K \ln K_{it} - \alpha_M \ln M_{it}$$

where Y_{it} is firm i's output in year t measured by total sales revenue, L_{it} is firm i's labor in year t measured by number of workers, K_{it} is firm i's capital in year t measured by net value of fixed assets, and M_{it} is firm i's materials in year t measured by the value of non-labor raw material and energy inputs. Instead of estimating the production function and obtain the estimates of input coefficients, we assume constant returns to scale and compute the factor cost shares. Factor share of labor is calculated as the share of total annual wage bill in the firm's total sales revenue, and factor share of materials is calculated as the ratio of the total expenditure on material inputs to the firm's total sales revenue. The factor share of capital is hence the residual share after deducting the shares of labor and materials from one. We then take the median of the factor shares, and they are 0.19 for labor, 0.14 for capital and 0.67 for materials.

[23] Labor productivity is measured as value-added per worker.

Table 3
Prevalence of single- and multiple-product firms.

Type of firms	Share of firms (1)	Share of output (2)	Mean products, industries or sectors per firm (3)
Single product	0.53	0.50	1.00
Multiple product	0.47	0.50	2.76
Multiple industry	0.34	0.43	2.25
Multiple sector	0.09	0.25	2.08

Notes: Table classifies firms according to whether they produce single product, multiple products, multiple industries and multiple sectors. Columns (1) and (2) summarize the share of firms in each category in terms of firm number and aggregate output, respectively. Column (3) reports the mean number of products, industries and sectors in each category. The unconditional mean product per firm is 1.83. Data are for the 2004 and 2008 pooled sample and the number of observations is 271.

5. Product mix changes over time

In this section, we follow the empirical product mix change literature (e.g., Bernard et al., 2010; Goldberg et al., 2010; Navarro, 2008) to examine the importance of changes in firms' product margin over time. The average number of products across firms in our sample increased from 1.71 in 2004 to 2.03 in 2008.

We first illustrate the nature of product mix changes between 2004 and 2008 that resulted in the observed expansion of the extensive margin. We classify continuing firms into four mutually exclusive groups based on the manner in which they alter their product mix according to the 2004 data. The possible activities are: (1) no change—the firm does not change its product mix; (2) add only—the firm only adds products, i.e. some products are produced in 2008 but not in 2004; (3) drop only—the firm only drops products, i.e. some products are produced in 2004 but not in 2008; (4) both add and drop—the firm both adds and drops products, i.e. "churns" products.

Table 6 reports results based on this classification. The top panel displays the share of continuing firms engaging in each type of product-switching activity, and the bottom panel shows a similar breakdown but weighting each firm by its output. Three findings can be obtained. Above all, product mix changes are frequent among our sample firms and adding or churning products is more common than only shedding products. As indicated in the first column of the top panel, over the four year period 61% of the surviving firms alter their product mix, 26% by adding at least one product, 8% by dropping at least one product, and 27% by both adding and dropping at least one product. This suggests that the costs are relatively low to alter product lines. Secondly, smaller firms are more likely to switch product lines. Column (1) in the bottom panel suggests that product-switching firms that account for 61% of the firms only account for 36% of the total output. Thirdly, by comparing results in columns (2) and (3) we find that multi-product firms are more likely to change product mix than single-product firms, especially through product churning. When our results are compared to the findings from the US, India and Chile, the third result is similar, however Indian firms experience much less product switching than firms in our dataset, and in the US and India larger firms are more prone to alter product mix in comparable time intervals.

In order to investigate the contribution of changes in product mix to changes in output of continuing firms, we then decompose the aggregate changes in output into changes in output due to changes in product mix (i.e. the extensive margin) and changes in output due to existing products (i.e. the intensive margin). Let Y_{ijt} be the output of product j produced by firm i in period t, E be the set of products that a firm produces only in period t or $t-1$ (i.e. the extensive margin), and I be the set of products that a firm produces in both periods t and $t-1$ (i.e. the intensive margin). The changes in a firm's aggregate output between periods t and $t-1$ can be decomposed as $\Delta Y_{it} = \sum_{j \in E} \Delta Y_{ijt} + \sum_{j \in I} \Delta Y_{ijt}$. We can further decompose the (net) extensive margin and (net) intensive margin: the former into the margins due to product addition (A) and product dropping (D), and the

Table 4
Single- and multiple-product firm characteristics.

	Multiple product (1)	Multiple industry (2)	Multiple sector (3)
Output	0.751 (0.257)***	0.965 (0.263)***	1.564 (0.539)***
Employment	0.569 (0.173)***	0.741 (0.184)***	1.157 (0.325)***
Capital	0.753 (0.304)**	1.021 (0.328)***	1.932 (0.519)***
Probability of export	0.087 (0.058)	0.125 (0.061)**	0.207 (0.122)*
TFP	0.107 (0.111)	0.017 (0.102)	−0.070 (0.157)
Labor productivity	0.083 (0.188)	0.197 (0.200)	0.205 (0.434)

Notes: Table summarizes the characteristics differences between single- and multiple-product, single- and multiple-industry, and single- and multiple-sector firms. Each cell reports a separate OLS regression coefficient (standard error in parenthesis) of the (natural logarithm of) firm characteristics (except probability of export which is a binary dummy) on a dummy variable equal to one if the firm produces multiple product (column (1)), industry (column (2)) and sector (column (3)), respectively. Data for all regressions are from the 2004 and 2008 pooled sample. Regressions also include industry and year fixed effects. Coefficients on the constant and fixed effects are not reported. The standard errors are clustered at the firm level. Number of observation for each regression is 271. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 5
Mean distribution of within-firm output shares.

		Number of products produced by the firm					
		1	2	3	4	5	6
Average share of product in firm's output (high to low)	1	1.00	0.73	0.60	0.60	0.46	0.50
	2		0.27	0.28	0.24	0.27	0.21
	3			0.12	0.10	0.13	0.14
	4				0.05	0.10	0.08
	5					0.04	0.05
	6						0.02

Notes: Columns indicate the number of products produced by the firm. Rows indicate the share of the product in firm's total output, in descending order of size. Each cell is the average across the relevant firm-products in the sample. Data are for the 2004 and 2008 pooled sample and the number of observations is 271. Here the number of products is truncated at six since the survey asked product information up to six products. If a firm manufactured more than six products, some aggregation of the products was already taken place at the survey stage.

latter into the margins due to product growing (G) and product shrinking (S). Hence the change in aggregate output among continuing firms in our sample is

$$\Delta Y_t = \sum_i \left[\left(\sum_{j \in A} \Delta Y_{ijt} + \sum_{j \in D} \Delta Y_{ijt} \right) + \left(\sum_{j \in G} \Delta Y_{ijt} + \sum_{j \in S} \Delta Y_{ijt} \right) \right] \tag{2}$$

Table 7 presents the decomposition. Column (1) reports the aggregate output growth. Columns (2)–(4) report the contribution to growth from the firms' extensive margin. Columns (5)–(7) report the contribution to growth from the firms' intensive margin. As shown in the first column, aggregate output of continuing firms increases 59% from 2004 to 2008. (Net) extensive margin and (net) intensive margin contribute to 86% (0.51/0.59) and 14% (0.08/0.59) of the growth, respectively. This finding is at odds with those from the US and India, where firms' intensive margin accounts for the majority of the output growth during their sample periods. When looking at the decomposition within extensive and intensive margins, we find that our data indicate a high level of "excess reallocation" (as coined by Bernard et al., 2010) which highlights the fact that gross changes in product output are substantially larger than the associated net changes.[24] As can be seen from columns (2)–(4), both product additions and subtractions contribute to output changes so that the gross extensive margin (0.72 + 0.21 = 0.93) is almost twice as large as the net extensive margin (0.72–0.21 = 0.51). A similar pattern can be found in the resource reallocation away from shrinking products to growing products within the intensive margin.

6. Product mix changes and firm-level characteristics

6.1. Econometric models and results

In this section, we identify the factors that may affect the decision of a continuing firm to alter and upgrade product mix. Before presenting the econometric model, we first discuss our measures for product mix changes and upgrading.

We measure product mix changes in two ways. The first indicator is the growth rate in distinct products, calculated as the number of products produced by a continuing firm in 2008 divided by the number of products produced in 2004, minus one. The second indicator is a binary dummy which is equal to one if a continuing firm adds and/or drops products between 2004 and 2008, zero if not. This variable reveals the likelihood of a continuing firm to alter product mix, either in terms of changes in product number or changes in product portfolio composition with product number kept constant.

To determine whether product mix changes amounts to upgrading, we construct an index analogous to EXPY in Hausmann et al. (2007) but at the firm level. The key underlying assumption here is that productive firms produce more sophisticated products and unproductive firms produce less sophisticated goods. An index $PRODVAD_j$, similar to PRODY in Hausmann et al. (2007), is calculated as

$$PRODVAD_j = \sum_i \frac{s_{ji}}{\sum_k s_{jk}} \cdot VAD_i \tag{3}$$

where s_{ji} is the value share of product j in firm i's total sales, $\sum_k s_{jk}$ is the aggregate of value shares across all firms producing and selling the product, and VAD_i is the value-added per worker of firm i. This index hence represents the weighted average productivity level associated with product j among its producers. Compared to the value-added associated with each product

[24] Within extensive and intensive margins, gross change in output is defined as the sum of the absolute values of the breakdowns for output change, and net change is defined as the sum of the values of the breakdowns for output change.

Table 6
Firm activity for continuing firms.

	All firms (1)	Single-product firms (2)	Multiple-product firms (3)
Percent of firms			
No change	0.39	0.54	0.22
Add only	0.26	0.33	0.18
Drop only	0.08	na	0.18
Add and drop	0.27	0.13	0.42
Output-weighted percent of firms			
No change	0.64	0.72	0.55
Add only	0.20	0.24	0.15
Drop only	0.03	na	0.05
Add and drop	0.13	0.04	0.25

Notes: The top panel displays the share of continuing firms engaging in each type of product-switching activity between 2004 and 2008. The bottom panel shows a similar breakdown but weighting each firm by its output. Continuing firms are classified into four mutually exclusive groups: no change, add only, drop only, and both add and drop. This classification suggests that a single-product firm cannot drop a product only.

derived from estimating Eq. (1), this product level productivity measure takes the relative importance of each product in a firm into consideration. The productivity level associated with firm *i*'s entire product portfolio, $SALEVAD_i$, is in turn defined by

$$SALEVAD_i = \sum_j s_{ji} \cdot PRODVAD_j \tag{4}$$

This is the weighted average of $PRODVAD_j$ for that firm. *PRODVAD* and *SALEVAD* indices are calculated for 2004 and 2008 respectively.[25] In order to take account of the co-variation in different firms' overall productivity in a given year, we detrend this index by computing the percentage difference between $SALEVAD_i$ and median *SALEVAD* in respective years as

$$DeSALEVAD_i = \frac{SALEVAD_i - median(SALEVAD)}{median(SALEVAD)} \tag{5}$$

Product upgrading is hence defined as a positive change in a firm's $DeSALEVAD_i$ between the sample years, and represented by a binary dummy taking the value of one if a continuing firm experiences such a positive change and zero otherwise.

Wang, Wei, and Wong (2010) have identified some weaknesses associated with the PRODY and EXPY indices proposed by Hausmann et al. (2007). In particular, Wang et al. (2010) argue that the key assumption underlying PRODY—the more advanced countries produce more sophisticated products—may not be true. More advanced countries may often produce a larger set of products than poor countries. Moreover, larger countries may also often produce a larger set of goods than smaller countries. These features suggest that the PRODY index may overweight advanced and large countries. Secondly, detailed diversity in the quality and variety of goods within a product category may not be revealed by the indices. As analogues to the PRODY and EXPY indices, our measures *PRODVAD* and *SALEVAD* may suffer similar weaknesses. However, our product upgrading measure tries to partly mitigate the first pitfall mentioned above. The possible overweighting of productive and large firms in *PRODVAD* may render an upward biased computation of both $SALEVAD_i$ and median *SALEVAD*, but the differencing procedure in $DeSALEVAD_i$ construction tends to offset the upward bias.

The econometric model is specified as

$$change_{it} = \beta_0 + \beta_1 firm\,char_{it-1} + \beta_2 H_{it-1} + \beta_3 market_{it-1} + \beta_4 sec_{it-1} + \varepsilon_{it} \tag{6}$$

$change_{it}$ denotes the dependent variable of interest—product growth rate, the probability of a continuing firm to change product mix, and the probability of a continuing firm to upgrade product portfolio between the sample years. All models are estimated by OLS, and the initial year's data are used for all explanatory variables to mitigate potential endogeneity problems. Firm characteristics include ownership (private vs non-private), firm age, firm size (measured by capital stock) and technology level (measured by R&D intensity and computerization level). We also control for firm productivity level (measured by the natural logarithm of TFP) and product scope (single- vs multi-product). Human capital variables include age, experience, education and political connections of the manager, and education level of workers. Market environment variables include credit constraint and perceived raw material supply constraints (measured by perceived wood, energy and other raw material supply constraints). The definitions of these variables are listed in the top panel of Table 8. We also control for sector dummies to account for sector-specific market demand conditions and shocks.

Amongst the firm characteristics variables, ownership is one important variable. Compared to non-private firms, private firms have more discretion over product choice and less interference from the SFBs in their production decision-making. In all private firms the direct managerial group, consisting of manager, Communist Party leader, board chairman or partners, controls production decision-

[25] We suppress the time dimension of the indices to keep the expressions simple.

Table 7
Decomposition of output growth for continuing firms.

Period	Aggregate output growth	Extensive margin			Intensive margin		
		Net	Product entry	Product exit	Net	Growing products	Shrinking products
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2004–2008	0.59	0.51	0.72	−0.21	0.08	0.33	−0.25

Notes: Table reports the decomposition of aggregate output growth of continuing firms in our sample between 2004 and 2008 into contribution of the extensive and intensive product margins. Column (1) reports aggregate output growth. Columns (2)–(4) report the contribution to growth from the firms' extensive margin. Columns (5)–(7) report the contribution to growth from the firms' intensive margin.

making, whereas this is true for only two thirds of the non-private firms. Some studies have shown that restructuring of state-owned enterprises in China has had positive effects on labor productivity and profitability (Bai, Lu, & Tao, 2009; Dong, Putterman, & Unel, 2006), as well as on innovative effort and returns to capital (Jefferson & Su, 2006). In addition, technology level captures the investment and sunk costs associated with innovation. Firms with an R&D department are expected to undertake more innovative activities and hence have a higher chance of improving future productivity. Fisher-Vanden and Jefferson (2008) find that in-house R&D, together with autonomous technical change and purchase of imported technology are three sources driving technical change in Chinese industry. In-house R&D tends to be used for existing products, whereas foreign technology transfer focuses on new product development. However, computerization level may have two counteractive effects: on the one hand, it may be more costly for firms more highly computerized to switch from the production of one product toward alternative products; on the other hand, more highly computerized firms are more efficient in management of production hence are more likely to improve future productivity.

