家庭对女性高等教育投资动力、成本与启示分析

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摘要：本文旨在揭示家庭用于女性教育投资的动力、成本、风险和回报，通过发放调查问卷，收集并统计家庭投资子女教育的直接成本、间接成本以及大学毕业生和高中毕业生的基本收入情况，估算出家庭用于女性高等教育投资的总费用，以及家庭用于高等教育投资的回收期，从而揭示家庭投资于女性的教育风险，进而从政府、高校、用人单位及女性家庭自身等四个方面为家庭投资女性教育提供具体对策。

关键词：家庭教育投资　女性　 成本　风险　启示

一、女性高等教育投资的动力分析

随着经济社会的发展，女性在创造人类文明、推动社会发展的过程中越来越发挥巨大作用[1]，女性的社会经济地位和对自身的定位也在发生着相应的变化，越来越多的女性选择接受更高等的教育。从 2009 年到 2015 年，我国女研究生毕业人数由 17 万增长到 28.3 万，占研究生毕业总数的比重由 45.7%快速提升至 51.4%；其中，博士毕业生中女性数量由 1.75 万人增长至 2.26 万人，所占比重由 35.9%上升至 42%。女性接受教育投资的比例逐年递增，部分专业、甚至高校出现了女多男少的现象，那么，究竟是什么推动了女性在高等教育上的投资？根据对相关文献的梳理，本文拟从社会经济发展、思想观念转变、家庭经济背景、个人兴趣爱好四个方面论述女性教育投资的动力所在。

（一） 社会经济发展为女性教育投资提供了契机

1. 社会变迁

农业社会呈现的是“男耕女织”、“男主外、女主内”的家庭状态，女性受“男尊女卑”、“女子无才便是德”、“贤妻良母”等传统性别观念的影响，男性因为生理原因占据体力优势，所以男性在社会中的作用被认可。20 世纪初期，中国民族资本主义工业猛烈冲击着传统的农业经济，传统农业经济中手工业占优的地位逐渐式微，人力环境的变化使体力大小的经济意义越来越小，机器时代的到来为女性创造了一定的就业机会。新中国成立以来，以“妇女能顶半边天”为标志的妇女解放运动，使得女性的劳动参与率及高等教育参与率都大幅提高。在现代人事制度中，学历与工资待遇、干部聘用、职称晋升直接挂钩，还与社会地位息息相关，也导致女性报考大学以及被录取人数的逐年增加。

2. 经济发展

传统意义上，家务劳动被视为女性的重要职责，而家务劳动总是被认为低价值、低技能的，从未得到相应的报酬[2]。随着第三产业的快速发展，社会对女性的需求量逐渐增多，对于前台接待、心理咨询师、美容师、护士、幼师等职业，女性比男性更加的适合。21 世纪知识经济时代，社会生产从劳动密集型转向知识密集型，女性特有的亲和力、表达能力、交际能力、情感影响力使女性更能胜任人事类等公共行业的工作，女性的特质使女性成为组织合理配置人力资源、提高经济运行效益、实现组织可持续发展的不可忽视的动因。信息时代的到来，使女性的职业优势愈发凸显。许多岗位与女性适配度更高，比如，智能化办公，互联网的广泛应用使得办公地点更加灵活，女性足不出户也可以工作。

据调查显示，2018 年，互联网行业女性比例升至 45.4%，是科技创新相关行业中最高的。可见，女性教育程度的提高，能拓宽女性工作选择的范围，有助于女性进入互联网、金融等高薪和发展迅速的行业，给女性带来职业发展和收入的快速提升。

（二） 思想观念转变为女性教育投资提供了基础

1. 性别观念

随着社会发展，某些行业分工并不明显，如男性可以当美容化妆师，女性可以成为工程师或飞行员；更有一种说法是，具备双性化人格的人更能适应社会发展的需要，更有利于在社会中生存，男性的刚强、坚忍不拔的精神恰好是新时代女性所必备的素质，而女性的温柔、细致及善解人意的特性也需要男性借鉴，男女双性之间实现互补，有研究表明男女均衡的团队效率最佳，可以发挥各自的才能和创造力。