A growing body of literature shows that political connections can help firms obtain favorable regulatory conditions (Faccio, 2006), overcome institutional difficulties (Li, Meng, & Zhang, 2006), and achieve secure access to resources such as bank loans (Bai, Lu, & Tao, 2006; Khwaja & Mian, 2005) and courts to settle business disputes (Li, Meng, Wang, & Zhou, 2008). This will eventually increase the value of firms or improve their performance (Fisman, 2001; Johnson & Mitton, 2003). To control for political connections, we include in the econometric specification dummy variables indicating whether the current manager has ever been a government official and whether the manager also works as the leader of the Communist Party of China in that firm .[26]

Market environment variables measure two types of constraints on firm development—raw material supply constraints and credit constraint. The former capture some market and state failures particularly pertaining to the context of our sample area partly due to the practice of NFPP and the transitional nature of the economy. The latter measures a common phenomenon in the world. Many papers study the role of limited access to external finance and find that credit constraints hamper investment in high-return activities (Banerjee & Duflo, 2004; De Mel, McKenzie, & Woodruff, 2008; McKenzie & Woodruff, 2006; Poncet, Steingress, & Vandenbussche, 2010).

Table 9 reports the summary statistics of continuing firms. Product scope grows 27% among continuing firms from 2004 to 2008. Sixty-one percent of continuing firms alter their product mix and 60% of them actually upgrade their product bundle. Forty-six percent of the firms produce multi-products in 2004.

Table 10 presents the regression results of the product mix change models. We first investigate the determinants of product growth rate in column (1). The first set of variables we examine is firm characteristics. Older firms have higher product growth rate. An increase of one standard deviation in firm age will boost product growth rate by roughly 18.8% ($15.665 * 0.012 = 0.188$). This may be because older firms have more operating experience, so they are likely more able to discern and cater for the market demand shift. Alternatively, it could be that the product portfolio chosen by old firms, perhaps a long time ago, needs to be modified in the light of new economic incentives. Firms with an R&D department (in 2004) also tend to experience greater product expansion rate than firms without one. Existence of an R&D department suggests that more stable R&D activities are undertaken, and the chance that new ideas are tried out for new product development may be higher. The negative and statistically significant coefficient on multi-product indicates that product growth rate is lower in firms that produce multiple products in the initial year than those produce single product. This result resembles the prediction of conditional convergence in the neoclassical growth models that a country will grow faster if it has lower initial per capita income. All the other firm characteristics, including ownership, firm size, computerization and productivity level, play no significant roles in determining product growth rate. The second set of variables represents controls for human capital of firms. Firms that have a higher proportion of workers with college degree or above, and that are managed by an individual who works concurrently as the Communist Party leader, experience significantly lower subsequent product growth rate than firms without these characteristics. Firms with a higher proportion of well-educated workers tend to be more highly specialized in the production of certain existing product(s), suggesting that it is more costly for them to develop new products. The combination of manager and Party leader in one person reduces the number of top decision-makers in a firm, possibly implying more dictatorial and stereotyped production decisions. All the other human capital variables, including manager age, tenure, education and experience as a governmental

[26] According to the Constitution of the Communist Party of China (Articles 29, 30 and 32), in whatever working unit where there are three or more Party members, a branch of primary Party organization should be established and one leader and one vice leader be elected by the general member meeting. The main duty of the branch Party leader is to monitor the implementation of Party and state policies in firms, to participate in decision-making in key issues, and to supervise the manager, shareholders, or board of directors in exercising power.

Table 8
Variable definitions.

Variable name	Definition
Firm variables	
Firm characteristics	
Private	1 if at the beginning of year 2004 the firm is private-owned, 0 otherwise. A firm is categorized as "private-owned" if private owner(s) hold a dominant share in the equity. The original ownership type collected in our survey includes state-owned, collective, share-holdings, joint-venture, domestic private, and foreign private-owned.
Firm age	Number of years between year 2004 and the year a firm was established.
Firm size	Natural logarithm of a firm's net value of fixed assets in year 2004 (CNY).
R&D	1 if a firm has a research and development department in year 2004, 0 otherwise.
Computerization	Number of computers per worker in year 2004.
TFP	Total factor productivity measured as the residual of the log-form Cobb–Douglas production function.
Multi-product	1 if a firm produces more than one product defined by our definition, 0 otherwise.
Human capital	
Manager age	Age of the current manager of a firm in year 2004.
Manager tenure	Number of years the current manager has been in office until the end of year 2004.
Manager education	1 if the manager has a college education or above, 0 otherwise.
Worker education	Proportion of workers who have a college education or above in year 2004.
Manager been government official before	1 if the current manager has been a governmental official before, 0 otherwise. The government could be central or local government, and regional or subordinated SFB.
Manager also Party leader	1 if the current manager also works as the Communist Party leader in that firm in year 2004, 0 otherwise.
Market environment	
Credit constraint	1 if a firm has applied for a loan in any of the formal financial institutions but got rejected in 4 years until year 2004, 0 otherwise.
Wood supply constraint	1 if a firm perceives that it always or sometimes happens that the demand for wood as input cannot be met, 0 otherwise.
Energy supply constraint	1 if a firm perceives that it always or sometimes happens that the demand for energy as input cannot be met, 0 otherwise. Here energy includes solid (e.g., coal and charcoal), liquid (e.g., heavy oil, gasoline, diesel and kerosene) and gas fuels as well as electricity, 0 otherwise.
Other raw material supply constraint	1 if a firm perceives that it always or sometimes happens that the demand for other raw materials as input cannot be met, 0 otherwise.
Wood related product production	1 if a firm operates in a sector producing wood related products, 0 otherwise.
SFB variables	
Industrial gross output	Natural logarithm of an SFB's total industrial output value in year 2004 (CNY).
Private property rights development	Number of years an SFB has privatized part of its state-owned or collective-owned properties until year 2004.
SFB director age	Age of the current bureau director in year 2004.
SFB director tenure	Number of years the current bureau director has been in office until the end of year 2004.
SFB director also Party leader	1 if the current bureau director also works as the Communist Party leader in the bureau in year 2004, 0 otherwise.
Change of SFB directorship in 2004	1 if there is a change of SFB directorship in 2004, 0 otherwise.

Note: Table presents the definitions of explanatory variables used in the econometric models.

official, have no significant effects on product growth. The third set of variables measures the market environment in which firms operate. Only perceived wood supply constraint is marginally significant and the positive coefficient indicates that firms that perceive themselves to confront with wood supply difficulties in 2004 grow faster in product scope between 2004 and 2008 than firms that do not. This may imply that firms with such a perception shift away from producing wood related products to exploring new non-wood related product possibilities more rapidly in order to overcome this constraint.

We then move to analyze the determinants of the probability of a continuing firm to alter product mix in column (2). As discussed earlier, product mix changes measure either changes in product number or changes in product portfolio composition with product number holding constant. Some different patterns emerge when this more comprehensive product-switching indicator is used. Examining firm characteristics, the results suggest that firms equipped with a higher computerization level in the initial year have a significantly lower probability of changing their product mix in the following years. This may be because computerization is associated with high initial costs. Once these have been incurred, it is presumably profitable for the firm to stick to the initial product plan and not to change the product mix. In addition, firms that produce multiple products in the initial year are more likely to change product mix subsequently than single-product firms, which is consistent with the finding from Table 6. This may be because multi-product firms that are already selling their outputs in different product markets tend to have more experience in establishing distribution or sales networks or contacts. However, ownership type, firm age, size, having an R&D department or not, and productivity level of the initial year indicate no significant effects on the likelihood of following changes of product mix. Regarding human capital variables, only manager's education exerts a marginally significant impact on

Table 9
Summary statistics of continuing firms.

Variable	Mean	Median	Std. dev.	Min	Max
Product growth rate 2004–2008	0.274	0	0.691	−0.833	3
Product mix changes 2004–2008	0.608	1	0.491	0	1
Product upgrading 2004–2008	0.598	1	0.493	0	1
Firm characteristics					
Private	0.320	0	0.469	0	1
Firm age	14.866	9	15.665	0	58
Firm size	14.215	14.310	2.166	7.695	18.988
R&D	0.278	0	0.451	0	1
Computerization	0.028	0.019	0.034	0	0.167
TFP	2.611	2.463	0.851	0.034	7.529
Multi-product	0.464	0	0.501	0	1
Human capital					
Manager age	44.351	44	5.403	30	56
Manager tenure	4.010	3	3.435	0	14
Manager education	0.722	1	0.451	0	1
Worker education	0.070	0.028	0.110	0	0.650
Manager been government official before	0.773	1	0.421	0	1
Manager also Party leader	0.237	0	0.428	0	1
Market environment					
Credit constraint	0.113	0	0.319	0	1
Wood supply constraint	0.423	0	0.497	0	1
Energy supply constraint	0.103	0	0.306	0	1
Other raw material supply constraint	0.093	0	0.292	0	1

Notes: Table presents the summary statistics of variables for continuing firms used to estimate Eq. (6). For firm characteristics, human capital and market environment variables, 2004 data are used. The number of observations for all variables is 97.

the probability of a continuing firm to change product mix. Firms whose manager has received a college degree are 24% more likely to change product mix subsequently than firms managed by a less educated individual. The negative and marginally significant coefficient on credit constraint suggests that a higher incidence of getting rejected when applying for a loan in a formal

Table 10
Determinants of product switching and upgrading.

	Product growth (1)	Mix changes (2)	Upgrading (3)
Firm characteristics			
Private	0.042 (0.189)	0.185 (0.123)	−0.132 (0.133)
Firm age	0.012 (0.007)*	0.0004 (0.004)	−0.006 (0.004)
Firm size	−0.054 (0.037)	−0.040 (0.030)	−0.024 (0.030)
R&D	0.424 (0.219) *	0.098 (0.115)	0.207 (0.131)
Computerization	−2.385 (1.934)	−3.449 (1.470)**	0.750 (1.909)
TFP	0.031 (0.121)	0.004 (0.054)	−0.113 (0.062)*
Multi-product	−0.470 (0.156)***	0.337 (0.099)***	0.101 (0.122)
Human capital			
Manager age	−0.005 (0.017)	−0.015 (0.012)	−0.014 (0.011)
Manager tenure	−0.010 (0.024)	0.002 (0.019)	−0.003 (0.020)
Manager education	0.225 (0.220)	0.244 (0.146)*	0.075 (0.157)
Worker education	−1.694 (0.868) *	−0.354 (0.550)	−0.443 (0.728)
Manager been government official before	−0.252 (0.289)	0.082 (0.184)	−0.315 (0.145)**
Manager also Party leader	−0.413 (0.176)**	−0.063 (0.122)	0.249 (0.131)*
Market environment			
Credit constraint	−0.188 (0.247)	−0.359 (0.205)*	−0.461 (0.245)*
Wood supply constraint	0.317 (0.174)*	0.078 (0.119)	0.060 (0.129)
Energy supply constraint	−0.276 (0.334)	−0.160 (0.190)	−0.327 (0.194)*
Other raw material supply constraint	0.324 (0.274)	0.161 (0.222)	0.199 (0.232)
Sector dummies	Yes	Yes	Yes
Observations	97	97	97
R-squared	0.38	0.47	0.34
Joint significance test: F-stat (P value)	5.59 (0.000)	50.69 (0.000)	22,284.57 (0.000)

Notes: Table presents the regression results of Eq. (6). The dependent variable for each regression is reported in the column heading. All explanatory variables are using year 2004 data. Coefficient on the constant is not reported. Robust standard errors in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

financial institution leads to a lower chance of product-line switching afterwards. This result is consistent with the general finding in the literature that difficulty in accessing external finance hampers the investment in potential high-return activities.

We finally examine the determinants of the probability of a continuing firm to upgrade product mix in column (3). While not being an important determinant of product switching, initial productivity level plays an important role in determining subsequent product portfolio upgrading probability. Firms with lower initial productivity are more likely to upgrade product portfolio subsequently. An increase of one standard deviation in TFP will lower the probability of upgrading product mix by 9.6% ($0.851*0.113=0.096$). The key human capital variable in determining the probability of product mix upgrading is the political connections of the firm manager. However, the experience of working in government and the duality of working as both manager and Party leader have opposite impacts. One possible explanation could be exerted on the negative coefficient on experience of being a government official. Being government official and firm manager requires different sets of capabilities and skills, with the former focusing on administrative and coordinative ones and the latter on profit seeking and managerial ones. Therefore, the human capital accumulated from working in the governmental organizations might not be useful for doing business, and may instead shackle the thinking and practice. The positive coefficient on manager and Party leader in one person, however, reflects the advantage of centralization of power and of political connections in resource mobilization. Concerning market environment, difficulty in accessing external finance and in obtaining enough energy significantly reduces the likelihood of upgrading the product portfolio.

The lack of a relationship between ownership and firms' product switching and upgrading activities is somewhat surprising. A potential explanation is that what is important for product switching and performance improvement is not the ownership per se but the intrinsic differences of firms and differential treatments associated with ownership, such as corporate governance, access to know-how, credits and markets etc., as pointed out by Estrin, Hanousek, Kocenda, and Svejnar (2009). The short panel of two years and small sample size restrict the analysis from addressing the effect of ownership change on product-line changes. In the continuing firms, 32% of them were private in 2004, of which 26% were privatized before 2004. Twenty-eight percent were privatized between 2005 and 2008, whose impact cannot be taken into consideration by using our current model.

6.2. Robustness analysis

The analysis in the previous section is based on continuing firms between 2004 and 2008. The OLS estimates may suffer from selection bias posed by endogenous attrition if random factors that affect a firm's survival to 2008 also affect its product switching and upgrading during the time period. For example, some unobserved firm-specific characteristics, such as intrinsic managerial skills or a demand shock that maintain the firm in the market may also induce it to switch or upgrade products and thus introduce correlation between survival and product mix changes. To investigate whether endogenous attrition results in biased OLS estimates, we use Lee's (1983) method, which is a generalization of the approach proposed by Heckman (1976, 1979). We begin by estimating a multinomial logit modeling the probabilities that a firm remains in operation, exits due to systematic reasons, and exits due to random dropouts in 2008. That is,

$$\begin{aligned}\Pr(y_{it}=j|\mathbf{x}_{it-1}) &= \frac{\exp\left(\mathbf{x}_{it-1}\gamma_j\right)}{1+\sum_{h=1}^{2}\exp(\mathbf{x}_{it-1}\gamma_h)}, j=1,2 \\ \Pr(y_{it}=0|\mathbf{x}_{it-1}) &= \frac{1}{1+\sum_{h=1}^{2}\exp(\mathbf{x}_{it-1}\gamma_h)}\end{aligned} \tag{7}$$

where y_{it} is the survival variable: $y_{it}=0$ if a firm exits due to random dropouts, $y_{it}=1$ if a firm exits due to systematic reasons, and $y_{it}=2$ if a firm remains in operation in 2008; $\mathbf{x}_{it-1}\gamma=\gamma_0+\gamma_1 \textit{firm char}_{it-1}+\gamma_2 H_{it-1}+\gamma_3 \textit{market}_{it-1}+\gamma_4 \textit{wood product}_{it-1}+\gamma_5 \textit{SFB char}_{it-1}$, and γ denotes the parameter vector to be estimated. This model is estimated using all firms present in 2004 in our sample.

Besides firm characteristics, human capital and market environment variables controlled for in the product switching Eq. (6), the survival model (7) includes a set of variables that determines selection but has no direct effect on product switching and upgrading behavior. To facilitate identification, instead of controlling for sector dummies, we use a binary dummy differentiating whether a firm operates in a sector producing wood related products or not. We also include some SFB characteristics, i.e. industrial gross output, private property rights development, human capital (age, tenure, political connections)[27] of the bureau director, and change of directorship in 2004. The definitions of these variables are listed in the bottom panel of Table 8. Industrial gross output represents the economic status of a bureau. Better economic status may be positively associated with firm survival, for example, because economically sound bureaus are better equipped to bail out loss-making firms. However, bureau performance and firm survival may be negatively correlated if, for example, strong bureaus choose not to help out struggling firms. Private property rights development indicates how well the idea and practice of private property rights have been developed, spread and recognized in an SFB. Firms administered by an SFB that has a longer history of private property rights development tend to be less affected by the turmoil caused by transition of ownership and be better prepared in terms of institutions and technologies to survive in the market without help from superior authorities. The human capital of the bureau director may also impact on the likelihood of a firm to survive. Similar as the case for firm manager but at a higher level, bureau director and Party leader in one person may have two counteractive effects: for one thing, this duality reduces the number of top

[27] We do not control for education of bureau director defined in the same way as manager education, because all directors have a college education or above.

decision-makers in a bureau and loses the supervision function of the Party leader, which may lower his or her motivation and impetus to make effort for the development of the bureau, which in turn may reduce the probability of survival of its administered firms; for the other, the concentration of power and the affiliation with the ruling Party may make it easier for the director to mobilize resources so as to develop the bureau, which on the other hand may raise the likelihood of survival of the firms. Change of directorship in 2004 measures the stability and continuity of the top administrative function. Such a change may disrupt the consistency of policies towards firms a bureau administers, and the adaptation to new managerial style or new rules may increase the probability of firm exit in subsequent years. The summary statistics of all firms are reported in Table A2 in Appendix A.

Table 11 reports the regression results of the Lee's (1983) model. Columns (1) and (2) show the log-odds (i.e. logged relative probability) estimates of the survival equation for randomly dropped-out firms and systematically exited firms respectively, where the survival firms are used as the base category omitted from the estimation. When comparing the results, we can see that for randomly dropped-out firms only two firm-level variables are statistically significant and no exclusion restrictions are significant at conventional levels, whereas for systematically exited firms three firm-level variables and four SFB level variables are significant. This difference suggests that systematic exit can well represent exit. Hence, in the following we focus our discussion on the systematically exited firms. Four significant exclusion restrictions out of six indicate that they are relevant. As predicted, the log-odds between exited firms and surviving ones decreases by 11% with one year increase in private property rights development, whereas the log-odds increases by 97% for one year longer tenure of bureau director and increases by 412% if the bureau under which a firm is administered changed directorship in 2004. Bureau director and Party leader in one person significantly increases the log-odds between exited and surviving firms, indicating that the disadvantage of power centralization dominates the advantage. Besides SFB characteristics, firm age, size and productivity level are also significant determinants of a firm's relative chance of survival. The log-odds between exited and surviving firms is reduced by 6%, 44% and 104% with one year

Table 11
Determinants of product switching and upgrading using Lee's (1983) method.

	(1) Random dropout	(2) Systematic exit	(3) Product growth	(4) Mix changes	(5) Upgrading
Firm characteristics					
Private	0.240 (0.649)	0.461 (0.639)	0.041 (0.191)	0.182 (0.125)	−0.134 (0.132)
Firm age	−0.007 (0.022)	−0.057 (0.033)*	0.013 (0.007)*	0.002 (0.004)	−0.006 (0.004)
Firm size	−0.212 (0.128) *	−0.444 (0.142) ***	−0.046 (0.040)	−0.027 (0.032)	−0.014 (0.040)
R&D	−0.601 (0.656)	−0.031 (0.637)	0.432 (0.217)*	0.112 (0.117)	0.218 (0.130)*
Computerization	−13.180 (9.688)	6.393 (6.050)	−2.396 (1.964)	−3.467 (1.591)**	0.736 (2.047)
TFP	−0.185 (0.268)	−1.043 (0.400)***	0.046 (0.134)	0.030 (0.063)	−0.092 (0.064)
Multi-product	−0.008 (0.529)	−0.232 (0.576)	−0.461 (0.159)***	0.352 (0.098)***	0.113 (0.122)
Human capital					
Manager age	−0.065 (0.054)	−0.055 (0.052)	−0.003 (0.018)	−0.012 (0.012)	−0.012 (0.012)
Manager tenure	0.034 (0.077)	0.003 (0.086)	−0.012 (0.025)	−0.0002 (0.018)	−0.005 (0.020)
Manager education	−0.327 (0.579)	−0.781 (0.627)	0.248 (0.220)	0.281 (0.156)*	0.105 (0.165)
Worker education	−0.999 (2.943)	0.025 (2.113)	−1.691 (0.895)*	−0.348 (0.582)	−0.438 (0.719)
Manager been government official before	−0.116 (0.610)	0.947 (0.670)	−0.258 (0.293)	0.073 (0.191)	−0.322 (0.142)**
Manager also Party leader	−0.096 (0.618)	−0.128 (0.709)	−0.417 (0.176)**	−0.070 (0.123)	0.243 (0.129)*
Market environment					
Credit constraint	0.261 (0.760)	0.524 (0.637)	−0.199 (0.245)	−0.376 (0.199)*	−0.474 (0.241)*
Wood supply constraint	0.891 (0.569)	0.372 (0.578)	0.295 (0.190)	0.042 (0.134)	0.031 (0.137)
Energy supply constraint	0.270 (0.841)	1.391 (0.911)	−0.282 (0.334)	−0.168 (0.188)	−0.334 (0.193)*
Other raw material supply constraint	0.475 (0.939)	−0.891 (1.181)	0.336 (0.274)	0.180 (0.224)	0.214 (0.233)
Wood related product production	−1.512 (0.815)*	−0.462 (0.855)			
SFB characteristics					
Industrial gross output	0.107 (0.385)	0.158 (0.381)			
Private property rights development	−0.025 (0.046)	−0.111 (0.059)*			
SFB director age	−0.011 (0.060)	0.046 (0.063)			
SFB director tenure	−0.262 (0.268)	0.970 (0.315)***			
SFB director also Party leader	0.542 (0.747)	2.011 (0.795)**			
Change of SFB directorship in 2004	1.069 (0.967)	4.115 (1.430)***			
Sector dummies	No	No	Yes	Yes	Yes
Observations	174	174	97	97	97
Inverse Mills ratio			0.109 (0.234)	0.180 (0.196)	0.145 (0.299)
(Pseudo) R-squared	0.30	0.30	0.38	0.47	0.35
Joint significance test: LR chi2 /F-stat (P value)	102.66 (0.000)		5.58 (0.000)	45.69 (0.000)	116.77 (0.000)

Notes: The dependent variable for each regression is reported in the column heading. Columns (1) and (2) report the results for the survival equation. Columns (3)–(5) report the results for the product switching equation. All explanatory variables are using year 2004 data. Coefficient on the constant is not reported. Robust standard errors in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

older in firm age, one log point larger capital stock and one log point higher TFP, respectively. These findings are consistent with those of Jovanovic (1982)'s learning model and those from many firm-level empirical studies in both developed and developing countries.

Columns (3)–(5) of Table 11 report the results of the product-switching equation. The results are very similar to those from the OLS estimations presented in Table 10. The insignificant coefficients on the inverse Mills ratio in all three models suggest that the issue of endogenous exit of firms has little effect on the parameters of the product-switching equation. That is, there is no strong evidence of a sample selection problem or that OLS estimates are biased by endogenous attrition.

7. Conclusions

We analyze how firms in China's state-owned forest areas select, switch and upgrade their product mix during a period of gradual institutional and managerial reforms. We find that product-specific value-added has a very wide dispersion, indicating that what type of product firms produce matters for their overall efficiency and long-run development. Within the same industry, multi-product firms tend to be larger, more productive and more likely to export than single-product firms. We also find that changes in firm's product mix are pervasive among our sample firms and can be mainly attributed to adding or churning products rather than only shedding products. Moreover, changes in firms' product mix have made a significant contribution to the aggregate output growth during our sample period, accounting for approximately 86% of the net increase in the aggregate output (the remaining 14% is attributable to growth at the intensive margin).

We estimate the effects of firm characteristics, human capital and market environment on a continuing firm's decision to alter and upgrade product portfolio. The empirical results indicate that some firms are more prone to diversify and upgrade their product mix than others. Firms that are older, have an R&D department, produce single product, have a lower proportion of workers with college degree or above, have separate manager and Communist Party leader, and face wood supply constraint in 2004 have higher product growth rate between 2004 and 2008. Firms that are less computerized, produce multiple products, have a manager with college degree or above, and have less difficulty in accessing external finance are more likely to change their product mix. Moreover, firms that are less productive, whose manager has no experience of working in governmental organizations but works concurrently as the Party leader, and that are not confronted with constraints in either external finance or energy supply tend to have higher probability to upgrade product portfolio subsequently. These results hold when we take the factors affecting firms' survival into account.

More generally, quantifying the impacts of firm characteristics, human capital and market environment is fundamental to improving our understanding of the factors underlying the observed patterns of product switching and upgrading within firms. Therefore, findings of this paper provide the basis for directions of future reforms in China's state-owned forest areas in order to enhance efficiency and better handle volatilities in the markets. However, we recognize that the small sample size hinders us from obtaining results of more explanatory power from the econometric analysis. Moreover, the short longitudinal dimension of the data restricts us from addressing the effects of the dynamics of the institutional and managerial reforms on product portfolio adjustment. Future research could be directed to this field as bigger and longer panel data become available.

Acknowledgements

We thank Peter Berck, Haoran He, Ruyi Gan, Xuemei Jiang, Jintao Xu, seminar participants at the University of Gothenburg and the Singapore Economic Review Conference 2011, and an anonymous referee for helpful comments. The financial support from the National Natural Science Foundation of China (Project Number: 70821140353) and the World Bank and the Environment for Development Initiative is also gratefully acknowledged. Any views expressed in this paper are those of the authors.

Appendix A

Table A1
Examples of sectors, industries and products.

ICNEA	CPC	Description	
20		Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products (Sector)	
201		Processing of sawnwood and wood chips (Industry)	
	20110101	Products	Regular size sawnwood
	20110204		Sawnwood for bunton
	20110205		Sawnwood for packing cases
	20110301		Not impregnated sleepers
	20110302		Impregnated sleepers
	20120101		Wood chips

Table A1 (*continued*)

ICNEA	CPC	Description	
202		Manufacture of panel board (Industry)	
	20201101	Products	Plywood
	20202101		Fiberboard
	20203101		Particle board
	202041		Block board
	202099		Other panel board
	20250101		Sliced veneer
	20250102		Rotary cut veneer
	20250103		Micro veneer
	20250199		Other veneer
	202503		Glued laminated timber

Notes: Table presents an example of sector, industry and product mapping hierarchy considered in this study. For ICNEA 201 there are a total of 17 products, but only a subset are listed in the table. For ICNEA 202, all products are listed in the table. CPC 20110101 is based on author created eight-digit codes that are only disaggregated to the six-digit level in CPC. Data are for the 2004 and 2008 pooled sample.

Table A2
Summary statistics of all firms.

Variable	Mean	Median	Std.dev.	Min	Max
Firm variables					
Survival 2004–2008	0.557	1	0.498	0	1
Firm characteristics					
Private	0.379	0	0.487	0	1
Firm age	12.563	8	13.640	0	58
Firm size	13.630	13.816	2.169	7.313	18.988
R&D	0.247	0	0.433	0	1
Computerization	0.028	0.016	0.039	0	0.238
TFP	2.465	2.400	0.947	−1.598	7.968
Multi-product	0.408	0	0.493	0	1
Human capital					
Manager age	43.621	43	5.584	28	57
Manager tenure	3.966	3	3.606	0	15
Manager education	0.621	1	0.487	0	1
Worker education	0.070	0.025	0.122	0	1
Manager been government official before	0.724	1	0.448	0	1
Manager also Party leader	0.218	0	0.414	0	1
Market environment					
Credit constraint	0.144	0	0.352	0	1
Wood supply constraint	0.466	0	0.500	0	1
Energy supply constraint	0.132	0	0.340	0	1
Other raw material supply constraint	0.092	0	0.290	0	1
Wood related product production	0.851	1	0.358	0	1
SFB variables					
Industrial gross output	18.867	18.790	0.716	17.093	20.017
Private property rights development	5.534	4	6.480	0	21
SFB director age	46.897	48	5.539	34	54
SFB director tenure	2.983	3	1.571	0	6
SFB director also Party leader	0.207	0	0.406	0	1
Change of SFB directorship in 2004	0.167	0	0.374	0	1

Notes: Table presents the summary statistics of variables for all firms used to estimate Eq. (7). For all variables except *survival 2004–2008*, 2004 data are used. The number of observations for all variables is 174.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.chieco.2012.04.002.