2. 生活观念

女大学生毕业后，愿意从事一份工作共同支付家庭开支，伴随收入的增加，不仅提高了生活质量，她们对价格也不再敏感，拥有着“高消费”的特点与需求。工作带来的社会地位感和可足够支配资金有利于缓解生活压力，分担配偶及家庭的经济压力。若配偶一方或家庭突遇变故致使主要经济来源者无法继续从事工作，拥有一定教育水平的女性能够更快替代主要经济来源者支撑起整个家庭，避免家庭的生活质量大幅度下滑。

3. 生育观念

由于生理因素，男女劳动力的供给特点有所不同 。这主要表现在女性劳动力与生育年龄人群重合，即妇女的生育大多数发生在作为劳动力而活跃在劳动力市场上的时期 ，而生育行为影响她们的劳动力供给行为[3]。传统上，女性的生育时间较为早，而随着生育观点的改变，很多人的生育时间越来越晚。这就赋予了女性越来越多的时间可以用于工作或者继续学习。特别是在当下环境中，传统的多生多育和养儿防老观念开始慢慢淡化[4]，女性不必多生多育，这也导致了家庭教育资源可以更多地向女性倾斜。

近日，欧莱雅集团联合全球领先的职业社交网站领英中国发布了《2018 女性形象认知与家庭事业观调查》，调查显示，95 后群体中，向往“特例独行酷女人”占比为 19%，“经济女强人”为 58%，而“贤妻良母”型占比为 23%。在快节奏的生活和竞争激烈的社会中会区别于传统观念中依附男性的女性形象，女性愿意投入更多的时间和精力，也更具有职场竞争力，近半数的 95 后女性愿意主动加班，来换取更高的工作报酬。在经济全球化的今天，女性的视野愈发开拓，“谁说女子不如男”，她们在政治、经济、文化等领域都获得越来越高的地位，人们女性的称呼也从“妇女”转变成“女神”。

（三） 家庭经济背景为女性教育投资提供了支持

1. 经济实力

家庭高等教育投资是一种较高层次的人力资本投资，是受未来回报导向的投资行为，家庭背景所体现出的资源多寡直接影响个人的教育水平[5]。传统家庭受落后的传统文化影响，认为女孩早晚要成为别家的人，对女孩的教育投资时间越长，对家庭的回报时间就越短，受限于家庭经济情况，父母倾向于将有限的教育机会给予男孩。随着家庭教育支出能力的提升、父母文化程度的提高以及重男轻女现象的弱化，大多数父母都期望孩子能达到本科毕业或更高，这使得子女性获得的教育机会越来越多。

2. 代际效益

印度女教育家卡鲁纳・卡兰说过：教育一个男孩只教育了一个人，教育一个女孩是教育了一代人，她的效益可以外溢到子女身上。女性作为子女的启蒙老师，她们的爱好、情绪、行为和言语等，都对子女有着潜移默化的影响，和子女的沟通和理解需要与时代同步，了解和掌握新知识才能引导下一代走上健康向上的道路，教育水平高的女性更加关注子女的教育水平，对于子女的成长将产生深远影响。此外，女性的教育程度对家庭整体健康水平有重要的影响，受过高等教育的女性能够更具有现代意识而不是拘泥于传统观念，能够性别平等的看待教育投资选择。

（四） 个人兴趣爱好为女性教育投资提供了动因

1. 成就动机

互联网技术使得人们的视野变得更加广阔，自我意识的觉醒使得更多女性不在局限于自己狭隘的空间，英国第一首相铁娘子撒切尔夫人、美国前国务卿希拉里·克林顿等，激发了多少女性内心的成就需求。新时代，女性为了追求理想与更高成就，更愿意通过教育投资提高自身的能力，实现自身价值。

2. 就业机会

文凭作为劳动者生产能力的象征之一，是雇主筛选劳动力的依据。在竞争激烈的社会中，受过良好教育的人越容易得到更好的就业机会，包括获得更好的工作岗位（如律师、医生、教师、工程师等）、更优的工作环境和更高的收入，经济收入为女性人格独立提供了一定的经济基础和经济保障。由于高薪岗位多数要求具有大学本科甚至研究生学历，家长望女成凤，愿意投资高等教育。