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Online Appendix for

Multi-product firms, product mix changes and upgrading: Evidence from China's state-owned forest areas

Måns Söderbom and Qian Weng

This appendix presents the full list of sector, industry and product classification considered in this study. The classification procedure is as follows. Since the reporting of products by our sample firms is not governed by any particular product classification, and the names of products reported could differ in aggregation or the way firms called them, we standardize the product names and define product, industry and sector according to two national standards. One is China's Industrial Classification for National Economic Activities (2002), henceforth ICNEA, which categorizes economic activities in China into four levels, using English alphabets, two-, three- and four-digit codes respectively. ICNEA is comparable to the UNSD: 1989, International Standard Industrial Classification of All Economic Activities, NEQ. The other is China's Products Classification for Statistical Use (2010), henceforth CPC, which classifies products to a more disaggregated level. CPC uses a five-level coding system, with two-, four-, six-, eight- and ten-digit codes. ICNEA and CPC are harmonized at the two- and four-digit code levels. At the four-digit level, ICNEA and CPC assign the same code to most, but not all economic activities. We map all reported product names into six-, eight- or ten-digit CPC codes and take this as the definition of a "product". Eight-digit codes are our primary standard of classification. Two products are classified at the ten-digit level. Since for some products six-digit codes that are the most disaggregated level in CPC are not disaggregated enough for our analysis, we create the eight-digit codes by ourselves. This applies to eight products and they are marked with * in the list. We refer to the three-digit ICNEA categories as "industries" and two-digit ICNEA categories as "sectors". There are a total of 90 products linked to 26 industries across 17 sectors in our data. In our sample there are four products that ICNEA and CPC assign different codes at the four-digit level. We take the CPC codes as our standard and use the corresponding 3-digit codes in ICNEA as our classification for industries.

Sector		Industry		Product	
02	Forestry	021	Nurture and planting of trees	02110101	Coniferous tree seeds
		022	Harvesting and transport of timber and bamboo	02214001	Softwood small size lumber
03	Husbandry	033	Poultry feeding	03301041	Chicken
		039	Other husbandry	03387503	Pilos antler
13	Processing of food from agricultural products	137	Processing of vegetables, fruits and nuts	13714011	Dried mushrooms and truffles
				13716011	Sweet and sour pickles
				13716021	Pickles
14	Manufacture of food	145	Manufacture of canned food	14504199	Other canned fruit
15	Manufacture of beverages	152	Manufacture of alcoholic beverages	152151	Liquid distillate spirits
				152910	Fruit wine
				152970	Compound liquor
		153	Manufacture of soft drinks	15302101	Bottled drinking mineral water
				15303111	Fruit juice
				15303170	Concentrated fruit juice
				15303511	Fruit juice beverage
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products	201	Processing of sawnwood and wood chips	20110101*	Regular size sawnwood
				20110102*	Small size sawnwood
				20110103*	Wood in the rough
				20110104*	Wood strips
				20110105*	Dressed timber
				20110106*	Sawnwood for wall plank
				20110107*	Sawnwood for furniture
				20110108*	Sawnwood for wood flooring
				20110202	Sawnwood for motorlorry
				20110204	Sawnwood for bunton
				20110205	Sawnwood for packing cases
				20110206	Sawnwood for drill frame
				20110299	Sawnwood of other special types

		20110301	Not impregnated sleepers
		20110302	Impregnated sleepers
		201199	Other sawnwood
		20120101	Wood chips
202	Manufacture of panel board	20201101	Plywood
		20202101	Fiberboard
		20203101	Particle board
		202041	Block board
		202099	Other panel board
		20250101	Sliced veneer
		20250102	Rotary cut veneer
		20250103	Micro veneer
		20250199	Other veneer
		202503	Glued laminated timber
203	Manufacture of wood products	20310101	Solid wood doors
		20310103	Wooden door frames and sills
		20310201	Wooden windows
		203103	Mouldings
		20310401	Solid wood flooring
		20310402	Composite wood flooring
		203199	Other wood products used in construction
		20320102	Wooden trough
		20320202	Packing boxes
		20320203	Crates
		20320302	Box pallets
		20320304	Pallets and protection frames
		20350301	Agglomerated cork articles in brick, block, or strip
		20390401	Wooden chopsticks
		20390404	Wooden chopping board

				20390499	Other kitchenware of wood
				20390501	Wooden frames for paintings, photographs, mirrors or similar objects or similar objects
				20390502	Wooden hangers
				20390503	Wooden tools and tool handles
				20390599	Other articles of wood
21	Manufacture of furniture	211	Manufacture of wooden furniture	21100101	Wooden beds
				2110010202	Wooden wardrobe used in the bedroom
				2110010299	Other wooden furniture used in the bedroom
				21100203	Seats with wooden frames
				21100301	Wooden desks
				21100401	Redwood furniture used in the dining room and kitchen
				21100403	Panel board furniture used in the dining room and kitchen
				21100501	Wood kitchen cabinets
				211099	Other wooden furniture
		219	Manufacture of furniture with other materials	215102	Mattresses
22	Manufacture of paper and paper products	222	Manufacture of paper	22210202	Liner board
				22230601	Corrugated paper
		223		223001	Packing containers of paper and paperboard
24	Manufacture of articles for culture, education and sport activities	241	Manufacture of articles for education activities	24121140	Pencils
26	Manufacture of raw chemical materials and chemical products	266	Manufacture of specialty chemical products	26634101	Pyrolysis wood products
27	Manufacture of medicines	274	Manufacture of Chinese medicine	27403107	Oral tonifying medication
				27403108	Tonifying capsules

				27404308	Qi-regulating capsules
				27407308	Menstruation-regulating capsules
31	Manufacture of non-metallic mineral products	311	Manufacture of cement, lime and plaster	31112010	Cement of general purpose
		312	Manufacture of articles of plaster and lime	31216010	Bricks of cement and concrete
		319	Manufacture of graphite and other non-metallic mineral products	317610	Natural abrasive
35	Manufacture of general purpose machinery	355	Manufacture of shaft bearings, gears, gearing and transmission parts	34941011	Articulated link chain
37	Manufacture of transport equipment	372	Manufacture of motor vehicles	372610	Maintenance and repair services of motor vehicles
41	Manufacture of measuring instruments and machinery for cultural activity and office work	413	Manufacture of clocks, watches and chronometric instruments	413010	Clocks
42	Manufacture of artwork and other manufacturing	421	Manufacture of artwork	42113001	Wood carvings
				42113099	Other natural plant carving artwork
58	Storage services	589	Other storage services	58020101	Storage services of cruid oil and refined oil

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Paper IV

Is R&D cash-flow sensitive? Evidence from Chinese industrial firms

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Abstract

We hypothesize that research and development (R&D) is sensitive to cash-flow fluctuations due to asymmetric information and agency problems in the credit market. We adopt a variant of the *Q* model for R&D investment using the value of the firm, physical capital and employment to capture firm fundamentals as proxies for investment opportunities. We add cash flow to this specification, and estimate the augmented model separately for R&D participation and spending using data on Chinese industrial firms for the period 2001-2006. We find that R&D spending is sensitive to cash-flow fluctuations, conditional on firm fundamentals. We also find that the cash-flow sensitivity of R&D varies across firms depending on ownership. We conclude that credit market imperfections pose a constraint for R&D in Chinese industry.

Keywords: Physical investment; R&D; cash flow

JEL classification: G32; O32

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Acknowledgements: We thank Yinan Li, Florin Maican, Penelope Prime, and participants at the 2013 Chinese Economists Society Annual Conference in Chengdu for helpful discussions and comments.

1. Introduction

Research and development (R&D) is considered one of the essential driving forces of endogenous economic growth (e.g., Grossman and Helpman, 1991; Aghion and Howitt, 1998). Like in other parts of the world, R&D has become an increasingly more important type of investment in China during the past decades. Figure 1 plots the gross domestic expenditure on R&D as percentage of GDP for Japan, the US, the Organization for Economic Cooperation and Development (OECD), the European Union (EU, 15 countries) and China for the past twenty years. In the early 1990s there was a significant gap between China and other economies represented in the graph. This gap has been gradually reduced over the last 20 years, and by 2012 the difference between the EU and China was negligible. The boom in R&D in China after 2000 is the result of two broad developments: First, the advantage of cheap labor, which played a central role in China's rapid economic growth since its economic reforms starting in 1979, has gradually been eroded due to the rise in labor costs since the late 1990s (Li et al., 2011). Second, moving up the product sophistication ladder by altering the production structure to products that embody high productivity and generate positive learning spillovers to the rest of the economy requires R&D (Hausmann et al., 2007).

<Figure 1 about here>

A natural question to ask then is how R&D gets financed. R&D has distinct features from investment in tangible assets. First, the spillover of R&D output across firms or even countries leads to protection of proprietary information from competitors and even from potential investors or creditors in order to appropriate the returns (Bhattacharya and Ritter, 1983). Second, R&D projects are riskier and more difficult to assess for outsiders (Leland and Pyle, 1977). Third, R&D is harder to collateralize than investment in fixed capital. These features suggest that firms that invest in R&D tend to face more pronounced asymmetric information and agency problems, and hence it may be more costly to finance R&D through external funds (Hall and Lerner, 2010). There is a rich empirical literature on the role of internal finance in determining firm-level physical investment, typically documenting a significant and positive relationship between proxies for changes in internal funds and investment (see, e.g., Schiantarelli, 1996, Hubbard, 1998, and Bond and Van Reenen, 2007 for surveys of this literature). However, there are relatively few studies investigating the cash-flow sensitivity of R&D, and the results in these studies are inconclusive depending on countries and types of firms (see, e.g., Hall and Lerner, 2010 for a review).

In this paper, we estimate the sensitivity of R&D to cash flow conditional on controlling for investment opportunities for Chinese industrial firms over the period 2001-2006. The dataset, developed and maintained by the National Bureau of Statistics of China (NBS), covers all "above-scale" Chinese industrial firms (i.e., all state-owned firms and non-state-owned firms with annual sales above 5 million Chinese yuan (CNY)[1]). The firms are mainly unlisted and there is significant variation across the firms in terms of age, size, ownership and industry. We adopt a variant of the *Q* model for R&D investment using the value of the firm, physical capital and employment to capture firm fundamentals as proxies for expected future profitability of capital (i.e., investment opportunities).[2] Following Gilchrist and Himmelberg (1995), we estimate a log-linear forecasting equation using firms' stream of profits to date to construct the expected future profits and consequently the value of the firm. We subsequently estimate regressions separately for R&D participation and spending decisions controlling for firm value, physical capital and employment, with and without cash flow added to the specifications. The simple idea behind this strategy is that, if R&D is sensitive to changes in cash flow conditional on firm value, this can be considered evidence of capital market imperfections.

Our study complements previous research in the following aspects. Existing evidence of R&D-cash flow sensitivity is typically drawn from estimation of a Tobin's *Q* model, Euler equation or reduced-form investment models such as error correction or accelerator models. These approaches have often proved problematic, however. Tobin's *Q*, constructed using stock market data, may not adequately capture future investment opportunities, hence the evidence on sensitivity of investment to cash flow cannot be decisively interpreted as suggesting the existence of capital market imperfections (Gilchrist and Himmelberg, 1995). The Euler equation approach has often proved non-robust to seemingly minor alterations to the specification (Whited, 1998; Gilchrist and Himmelberg, 1995).[3] Reduced-form investment models tend to lack clear theoretical underpinnings. Moreover, studies to date in the literature are mostly based on the largest and most important publicly traded manufacturing firms from advanced economies. There are still few studies from developing countries. Most research on

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[1] The average exchange rate in April 2014 was 1 USD = 6.16 CNY.

[2] While the Q model is traditionally developed to study physical capital investment, it can accommodate R&D investment if we assume that the production function includes not only stocks of physical capital and labor but also a stock of technology which is acquired and accumulated through R&D investment (Himmelberg and Petersen, 1994).

[3] In fact, in an early phase of this project we estimated Euler equations along the line of Bond and Meghir (1994). This approach did not work well, for several reasons. First, since we do not have continuous R&D data, in order to estimate a dynamic equation without losing too many observations, we would need to impute R&D data for the gap year. This imputation led to potentially large measurement errors in R&D. Second, our results turned out to be very sensitive to the instruments chosen, and overidentifying restrictions were nearly always rejected. Third, parameter estimates were often extremely high, and the standard errors were also very high. In the end, we learned little from the results obtained from this approach.

the effects of financing frictions for Chinese firms focuses on physical investment and the research on R&D is limited.

China's stock markets were developed in the early 1990s and only the largest and most prominent firms are publicly listed. Most firms rely on internally generated profits, credit from banks and/or other sources for investment. A typical Chinese phenomenon as a legacy from the planned economy era is banks' differential treatments to firms of distinct ownerships. Chinese banks, which are predominantly state-owned or state-influenced, were instructed by law to lend only to state-owned firms that serve political and social functions other than only pursuing profits until 1998. The "political pecking order" in credit allocation where private Chinese firms were considered low in political status and discriminated against should in principle have been mitigated after the system was liberalized at the end of 1990s. However, private firms are still found to rely exclusively on internal funds for investment (Poncet et al., 2010; Guariglia et al., 2011).

We find that, for the full sample, firm fundamentals significantly affect R&D participation and spending decisions. Moreover, controlling for investment opportunities, R&D is sensitive to cash flow. Hence, the hypothesis of perfect capital markets is rejected. Firms of different ownerships are heterogeneous in the degree of dependence on internal finance. For private firms we find that R&D participation and spending are cash-flow sensitive, but not for foreign firms. For state-owned and collective firms the results are mixed: we find cash-flow sensitivities for the R&D spending of state-owned firms (but not for participation), and for R&D participation of collective firms (but not for spending).

The remainder of the paper is structured as follows. Section 2 reviews the literature on the link between internal finance and R&D. Section 3 introduces our empirical model and describes the estimation procedure. Section 4 describes the dataset and presents summary statistics. Section 5 reports the econometric results, and section 6 concludes with a brief discussion on policy implications.

2. Internal finance and R&D

There is a large empirical literature concerned with the issue of whether investment spending is sensitive to fluctuations in internal finance. Under perfect capital markets, the firm's financial structure is irrelevant for its real investment decisions, because internal and external funds are perfect substitutes (Modigliani and Miller, 1958). However, because of transaction costs, asymmetric information and agency problems, capital markets may not be perfect[4]. In such a case, internal funds have a cost advantage over external funds, and so the firm's financial structure may matter for investment. In particular, if the firm's investment is sensitive to fluctuations in internal funds, conditional on the fundamental driving factors of investment, this would be consistent with the notion that the firm is financially constrained. Starting with Fazzari et al. (1988), the standard approach for studying financing constraints has been to add a measure of cash flow to Tobin's *Q* model and estimate investment-cash flow sensitivities. Numerous studies have found that investment responds strongly to cash flow, especially for firms categorized as financially constrained based on criteria such as size, age, dividend policies, etc. (see, e.g., Hubbard, 1998 for a review). The high explanatory power of cash flow together with the low explanatory power and the small coefficient estimate of Tobin's *Q* suggest that Tobin's *Q* is not a "sufficient statistic" for investment (see, e.g., Bond and Van Reenen, 2007 for a review). If Tobin's *Q* does not summarize all the information about expected future profitability that is relevant for the current investment decision, then sensitivity may merely reflect current cash flow as a firm fundamental rather than providing convincing proof for the existence of capital market imperfections.

Several methods have been explored to remedy these problems. Some studies find that the empirical performance of Tobin's *Q* model improves if an estimator that corrects for the bias resulting from measurement errors in Tobin's *Q* is used (see, e.g., Hayashi and Inoue, 1991; Blundell et al., 1992; Erickson and Whited, 2000, 2002, 2012; Almeida et al., 2010). A second approach is to estimate the firms' intertemporal first-order condition, the Euler equation, directly. One advantage of this approach is that marginal *q*, which is unobservable, does not enter the empirical specification (see, e.g. Bond and Meghir, 1994). Unfortunately, results from estimated Euler equations have often proved to be non-robust (Whited, 1998; Gilchrist and Himmelberg, 1995). A third approach attempts to measure marginal *q* itself by estimating an auxiliary model to forecast the future marginal profits to investment based on the information observable to researchers and discounting them back to the current period, i.e., to construct the "Fundamental *Q*" as Gilchrist and Himmelberg (1995) coin it (see, e.g., Abel and Blanchard, 1986; Gilchrist and Himmelberg, 1995; Bond and Cummins, 2001; Cummins et al., 2006). This approach avoids the use of share price data and can in principle relax the assumptions imposed in the *Q* model such as perfect competition and constant returns to scale (Bond and Van Reenen, 2007). Our approach is similar to the third approach.

[4] See, e.g., Fazzari et al. (1988) and Hubbard (1998).

A number of papers have estimated the cash-flow sensitivity of investment for Chinese firms. Investment has been found to be insensitive to cash flow in state-owned firms but sensitive to cash-flow in private firms, suggesting that state-owned firms are not financially constrained but private firms are (e.g., Poncet et al., 2010; Guariglia et al., 2011; Ding et al., 2013).[5] Hence, these studies are consistent with the notion of a "political pecking order" in the allocation of credit in China. Furthermore, foreign capital has been found to help alleviate the financial constraints faced by domestic private firms (e.g., Héricourt and Poncet, 2009; Poncet et al., 2010).

The financing of R&D has received growing interest in the past decades. However, R&D is different in nature from fixed capital. First, there may be R&D spillovers to other firms or even countries. Therefore, firms tend to protect proprietary information from competitors and even from potential investors or creditors in order to appropriate the returns to R&D investment (Bhattacharya and Ritter, 1983). Second, investment in intangible assets is riskier and it is more difficult for investors to discover the quality of long-term R&D projects than that of other short-term or low-risk projects (Leland and Pyle, 1977). Third, R&D is harder to collateralize than investment in fixed capital. These differences suggest that it may be relatively more expensive to finance R&D than physical investment through external finance. Consequently, internal finance may play a more important role for R&D than for fixed capital investment (Hall and Lerner, 2010).

Similar to the studies of fixed capital investment, studies of R&D investment have primarily been based on Tobin's *Q* model, the Euler equation and reduced-form models. In contrast to the investment literature, the findings for R&D are mixed. While a small number of papers find evidence of sensitivity of R&D to cash flow for the US manufacturing firms (e.g., Hall, 1992; Himmelberg and Petersen, 1994; Hall et al., 1999; Mulkay et al., 2001), most other papers report weak or no evidence that internal finance matters for R&D, especially those studying European firms (e.g., Bhagat and Welch, 1995; Harhoff, 1998; Bond et al., 2005). Some recent studies augment this analysis with external sources of finance, such as debt and/or equity, and largely find a strong link between both cash flow and external equity and R&D in both US and European publicly traded firms (e.g., Brown et al., 2009 on US firms; Martinsson, 2010 on European firms).

The ability to innovate, acquire and diffuse new technologies has been shown to play a critical role in China's improvement of firm productivity, economic growth and convergence

[5] Guariglia et al. (2011) and Ding et al. (2013) also find investment-cash flow sensitivity in collective and foreign firms.

to the world's advanced economies. Jefferson et al. (2006) investigate the relations between R&D, innovation and firm performance in China's large and medium-sized manufacturing firms for the period 1997-1999. They find that approximately 12% of the returns to R&D expenditure can be attributed to the production of new products, and returns to R&D expenditure appear to be at least three to four times the returns to fixed production assets. Examining the contributions of three avenues of technological advance to productivity within Chinese industry using the same dataset over 1995-1999, Hu et al. (2005) show that in-house R&D significantly complements technology transfer irrespective of domestic or foreign origin, whereas foreign direct investment (FDI) does not facilitate the transfer of market-mediated foreign technology. Girma et al. (2008) study the link between FDI, access to finance and innovation activity in Chinese manufacturing firms of different ownerships for 1999-2005, and report that when the effect of FDI on technology transfer and the effect of FDI on domestic credit opportunities are distinguished, better access to credit is an important channel through which FDI affects the innovation of non-state-owned firms. De Waldemar and Poncet (2013) use data on more than 200 Chinese cities for the period 1997-2009, and find that cities specializing in more complex goods subsequently grow faster. Their results indicate that growth benefits pertain exclusively to the capabilities of domestic firms engaged in ordinary trade, which highlights the importance of technology advance in China via in-house R&D rather than via technology acquisition from assembling activities and FDI.

3. Empirical model and estimation

3.1 An R&D investment model

We assume that the firm's investment in R&D equates the marginal cost of investing in an additional unit of technology, denoted $G_{rd}(.)$, with the expected shadow value of having an additional unit of technology, $\lambda_{i,t}$:

$$G_{rd}\left(\frac{rd_{i,t}}{T_{i,t}}\right) = \lambda_{i,t}, \tag{1}$$

where $rd_{i,t}$ is investment in technology (R&D) and $T_{i,t}$ is the technology stock (the price of technology is normalized to unity). We specify the marginal cost function as

$$G_{rd}\left(\frac{rd_{i,t}}{T_{i,t}}\right) = b_i\left(\frac{rd_{i,t}}{T_{i,t}}\right)^{\rho}, \tag{2}$$

where b_i and ρ are strictly positive parameters. This equation has a natural interpretation as a marginal adjustment cost function. The shadow value of having an additional unit of technology is not directly observed in our data. Under constant returns to scale and perfect competition, $\lambda_{i,t}$ can be written as the ratio of the value of the firm ($V_{i,t}$) to the technology stock ($T_{i,t}$) (Hayashi, 1982), where

$$V_{i,t} = E_t\left[\sum_0^\infty \beta^s \Pi_{i,t+s}\right] \tag{3}$$

and $\beta = \frac{1}{1+\sigma} < 1$ is the one-period discount factor. Hence, the optimal investment model can be written in logarithmic form as

$$\ln b_i + \rho\,(\ln rd_{i,t} - \ln T_{i,t}) = \ln V_{i,t} - \ln T_{i,t}. \tag{4}$$

Assuming a Cobb-Douglas production function where output depends on technology, physical capital (K) and labor (L), where the latter two are flexible inputs, the first-order conditions for optimal capital and labor imply that $\ln T_{i,t}$ can be written as a linear function of $\ln K_{i,t}$ and $\ln L_{i,t}$. Hence, we can write our investment equation as

$$\ln rd_{i,t} = \gamma_{i0} + \gamma_1 \ln V_{i,t} + \gamma_2 \ln K_{i,t} + \gamma_3 \ln L_{i,t}\ . \tag{5}$$

This simple equation forms the basis for our empirical analysis. Our goal is not to estimate structural parameters. Indeed, we will have to modify Equation (5) to acknowledge the fact that there is a large proportion of zero R&D investments in the data, a point to which we return below. Because the value of the firm, $V_{i,t}$, is not directly observable in our data, we estimate it based on an auxiliary log-linear forecasting model for firm's profits. We assume that the logarithm of profits evolve according to a stationary stochastic process with a finite-order autoregressive representation. We specify this process in AR(2) form as follows,

$$ln\Pi_{i,t} = \rho_1 ln\Pi_{i,t-1} + \rho_2 ln\Pi_{i,t-2} + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{6}$$

where α_i is a vector of firm-specific effects to capture unobserved cross-sectional firm heterogeneity in the conditional and unconditional means of logarithm of profits, τ_t is a vector of time-specific effects to account for business cycle shocks common to all firms, and $\varepsilon_{i,t}$ is an idiosyncratic shock. The value of the firm ($V_{i,t}$) is estimated using Equation (3), plugging in current and future expected profits according to the procedure described in section 3.2 below. Once we have an estimate of $V_{i,t}$, we can easily obtain an estimate of Tobin's Q, by dividing $V_{i,t}$ by the value of the capital stock. To check whether our general approach for controlling for the fundamental driving factors of investment decisions appears appropriate, we will investigate how estimates of a standard physical investment Q model compare to existing results in the literature. We will also use our measure of Q to identify outliers.

3.2 Estimation

Estimation of the model proceeds in three steps. We first estimate the AR(2) process based on the stream of profits to date to obtain the parameters that will be used to forecast expected future profits. To account for the sector-specific shocks, we estimate one AR(2) model for each sector. It is estimated by first-differenced GMM using lagged $ln\Pi_{i,t}$ levels dated *t*-3 and *t*-4 as instruments.[6] If the error term is iid, instruments starting from dated *t*-2 will be valid. However, we use these more conservative instruments in case the error term follows a firm-specific MA(1) process. We show the AR(2) regression results in Appendix A and discuss the validity of the instruments and the model specification in section 5. After we have obtained the parameter estimates $\hat{\rho}_1$, $\hat{\rho}_2$ and a vector of estimates on the period dummies $\hat{\theta}_t$, we take the within-firm average over time to generate the firm fixed effects $\hat{\alpha}_i$, that is,

$$\hat{\alpha}_i = \overline{ln\Pi_{i,t}} - \hat{\rho}_1\overline{ln\Pi_{i,t-1}} - \hat{\rho}_2\overline{ln\Pi_{i,t-2}} - \hat{\theta}_t\overline{\tau_t}, \tag{7}$$

where $\overline{ln\Pi_{i,t}} = \sum_{t=1}^{T} ln\Pi_{i,t}/T$.

The second step is to use the estimated parameters of the AR(2) process to construct $V_{i,t}$. We start with calculating the expectation of $\Pi_{i,t+s}$ given $\Pi_{i,t}$ for $s \geq 1$. For example, $\Pi_{i,t+1}$is derived by exponentiating Equation (6) and moving forward one period, namely,

$$E_t(\Pi_{i,t+1}) = \left(\Pi_{i,t}\right)^{\widehat{\rho}_1} \cdot \left(\Pi_{i,t-1}\right)^{\widehat{\rho}_2} \cdot\ e^{\widehat{\alpha}_i}\ \cdot E_t(e^{\varepsilon_{i,t+1}}) \cdot E_t(e^{\tau_{t+1}})\ , \tag{8}$$

which is a function of realized profits and parameter estimates multiplied by two adjustment factors. Assuming homoskedasticity across periods, $E_t(e^{\varepsilon_{i,t+1}})$ is equal to $E_t\left(e^{\hat{\varepsilon}_{i,t}}\right)$ computed as the sample mean of the exponent of the error term. $E_t(e^{\tau_{t+1}})$ captures the expected value of the exponent of the trend growth, which is assumed to be constant across periods and equal to the sector weighted average trend growth rate over the sample period. This growth rate is calculated as the total growth rate measured by the coefficient on the last period dummy divided by the number of periods covered in the sample and taking the sector size weighted average. We conduct repeated substitution in Equation (8) *s* times to generate $E_t(\Pi_{i,t+s})$. In principle, the horizon for calculating the value of the firm should be infinity. Here we set *s* to 100 for simplicity. We then calculate the value of the firm as the sum of the discounted expected future profits, assuming that the one-period discount rate σ is 10%.

[6] We have tried system GMM estimator which jointly estimates first-differenced and level equations with the lagged levels as instruments for the differenced equation and lagged differences as instruments for the level equation. A Difference-in-Hansen statistic that specifically tests the additional moment conditions/instruments used in the level equation rejects their validity at conventional levels. This hence suggests the use of the first-differenced rather than the system GMM estimator.

The last step is to estimate the R&D investment model. A high proportion of R&D expenditure observations are zero in our data, so Equation (5) cannot literally be the correct specification for R&D investment for all firms. We view Equation (5) as an appropriate specification for positive R&D investment, and assume that the determinants of the decision to carry out *any* R&D investment are the same as those determining the amount of investment conditional on positive investment. We thus model the decision to invest in R&D and R&D expenditure using two separate equations, specified as follows:

$$R\&D\ participation_{i,t} = \delta_{i0} + \delta_1 \ln V_{i,t} + \delta_2 \ln K_{i,t} + \delta_3 \ln L_{i,t} + \varphi_t + \omega_{i,t}, \quad (9)$$

$$\ln rd_{i,t} = \gamma_{i0} + \gamma_1 \ln V_{i,t} + \gamma_2 \ln K_{i,t} + \gamma_3 \ln L_{i,t} + \phi_t + \nu_{i,t}, \quad (10)$$

where $R\&D\ participation$ is a dummy variable equal to one if the firm invests in R&D in period t and zero otherwise. The large number of zero R&Ds may reflect high fixed adjustment costs firms need to bear to start an R&D project. Alternatively, the zeroes could be measurement errors.[7] It should be noted that our estimation framework is similar to the "exponential type II tobit model" discussed by Wooldridge (2010; section 17.6.3). The only difference is that we use a linear probability model, rather than a probit, to estimate the participation equation.

Equations (9) and (10) give the empirical specifications that we will estimate under the null hypothesis that capital markets are perfect. To test for sensitivity of R&D to cash flow, we add cash flow into above specifications. A positive and statistically significant coefficient on cash flow indicates a rejection of the null.

4. Data and sample descriptive statistics

4.1 Dataset

This study uses annual survey data for all "above-scale" Chinese industrial firms for the period 1998-2007. These data are developed and maintained by the NBS [8]. Over 160,000 firms per year are included in the dataset, spanning 39 two-digit industries in the mining, manufacturing and public utilities sectors and all 31 provinces or province-equivalent municipal cities. They are used to compile the "industry" section of the China Statistical Yearbook, and account for most of China's industrial value added. The dataset contains firm

[7] R&D expenditure can be reported as zero because (i) firms did not invest in R&D; (ii) the person answering the survey did not know about the information and arbitrarily reported zero; or (iii) firms did not report any information and the statistical authority converted blank observations to zero (Nie et al., 2012). It is not possible to distinguish between the non-performers and non-reporters directly from the dataset.

[8] The unit of analysis is firm, not plant. Brandt et al. (2012) suggest that more than 95% of all observations in the survey are single-plant firms.

identification information, and rich operation and performance information extracted from balance sheets and income statements.

We clean the dataset according to the following criteria. First, we delete firms whose identification number is missing or not unique in any sample year. Second, we drop firms that have a negative value for one of the following key variables in any sample year: R&D expenditure, sales, total assets, total liquid assets, total fixed assets, current depreciation, total assets minus liquid assets, total assets minus total fixed assets, accumulated depreciation minus current depreciation, total liabilities, current liabilities, and non-current liabilities. We also drop firms whose equity is not equal to the difference between total assets and total liabilities in any sample year. Third, observations with sales below 1 million CNY are excluded. Fourth, firms that have negative cash flows over the whole sample period are eliminated. Fifth, the reported establishment year must be valid. Firms in which the opening year is after 2007 or the opening year in a given sample year is after that year are dropped. Firms that report establishment before 1900 are also excluded. Sixth, we eliminate observations that have a *Q* value greater than 20. Finally, to reduce the influence of outliers, we trim the one percent tails of each of the regression variables except R&D participation.

For our analysis, we focus only on firms operating in the manufacturing and mining sectors. We adapt the method used by Brandt et al. (2012) to classify one or several two-digit industries into one sector and estimate the AR(2) model for each sector. Table A1 in Appendix A provides a complete list of our industry-sector correspondence. There are 36 industries classified into 13 sectors. It is possible that a firm changes the sector it operates in during the sample period. Since the sector classification only affects the parameter estimates in the AR(2) model, in our subsequent analysis, we use a time-invariant measure of sector. That is, we classify a firm into a sector based on the sector it operates in for most years over the sample period. Data on R&D expenditure were recorded for the first time in 2001 and in 2006 China's Accounting Standards for Business Enterprises was amended which affected how R&D would be recorded. Moreover, no R&D data were collected for 2004. For these reasons we use data for 2001-2003 and 2005-2006 to estimate the R&D investment equations. Our sample is an unbalanced panel of 494,091 observations representing 193,445 firms[9]. All monetary variables are expressed in 1998 constant prices.[10]

[9] Most of these firms are unlisted. According to Guariglia et al. (2011) and Ding et al. (2013), there are only slightly over 1000 listed firms operating in the manufacturing and mining sectors during our sample period. Publicly listed firms in China are not treated separately by the NBS.
[10] Industry-specific producer price indices taken from various issues of the China Statistical Yearbook are used to deflate the variables.

The NBS dataset has previously been used to investigate issues such as productivity growth and its contributing factors (e.g., Jefferson et al., 2008; Cai and Liu, 2009; Hsieh and Klenow, 2009; Song et al., 2011; Brandt et al., 2012), international trade (e.g., Sun, 2009; Yu, 2010; Feenstra et al., 2013; Yu, 2013), FDI (e.g., Sun, 2010; Chen et al., 2011; Du et al., 2012; Xu and Sheng, 2012), causes and consequences of privatization (e.g., Dougherty et al., 2007; Bai et al., 2009; Tong, 2009), determinants and impacts of industrial agglomeration (e.g., Lu and Tao, 2009; Lin et al., 2011; Li et al., 2012), etc. These studies complement our paper and altogether provide an overarching picture of Chinese industrial economy.

4.2 Descriptive statistics

R&D expenditure is the expenses attributable to the firm's research and development of new products, technologies, and processes in its production and operation in a fiscal year. According to China's Accounting Standards for Business Enterprises in 2001, R&D is expensed as it is incurred rather than capitalized and depreciated, constituting part of the firm's management expenses.[11] The dash line in Figure 2 plots gross R&D expenditure for our sample firms as percentage of gross value added. It shares the smooth upward trend with the aggregate R&D intensity for China represented by the solid line, but is in general a bit higher than the country aggregate. As noted above, there is no data point for 2004.

<Figure 2 about here>

Table 1 reports descriptive statistics for the regression variables for the sample used in the R&D participation regressions.[12] We first show statistics for the full sample, and then for the subsamples of firms sorted into different ownership groups. Besides the ownership registration code, the NBS dataset provides a continuous measure of ownership based on the fraction of paid-in capital owned by six different types of investors, namely, the state, collective investors[13], legal entities[14], private individuals, investors from Hong Kong, Macao

[11] The Accounting Standards was amended in 2006 and from 2007 a firm's in-house R&D expenditure is expensed if it is incurred during the research phase of a project and is capitalized during the development phase.
[12] Table A2 in Appendix A presents the definitions of the variables. Because R&D is treated as a current expense for accounting purposes, it is net out from profits and consequently from our (net) cash flow variable (after-tax profits plus depreciation). While a typical cash flow measure in studies using R&D data is constructed by adding back R&D expenditure to the net cash flow (e.g., Hall, 1992; Himmelberg and Petersen, 1994; Brown et al., 2009; Brown et al., 2012), we share the concern of Bond et al. (2005) that using gross cash flow could generate a positive endogeneity bias since R&D would appear on both sides of the investment equation, and it may disguise the different composition of net cash flow and R&D expenditure across firms.
[13] Collective firms are owned collectively by the working people of communities in urban or rural areas. Those in rural areas are known as Township and Village Enterprises.
[14] Legal entities represent a mixture of various types of domestic institutions, including industrial and commercial enterprises, banks, other financial institutions, etc., which are mainly joint stock companies.

and Taiwan, and foreign investors excluding those from Hong Kong, Macao and Taiwan[15]. Following Guariglia et al. (2011) and Ding et al. (2013), we derive ownership using this continuous measure since registration codes are not entirely reliable.[16] We further follow these papers and group all foreign-owned firms either from Hong Kong, Macao and Taiwan, or from other parts of the world into a single category which is labeled *foreign*, and all firms owned by legal entities and private individuals into a single category which is labeled *private*. We use a time-invariant measure of ownership, constructed by classifying firms into one of the four ownership categories based on their majority (i.e., greater than 50%) average ownership share calculated over the sample period.[17]

<Table 1 about here>

Column (1) provides information for the full sample. On average 13.3% of our sample firms perform R&D. For firms carrying out any R&D (subsequently referred to as "R&D performers"), the average log R&D expenditure is 5.131, which corresponds to 169.2 thousand CNY. Dividing R&D expenditure by sales, we obtain a similar intensity as those from previous studies examining Chinese manufacturing firms (e.g., Jefferson et al., 2006; Girma et al., 2008). Turning to the sample splits by ownership (columns (2) to (5)), we find some notable differences across these groups. First, the proportion of R&D performers is the highest in state-owned firms (22.4%). This is more than twice as high as the proportion of R&D performers in collective firms (9.4%) and foreign firms (10.6%). However, conditional on incurring the fixed cost to perform R&D, foreign firms on average spend the most on R&D investment (the average log value corresponds to 219.2 thousand CNY), followed by state-owned firms (193.8 thousand CNY). Second, when it comes to the firm fundamentals, we see that state-owned firms typically have lower firm values (the average of the log value corresponds to 16.4 million CNY), but larger size, regardless of whether size is measured by physical capital (average log value corresponds to 11.9 million CNY) or employment (average log value corresponds to 217.9 workers). Since Q is defined as the value of the firm over beginning-of-period physical capital, state-owned firms have a much lower average Q value than the other ownership groups. Third, looking at internal source of finance, we again

[15] The rationale for differentiating foreign investors between those from Hong Kong, Macao and Taiwan and those from other parts of the world is that the former measures the "round-tripping" FDI that domestic firms may register as foreign invested from nearby regions simply to take advantage of the tax or legal benefits granted to foreign owned firms (Guariglia et al., 2011; Ding et al., 2013).

[16] Registration codes are usually updated with considerable delay (Dollar and Wei, 2007) and firms might have an incentive to falsely register foreign investment to take advantage of tax or legal benefits.

[17] If the largest average ownership share is less than 50%, then the firm does not have a majority average share, and it is excluded from the sample split analysis. This accounts for 4.0% of the sample observations.

find that state-owned firms display the lowest cash flow-physical capital ratio, whereas foreign firms exhibit the highest.

Table A3 in Appendix A provides descriptive statistics for the regression variables only for the R&D performers. R&D performers tend to have higher firm value, larger size in terms of both physical capital and employment and greater profitability as reflected in cash flow than non-performers. We can hence infer that R&D performers tend to have stronger fundamentals than non-R&D performers.

5. Econometric results

In this section, we report the results from estimating the AR(2) model, the R&D investment model under the assumption of perfect capital markets, and the model augmented with cash flow. To check whether our general approach for controlling for the fundamental determinants of investment decisions (firm value) appears appropriate, we will also investigate how estimates of a physical investment Q model compare to existing results in the literature. After presenting our baseline model results, we extend the discussion to the ownership subsamples.

5.1 AR(2) results

Table A4 in Appendix A reports the first-differenced GMM regression results for the AR(2) profit model, for each sector for the period 1998-2007. We can see that the coefficients on $ln\Pi_{i,t-1}$ and/or $ln\Pi_{i,t-2}$ are statistically significant in most sectors at conventional levels. While in two sectors none of them is significant individually, they are jointly significant (sum $ln\Pi$ *p*-value). The instruments are lagged $ln\Pi_{i,t}$ levels dated *t*-3 and *t*-4, which are valid even if the error structure is MA(1). The *p*-values for the $m1$ statistics show first-order autocorrelation in the first-differenced error terms in most sectors, which is expected in the first-differenced estimation. The $m2$ statistics reject the null of no second-order autocorrelation in only one sector. The Hansen tests reject the validity of the overidentifying restrictions in four sectors at the 5% significance level; for the other sectors the validity of the overidentifying restrictions is not rejected. The results provide strong evidence that profits are persistent, which suggests that expectations about future profits are formed taking current profits into account.

5.2 Physical investment full sample

Before estimating the R&D investment model, we first estimate a standard physical investment Q model for the corresponding time span of R&D for 2001-2006. The purposes of doing so are twofold. First, we wish to compare our coefficient estimate on *Q* with existing evidence from studies using the same modeling approach. Such a comparison sheds light on whether our way of constructing measures of firm value is sensible. Second, we also estimate this model augmented with cash flow to compare the estimate on cash flow with those from other studies on Chinese industrial firms to see whether our findings with respect to capital market imperfections are consistent with theirs.

Table 2 presents the regression results for the physical investment *Q* model for the full sample estimated with firm fixed effects. In both the baseline and the cash flow augmented models, the *Q* coefficient is statistically significant, and it is similar in magnitude to what has been reported in previous studies using "Fundamental *Q*" (e.g., Gilchrist and Himmelberg, 1995; Bond and Cummins, 2001; Cummins et al., 2006) and greater than that found from studies using Tobin's *Q* (Hubbard, 1998). This suggests that our method of proxying firm's present net worth by its expected discounted stream of profits captures firms' investment opportunities reasonably well. Consequently, we will have more faith to designate the sensitivity of investment to cash flow as a sign of the existence of capital market imperfections. Turning to the augmented model, the statistically significant coefficient on cash flow indicates that physical investment in Chinese industrial firms on the whole is sensitive to internal finance. This result is consistent with findings from Poncet et al. (2010) and Guariglia et al. (2011), although they estimate an Euler equation and a reduced-form dynamic asset growth model, respectively.[18] The result that cash flow adds additional explanatory power to the investment equation even after we control for its forecasting role through *Q* supports a financing role of cash flow. In addition, the magnitude of the cash flow coefficient is comparable to that in Gilchrist and Himmelberg (1995). Overall, these results are encouraging. We now proceed to the R&D investment model estimations.

<Table 2 about here>

5.3 R&D investment full sample

Table 3 reports the regression results for R&D investment for the full sample. Columns (1) and (2) contain the estimation for the decision of performing R&D or not from a linear probability model with firm fixed effects. Columns (3) and (4) show results from fixed effects regressions modeling R&D expenditure conditional on positive expenditures. Under the

[18] Poncet et al. (2010) and Guariglia et al. (2011) estimate the investment model only for each ownership group, not for the full sample. We will report the regression results for the ownership sample splits in Table 4 and make comparison to their results in section 5.4.

assumption of perfect capital markets (column (1)), we find that the value of the firm and the factor inputs physical capital and employment are all statistically significantly and positively correlated with the probability of conducting R&D. These results are as expected: firms with better prospect and bigger size face better investment opportunities, they hence are more likely to invest in R&D. When cash flow is introduced (column (2)), the coefficient on the firm value becomes less statistically significant, whereas the estimates on the factor inputs have the same sign, magnitude and significance as before. Cash flow adds significant explanatory power to the model, suggesting that firms' R&D participation decision is affected by cash flow.

<Table 3 about here>

When R&D expenditure is considered, provided that an R&D program is set up (column (3)), the estimated coefficients on the variables reflecting firm fundamentals are again all positive and highly significant. These coefficients are larger compared to those in the R&D participation estimation. When the model is augmented with cash flow (column (4)), the coefficient estimates on the firm fundamentals remain positive and highly statistically significant. Cash flow is again found to add significant explanatory power, which indicates sensitivity of R&D expenditure to cash flow. Our results on R&D investment once again manifest cash flow as a direct source of finance besides its role in providing information on investment opportunities.

We note that in contrast to Gilchrist and Himmelberg (1995) the inclusion of cash flow does reduce the magnitude of the coefficient on Q in physical investment. In addition, comparing the magnitude of the coefficients on Q and cash flow reveals that physical investment is relatively more responsive to cash flow than to Q. These findings suggest that physical investment decision is more likely to be influenced by more short-run strategy based on the firm's most recent profit experience rather than by its long-term consideration based on firm fundamentals. However, this is not the case for R&D investment. The inclusion of cash flow does not reduce the magnitude of the coefficients on the value of the firm or on the factor inputs in R&D participation or expenditure estimations, and R&D is not more responsive to cash flow than to firm fundamentals. The difference may reflect high adjustment costs for R&D (e.g., Himmelberg and Petersen, 1994; Hall and Lerner, 2010). A sizable proportion of a firm's R&D investment is payment to highly trained scientists, engineers and other specialists. The temporary hiring and firing of these human resources in response to a transitory shock to finance is very costly. The costs include training new workers to acquire firm-specific knowledge and preventing proprietary information from dissemination by fired workers to competitors, etc. High adjustment costs hence imply that firms tend to maintain a relatively stable R&D status and a relatively smooth flow of R&D spending in accordance with the "permanent" level of available finance in face of transitory finance shocks.

5.4 Physical investment sample splits by ownership

We now test whether there is heterogeneity in the sensitivity of physical investment to cash flow across ownership subsamples. While this analysis may seem off track given the main theme of the paper, we include it to verify findings from other studies on Chinese industrial firms. The conventional wisdom for China or even many transition economies is that state-owned firms are less dependent on internal finance than firms of other ownerships, because they tend to face soft budget constraints and enjoy favoritism from state-owned or state-influenced banks for loans to serve their political and social functions (Bai et al., 2006; Poncet et al. 2010; Guariglia et al., 2011). However, using Chinese-listed firms over 1999-2008 and accounting for firms' equity financing behavior, Lin and Bo (2012) do not find that state-ownership necessarily help reduce firms' financing constraints on investment via the state controlled banking sector.

Table A5 in Appendix A reports descriptive statistics for physical investment regression variables for the full sample and the ownership subsamples. We see a different pattern from that in R&D investment. State-owned firms exhibit the lowest fixed capital investment rate, although they have the highest proportion engaged in R&D and high R&D expenditure. Private firms on the other hand display the greatest investment opportunities measured by Q.

Table 4 presents the regression results for the physical investment Q model for the full sample split by ownership estimated with firm fixed effects. Overall, the Q coefficients are statistically significant and positive in all ownerships, even when cash flow is controlled for. For the cash flow augmented models (columns (2), (4), (6), (8)), cash flow adds additional explanatory power to investment for all ownerships. Therefore, we reject the baseline Q model for firms of all ownerships. Our results are broadly in line with findings from Guariglia et al. (2011) and Ding et al. (2013) who use the same dataset and the same ownership categorization,[19] with the only exception that they find investment in state-owned firms to be insensitive to internal finance. Our result lends support to the finding in Lin and Bo (2012)

[19] Instead of using the majority average ownership share of the paid-in capital over the sample period to define firm ownership as Ding et al. (2013) and we do, Guariglia et al. (2011) adopt the largest average ownership share and the 100% rule.

that Chinese listed firms with the state as the largest shareholder or with a higher state share do not necessarily face no or less financing constraints. Since listed firms are less likely to be financially constrained due to the possibility of acquiring external funds from new equity issuance besides bank loans, our results for mainly unlisted firms are not unreasonable. It could be because, as Lin and Bo (2012) claim, China's corporatization movement has been effective in terms of removing the soft budget constraints once enjoyed by state-owned enterprises and throwing firms into the market.

<Table 4 about here>

5.5 R&D investment sample splits by ownership

Having identified the sensitivity of physical investment to cash flow for firms of various ownerships, we proceed by investigating the sensitivity of R&D investment. Table 5 reports the regression results for R&D investment for the full sample split by ownership. We observe some heterogeneity across ownership groups. For state-owned firms, firm value is not a determinant of R&D participation decision (columns (1)-(2)), whereas firm size in terms of both physical capital and employment is statistically significantly and positively correlated with R&D participation. In addition, cash flow does not add any explanatory power to R&D participation. The insensitivity to internal finance suggests that the decision of state-owned firms to set up an R&D program responds primarily to firm fundamentals rather than to most recent profit experience. When it comes to R&D expenditure, under perfect capital markets (column (3)), firm value and employment significantly affect R&D expenditure, whereas physical capital does not. When cash flow is added to the specification (column (4)), the coefficient on employment is still significant, whereas the estimate on the value of the firm becomes insignificant, and the coefficient on physical capital becomes significant. Moreover, cash flow adds additional explanatory power to R&D expenditure. These results suggest that internal funds are important for R&D spending, and that the result that physical capital does not matter for R&D spending in column (3) is spurious. These findings further indicate that the effects of cash flow on R&D participation and expenditure decisions are very different.

<Table 5 about here>

For collective firms, firm fundamentals and cash flow also exert different effects on R&D participation and expenditure. While firm size in terms of both physical capital and employment is positively and statistically significantly correlated with R&D participation (columns (5)-(6)), physical capital is not correlated with R&D spending (columns (7)-(8)). A counter-intuitive result is that the probability of conducting R&D responds negatively to the value of the firm. Moreover, cash flow adds additional explanatory power to R&D participation, but not to R&D expenditure. In contrast to the finding for state-owned firms, this result suggests that only when collective firms have and expect to have strong cash flow they are more likely to set up an R&D program. When the decision to engage in R&D is made, they are able to conform to the long-term commitment to financing an inflexible R&D budget.

For private firms (columns (9)-(12)), the estimated coefficients on all explanatory variables are positive and statistically significant, suggesting that both R&D participation and spending decisions are affected by firm fundamentals and cash flow. The coefficients are no less in magnitude than those for state-owned and collective firms. These results are not surprising. On the one hand, private firms came into existence only after the economic reforms and for the sole purpose of pursuing profits. Hence, they are more responsive to the market, and economic fundamentals should be more important for long-term investment decisions for them than for state-owned firms. On the other hand, while private firms have enjoyed high productivity and profitability (e.g., Dougherty et al., 2007; Bai et al., 2009), their political status has been weak. Furthermore, private firms are considered riskier than their state counterparts due to shorter credit history and lower chance of being bailed out by the government in case of management difficulty (Poncet et al., 2010; Guariglia et al., 2011). For these reasons, private firms rely more extensively on internal capital for investment. This is particularly pronounced for R&D investment due to the significant asymmetric information and agency problems and lack of collateral value.

For foreign firms, firm fundamentals significantly determine R&D participation regardless of whether cash flow is controlled for (columns (13)-(14)). When R&D expenditure is considered, employment is no longer a significant determinant, and its coefficients are much smaller than those for firms of other ownerships in corresponding models (columns (15)-(16)). In addition, the close to zero and insignificant coefficients on cash flow show that there is no evidence of sensitivity of R&D participation or spending to cash flow. This suggests that R&D in foreign firms is not responsive to profits that they generate internally, since they can finance investment through their foreign parent company that can raise funds outside China. Furthermore, judged by the estimated coefficient on firm value in the cash flow augmented R&D expenditure equation, the value of the firm seems to be more important for foreign firms than for private firms, and more important for private firms than for state-owned firms. This may reflect the difference in the degree of corporatization in firms of different ownerships. Although China has made a progress of corporatization since its economic reforms, the government could still intervene in, or influence, firm decisions, especially for state-owned firms. Therefore, the objective and governance structure of state-owned firms are least like modern corporations, and consequently their R&D investment decisions are least determined by the long-term prospect. On the other hand, the governance structure and management philosophy from the foreign parent company may well have rooted in those of foreign firms, and the expected future profitability may hence play a more important role in their R&D spending decisions. Following this logic, the importance of firm value in the R&D decision for domestic private firms is between that for state-owned firms and for foreign firms.

6. Conclusions

In this paper, we estimate R&D regressions with and without controls for cash flow, to assess the importance of capital market frictions for Chinese industrial firms. We find that for the full sample, firm fundamentals significantly affect R&D participation and expenditure, and that R&D is sensitive to cash flow conditional on such fundamentals. We therefore reject the hypothesis that capital markets are perfect. The R&D investment of Chinese industrial firms on the whole depends on internal finance. Moreover, firms of differing ownership are heterogeneous in the degree of dependence on internal finance. For private firms, both R&D participation and spending are found to be dependent on internal finance. In contrast, for foreign firms both decisions are independent of internal finance. For state-owned firms and collective firms the results are mixed.

Our findings contribute to the literature on the connections between finance and economic growth. While R&D in domestically owned firms (86% of the firms in our sample) is sensitive to internal finance , these firms' ability to generate cash flow may on the other hand provide an explanation for why the Chinese economy has grown at dramatic rates in recent years, especially so for private firms. However, in order to maintain the growth momentum of the Chinese economy, measures need to be taken to introduce a more widespread access to external finance, including both institutional debt and new equity generation.

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Table 1. Sample descriptive statistics for R&D investment

Variables and statistics	Full (1)	State-owned (2)	Collective (3)	Private (4)	Foreign (5)
R&D participation					
Mean	0.133	0.224	0.094	0.134	0.106
Median	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.339	0.417	0.291	0.341	0.308
$ln(rd_{i,t})$					
Mean	5.131	5.267	4.463	5.122	5.390
Median	5.074	5.278	4.430	5.061	5.369
Std. Dev.	1.946	2.037	1.743	1.916	2.060
$ln(V_{i,t})$					
Mean	9.992	9.704	9.750	9.901	10.633
Median	9.950	9.629	9.754	9.869	10.567
Std. Dev.	1.521	1.836	1.489	1.448	1.548
$ln(K_{i,t})$					
Mean	8.720	9.383	8.457	8.573	9.269
Median	8.620	9.441	8.391	8.484	9.236
Std. Dev.	1.413	1.641	1.302	1.353	1.433
$ln(L_{i,t})$					
Mean	4.912	5.384	4.891	4.790	5.278
Median	4.828	5.394	4.836	4.718	5.257
Std. Dev.	1.008	1.182	0.965	0.964	1.026
$ln(CF_{i,t}/K_{i,t-1})$					
Mean	-1.425	-2.091	-1.473	-1.402	-1.252
Median	-1.376	-2.063	-1.391	-1.359	-1.263
Std. Dev.	0.935	1.112	1.009	0.904	0.841
$Q_{i,t}$					
Mean	6.103	3.300	6.123	6.324	6.169
Median	4.559	1.587	4.567	4.833	4.664
Std. Dev.	5.147	4.118	5.216	5.171	5.049
Observations	398,988	20,331	36,939	269,923	56,026
Firms	182,329	8,787	15,735	126,781	24,612

Notes: Table presents descriptive statistics for the regression variables for the sample used in the R&D participation regressions for the full sample and the ownership subsamples. Descriptive statistics for $ln(rd_{i,t})$ are for the sample used in the R&D expenditure regressions. The sample coverage is reported in the column heading.

Table 2. *Q* model for physical investment

	Baseline	Augmented
	(1)	(2)
$Q_{i,t}$	0.134***	0.097***
	(0.001)	(0.001)
$CF_{i,t}/K_{i,t-1}$		0.641***
		(0.013)
Observations	489,936	489,936
Firms	191,913	191,913
F statistic	2185.27***	2194.12***

Notes: Table reports the regression results for the physical investment *Q* model for the full sample estimated with firm fixed effects. The dependent variable is $I_{i,t}/K_{i,t-1}$. $Q_{i,t}$ is restricted to no more than 20. Year dummies are included in both regressions. Standard errors robust to heteroskedasticity and under firm-level clustering are reported in parentheses. The *F* statistic is an *F* test of the null hypothesis that the model is jointly insignificant. *** indicates statistical significance at the 1% level.

Table 3. Variant of *Q* model for R&D investment

	R&D participation		R&D expenditure	
	(1)	(2)	(3)	(4)
$ln(V_{i,t})$	0.006***	0.004*	0.268***	0.187***
	(0.002)	(0.002)	(0.041)	(0.040)
$ln(K_{i,t})$	0.016***	0.016***	0.178***	0.187***
	(0.001)	(0.001)	(0.026)	(0.026)
$ln(L_{i,t})$	0.025***	0.025***	0.330***	0.315***
	(0.002)	(0.002)	(0.038)	(0.038)
$ln(CF_{i,t}/K_{i,t-1})$		0.003***		0.105***
		(0.001)		(0.015)
Observations	398,988	398,988	52,432	52,432
Firms	182,329	182,329	31,138	31,138
F statistic	104.77***	93.54***	166.84***	151.63***

Notes: Table reports the regression results for R&D investment from our variant of the *Q* model for the full sample. R&D participation is estimated using a linear probability model with firm fixed effects. R&D expenditure is estimated with firm fixed effects. Observations with $V_{i,t}/K_{i,t-1}$ (i.e., $Q_{i,t}$) greater than 20 are dropped. Year dummies are included in all regressions. Standard errors robust to heteroskedasticity and under firm-level clustering are reported in parentheses. The *F* statistic is an *F* test of the null hypothesis that the model is jointly insignificant. * and *** indicate statistical significance at the 10% and 1% levels, respectively.

Table 4. *Q* model for physical investment by ownership

	State-owned		Collective		Private		Foreign	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Q_{i,t}$	0.117***	0.074***	0.114***	0.078***	0.142***	0.103***	0.116***	0.083***
	(0.007)	(0.007)	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)
$CF_{i,t}/K_{i,t-1}$		0.629***		0.574***		0.700***		0.495***
		(0.059)		(0.038)		(0.017)		(0.027)
Observations	28,656	28,656	44,410	44,410	326,424	326,424	70,940	70,940
Firms	10,555	10,555	16,600	16,600	131,715	131,715	26,203	26,203
F statistic	55.25***	60.48***	141.46***	149.85***	1660.22***	1675.55***	270.18***	261.15***

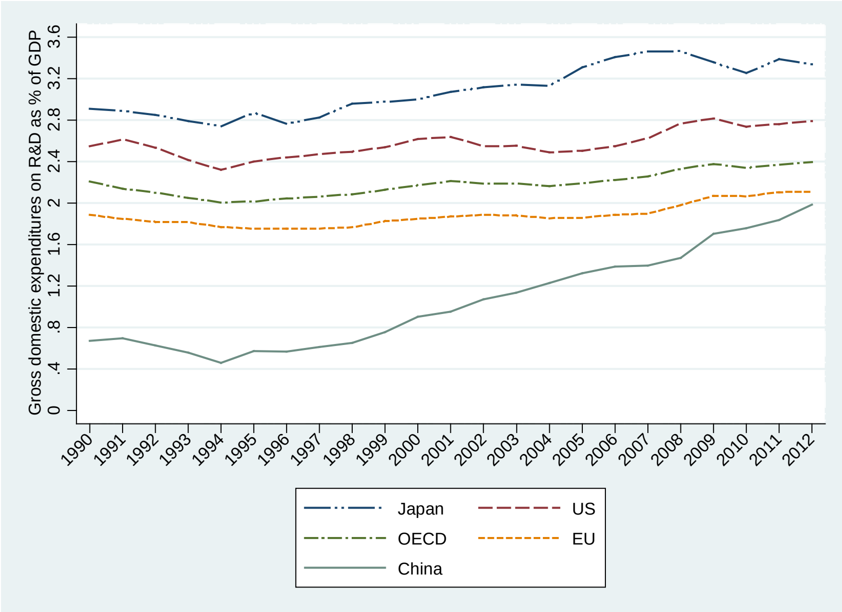
Notes: Table reports the regression results for the physical investment *Q* model for the ownership subsamples estimated with firm fixed effects. The dependent variable is $I_{i,t}/K_{i,t-1}$. $Q_{i,t}$ is restricted to no more than 20. Year dummies are included in all regressions. Standard errors robust to heteroskedasticity and under firm-level clustering are reported in parentheses. The *F* statistic is an *F* test of the null hypothesis that the model is jointly insignificant. *** indicates statistical significance at the 1% level.

Table 5. Variant of Q model for R&D investment by ownership

	State-owned				Collective				Private				Foreign			
	R&D participation		R&D expenditure		R&D participation		R&D expenditure		R&D participation		R&D expenditure		R&D participation		R&D expenditure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$ln(V_{i,t})$	0.002	-0.002	0.184**	0.088	-0.013	-0.017**	0.094	0.042	0.007**	0.006**	0.251***	0.170***	0.008**	0.008**	0.369***	0.387***
	(0.013)	(0.013)	(0.082)	(0.067)	(0.008)	(0.009)	(0.103)	(0.091)	(0.003)	(0.003)	(0.050)	(0.049)	(0.004)	(0.004)	(0.132)	(0.136)
$ln(K_{i,t})$	0.034***	0.034***	0.143	0.157*	0.007*	0.007*	0.154	0.167	0.017***	0.017***	0.187***	0.193***	0.013***	0.013***	0.170*	0.168*
	(0.007)	(0.007)	(0.091)	(0.090)	(0.004)	(0.004)	(0.118)	(0.118)	(0.002)	(0.002)	(0.031)	(0.031)	(0.004)	(0.004)	(0.092)	(0.092)
$ln(L_{i,t})$	0.038***	0.037***	0.467***	0.451***	0.025***	0.023***	0.368***	0.358***	0.026***	0.025***	0.376***	0.359***	0.015***	0.015***	0.050	0.053
	(0.011)	(0.011)	(0.160)	(0.157)	(0.006)	(0.006)	(0.137)	(0.138)	(0.003)	(0.003)	(0.046)	(0.045)	(0.005)	(0.005)	(0.098)	(0.098)
$ln(CF_{i,t}/K_{i,t-1})$		0.005		0.129***		0.006***		0.088		0.002**		0.105***		-0.0001		-0.026
		(0.004)		(0.048)		(0.002)		(0.059)		(0.001)		(0.019)		(0.002)		(0.048)
Observations	20,331	20,331	4,492	4,492	36,939	36,939	3,428	3,428	269,923	269,923	35,984	35,984	56,026	56,026	5,879	5,879
Firms	8,787	8,787	2,312	2,312	15,735	15,735	2,209	2,209	126,781	126,781	21,501	21,501	24,612	24,612	3,667	3,667
F statistic	7.20***	6.55***	20.84***	18.65***	12.43***	11.65***	3.71***	3.57***	74.73***	66.15***	121.50***	111.23***	13.04***	11.41***	16.20***	14.34***

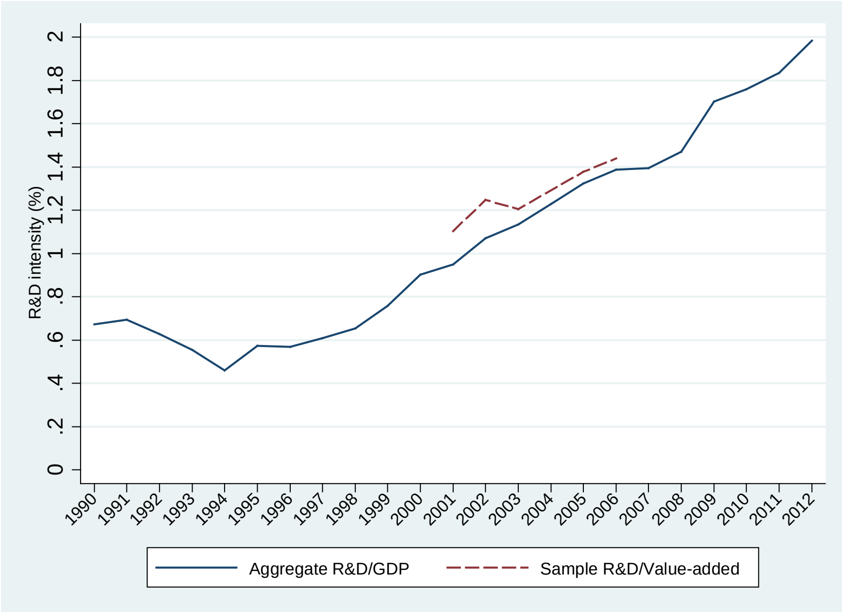
Notes: Table reports the regression results for R&D investment from our variant of the Q model for the ownership subsamples. R&D participation is estimated using a linear probability model with firm fixed effects. R&D expenditure is estimated with firm fixed effects. Observations with $V_{i,t}/K_{i,t-1}$ (i.e., $Q_{i,t}$) greater than 20 are dropped. Year dummies are included in all regressions. Standard errors robust to heteroskedasticity and under firm-level clustering are reported in parentheses. The F statistic is an F test of the null hypothesis that the model is jointly insignificant. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 1. Aggregate R&D intensity



Notes: Figure plots the gross domestic expenditure on R&D as percentage of GDP for Japan, the US, OECD, EU (15 countries) and China from 1990 to 2012. Data for Japan, the US, OECD, EU are obtained from OECD Main Science and Technology Indicators database. Data for China are obtained from China Statistical Yearbook (1991-2013).

Figure 2. R&D intensity



Notes: The solid line plots the gross domestic expenditure on R&D as percentage of GDP for China. It is the same as that plotted in Figure 1. Gross domestic expenditure is defined as the total R&D expenditure for all firms and public institutions in China that engage in R&D activities. Data are obtained from China Statistical Yearbook (1991-2013). The dash line plots the sum of R&D expenditure for industrial firms covered in the NBS dataset after author's data cleaning in proportion to the sum of value added over time. There are no data for 2004 in the sample.

Appendix A

Table A1. Sector classification

Sector	Two-digit industry	
Metallurgical Sector	32	Smelting and Pressing of Ferrous Metals
	33	Smelting and Pressing of Non-ferrous Metals
	34	Manufacture of Metal Products
Coal Sector	6	Mining and Washing of Coal
	7	Extraction of Petroleum and Natural Gas
	8	Mining and Processing of Ferrous Metal Ores
	9	Mining and Processing of Non-Ferrous Metal Ores
	10	Mining and Processing of Nonmetal Ores
	11	Other mining
Petroleum Sector	25	Processing of Petroleum, Coking, Processing of Nuclear Fuel
Chemical Sector	26	Manufacture of Raw Chemical Materials and Chemical Products
	27	Manufacture of Medicines
	28	Manufacture of Chemical Fibers
	29	Manufacture of Rubber
	30	Manufacture of Plastics
	43	Recycling and Disposal of Waste
Machine Manufacturing Sector	35	Manufacture of General Purpose Machinery
	36	Manufacture of Special Purpose Machinery
	37	Manufacture of Transport Equipment
	39	Manufacture of Electrical Machinery and Equipment
	40	Manufacture of Communication Equipment, Computers and Other Electronic Equipment
	41	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work
Building Materials Sector	31	Manufacture of Non-metallic Mineral Products
Timber Sector	20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products
	21	Manufacture of Furniture
Food Sector	13	Processing of Food from Agricultural Products
	14	Processing of Foodstuff
	15	Manufacture of Beverages
	16	Manufacture of Tobacco
Textile Sector	17	Manufacture of Textile
Tailoring Sector	18	Manufacture of Textile Wearing Apparel, Footware, and Caps
Leather Sector	19	Manufacture of Leather, Fur, Feather and Related Products
Paper Sector	22	Manufacture of Paper and Paper Products
Cultural, Educational & Handicrafts Articles sector	23	Printing, Reproduction of Recording Media
	24	Manufacture of Articles for Culture, Education and Sport Activities
	42	Manufacture of Artwork and Other Manufacturing

Note: Table reports the industry-sector correspondence used in the paper.

Table A2. Variable definitions

Variable	Definition
I_t	Difference between the book value of tangible fixed assets of end of year *t* and end of year *t*-1 adding depreciation of year *t*.
$R\&D\ participation_t$	Dummy variable equal to 1 if the firm invests in R&D in year *t*, and 0 otherwise.
rd_t	Expenses incurred during a firm's research and development of new products, technologies, and processes in its production and operation in year *t*. It includes expenses on direct consumption of materials, fuels and power in R&D activities; labor expenses of internal R&D personnel of a firm, such as wage, bonus, social insurance etc., and labor costs of external R&D personnel; depreciation or lease fee of fixed assets, such as apparatus, equipment, buildings, etc., used in R&D activities, and maintenance fee of these fixed assets; expenses on experimenting and manufacturing of models for new products, adjustment of equipment, and testing of trial products; expenses on evaluation of R&D outcomes and patent applications; expenditure on R&D commissions to other organizations or individuals; other expenses directly related to R&D activities, such as on books, conferences, training, consultancy, etc. (Ministry of Finance of China, 2007; Nie et al., 2008).
K_t	Book value of tangible fixed assets (including land and building, fixtures and fittings, and plant and vehicles) at end of year *t*.
L_t	Total number of people employed by the firm at end of year t.
CF_t	The sum of after-tax profits and depreciation in year *t*.

Note: Table presents the definitions of variables used in the paper.

Table A3. Sample descriptive statistics for R&D performers

Variables and statistics	Full (1)	State-owned (2)	Collective (3)	Private (4)	Foreign (5)
$ln(V_{i,t})$					
Mean	10.818	10.721	10.316	10.733	11.581
Median	10.844	10.879	10.320	10.739	11.717
Std. Dev.	1.607	1.775	1.561	1.554	1.540
$ln(K_{i,t})$					
Mean	9.577	10.399	9.063	9.415	10.069
Median	9.606	10.669	9.024	9.415	10.193
Std. Dev.	1.460	1.386	1.359	1.428	1.377
$ln(L_{i,t})$					
Mean	5.433	6.133	5.272	5.316	5.596
Median	5.403	6.296	5.220	5.278	5.613
Std. Dev.	1.064	1.043	1.020	1.036	1.027
$ln(CF_{i,t}/K_{i,t-1})$					
Mean	-1.385	-1.975	-1.427	-1.343	-1.150
Median	-1.335	-1.979	-1.341	-1.302	-1.152
Std. Dev.	0.908	1.016	0.966	0.870	0.817
$Q_{i,t}$					
Mean	6.124	3.310	6.097	6.385	6.908
Median	4.659	1.716	4.513	5.019	5.540
Std. Dev.	5.092	4.034	5.184	5.084	5.152
Observations	52,432	4,492	3,428	35,984	5,879
Firms	31,138	2,312	2,209	21,501	3,667

Notes: Table presents descriptive statistics for the regression variables for the sample used in the R&D expenditure regressions for the full sample and the ownership subsamples. The sample coverage is reported in the column heading.

Table A4. AR(2) regressions

	Metallurgical	Coal	Petroleum	Chemical	Machine Manufacturing	Building Materials	Timber	Food	Textile	Tailoring	Leather	Paper	Cultural, Educational & Handicrafts Articles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$ln(\Pi_{i,t-1})$	0.372***	-0.522	0.206	0.338***	0.518***	0.335	0.427*	0.680***	0.275***	-0.241*	0.813**	0.287	0.439***
	(0.144)	(0.559)	(0.222)	(0.117)	(0.091)	(0.227)	(0.235)	(0.188)	(0.106)	(0.145)	(0.402)	(0.224)	(0.147)
$ln(\Pi_{i,t-2})$	0.107**	0.311**	0.127	0.114***	0.061*	0.100	0.064	-0.004	0.130***	0.275***	-0.033	0.122*	0.121**
	(0.044)	(0.127)	(0.079)	(0.039)	(0.035)	(0.068)	(0.072)	(0.058)	(0.033)	(0.044)	(0.125)	(0.068)	(0.049)
Sum ln(Π) (*p*-value)	0.000	0.633	0.043	0.000	0.000	0.007	0.004	0.000	0.000	0.752	0.006	0.012	0.000
$m1$ (*p*-value)	0.001	0.952	0.152	0.000	0.000	0.051	0.028	0.000	0.000	0.526	0.047	0.068	0.001
$m2$ (*p*-value)	0.739	0.251	0.327	0.368	0.607	0.757	0.709	0.238	0.152	0.000	0.423	0.427	0.678
Hansen (*p*-value)	0.651	0.729	0.055	0.251	0.043	0.251	0.200	0.768	0.000	0.001	0.223	0.024	0.540
Observations	35,892	4,521	2,720	64,246	108,878	31,740	11,011	32,961	32,465	17,875	10,054	12,437	21,084
Firms	15,186	4,416	1,130	25,065	43,078	12,703	5,060	14,237	14,046	7,313	4,055	4,840	8,102
Wald χ^2	729.61***	558.75***	63.77***	1214.56***	3095.31***	861.15***	246.51***	743.07***	549.16***	195.30***	163.64***	224.06***	272.24***

Notes: Table reports the regression results for the AR(2) process for each sector estimated by one-step first-differenced GMM. The dependent variable is $ln(\Pi_{i,t})$. Lagged $ln(\Pi_{i,t})$ levels dated *t*-3 and *t*-4 are used as instruments. The sector name is specified in the column heading. Firm and year fixed effects are included in all regressions. Standard errors robust to heteroskedasticity and within-firm serial correlation are reported in parentheses. Sum $\ln(\Pi)$ tests the null hypothesis that the sum of the coefficients on the lagged $ln(\Pi_{i,t})$ levels is zero. The statistics $m1$ and $m2$ test the null hypotheses of no first- and second-order autocorrelation in the first-differenced residuals. Hansen tests the null hypothesis that the overidentifying restrictions are valid. Wald χ^2 is a χ^2 test of the null hypothesis that the model is jointly insignificant. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table A5. Sample descriptive statistics for physical investment

Variables and statistics	Full (1)	State-owned (2)	Collective (3)	Private (4)	Foreign (5)
$I_{i,t}/K_{i,t-1}$					
Mean	0.291	0.175	0.216	0.320	0.262
Median	0.083	0.045	0.055	0.093	0.087
Std. Dev.	0.831	0.652	0.748	0.875	0.735
$Q_{i,t}$					
Mean	5.865	2.908	5.818	6.124	6.023
Median	4.280	1.243	4.182	4.601	4.498
Std. Dev.	5.155	3.961	5.237	5.180	5.062
$CF_{i,t}/K_{i,t-1}$					
Mean	0.348	0.206	0.345	0.349	0.403
Median	0.244	0.117	0.238	0.249	0.279
Std. Dev.	0.385	0.311	0.389	0.373	0.438
Observations	489,936	28,656	44,410	326,424	70,940
Firms	191,913	10,555	16,600	131,715	26,203

Notes: Table presents descriptive statistics for the regression variables for the sample used in the physical investment Q model estimations for the full sample and the ownership subsamples. The sample coverage is reported in the column heading.

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