3. 兴趣爱好

天赋人权，现代女性可以根据自身兴趣发展自己，她们不再为了家庭舍弃事业，而是更希望找到其中的平衡点。如果她志在学术研究，她就会乐于徜徉于知识海洋而加大教育投资，从而培养自身的科学思维能力，为未来成功奠定基础。目前，越来越多的男性认为妻子应与他们一起承担家庭开销，反对女性放弃个人的兴趣或事业发展，甚至表示愿意回归家庭"大后方"，做好女性的"贤内助"，支持女性在事业上的发展。

4.攀比心理

通过高等教育投资，成绩优异，高考考入名校可以"光宗耀祖"，她会受到更多人的关注，家人也会为她感到骄傲。女性易受到周边事物以及攀比、从众心理的影响，在越来越多人选择继续接受高等教育时，如果周边的同学朋友考取了大学，感觉自己不比他们差，也想试试，跟着选择更高级教育投资。同时，有些女性把高校当成其潜在的婚姻市场，为追求优质婚姻而选择高等教育，尤其是进入到更高等学府的女性，她们选择到与其相匹配的优质男性的可能性更高，从而接受高等教育投资。

二、女性高等教育投资的"成本—收益"分析

（一） 女性高等教育投资成本分析

20 世纪五六十年代，以舒尔茨、沃尔什为代表的人力资本理论认为，教育不单是一种消费，更是一种生产性投资[6]。教育投资，是指投入教育领域用于培养不同熟练程度的后备劳动力和专门人才，以便提高他们智力水平的人力和物力的货币表现，不仅可以带来个人效益，也能够促进社会效益的提升[7]。教育投资是一种极为有效的人力资本形成的方式，一般而言，个人教育投资成本由下述两个部分组成：

一是教育投资的直接成本。指的是接受教育期间直接投入并用于教育的费用，如学费、书本费和辅导费等。由于无论是否接受教育都必须支付日常生活等其它费用，因此为教育而进行个人生活、健康投资费用则不计入教育投资的直接成本。

二是教育投资的间接成本。指的是因受教育而放弃的收入、也称机会成本，包括为求学而放弃的工作收益；因投资教育而放弃的利息收入；放弃闲暇导致的心理成本——即指为求学而放弃的闲暇心情以及在求学中产生的种种精神压力的非货币性成本[8]。

（二） 女性高等教育投资收益分析

伊兰伯格在《劳动经济学》一书中分析"学历—年龄—收益"之间的相互关联，揭示了一个人的学历越高，人力资本越高，不仅其收益愈高，而且收益增加的速度比个人学习投资增加的速度要快得多，越是往高层次学习付出的相对成本越少，获得的收益越多。笔者将因接受教育而获得的收益主要体现如下：

一是经济回报收益。经济收益是受教育者因为接受完本科及以上高等教育后带来比本科教育以下更高的经济收入，同时相对更能理性消费，合理安排支出。

二是生理健康收益。因为受过高等教育的大学生相对来说具有更高的经济收入和更好的保健意识，能更好地预防疾病和治疗疾病，利于保证自身及家庭成员拥有的良好身体素质。

三是社会心理收益。接受越高等的教育还会为个人带来社会地位的提高，进入上流社会的机会、成就感和良好的卫生保健等，这些构成个人投资研究生教育的社会心理收益[9]。

（三） 女性教育投资-收益估算

1. 家庭投资净现值计算

本文以福州大学 2017 届硕士研究生为样本对从出生到硕士毕业为止父母所花费的教育总投资进行调查，主要包括教育费用（学费、书籍费、课外辅导费）、生活费用（伙食费、服装费）、其他费用（医疗费、交通费、旅游费）组成。根据问卷调查及统计，福州大学 2017 届硕士研究生"父母对孩子成长投

资费用”如表 1 所示：

表 1 个人教育投资一览表（结果保留整数）

年级		教育费用(元／年)	生活费用(元／年)	其他费用(元／年)	总费用（元）	总费用终值（元）	教育费用终值（元）
学龄前(1—4)		O	1500	500	2000*4=8000	26500	0
幼儿园	小班	400=200*2	2000	1000	3400	9946	1170
	中班	400	2000	1000	3400	9472	1114
	大班	400	2000	1000	3400	9021	1061
小学	一年级	700=（50+300）*2（书、托管）	3000	1500	5200	13140	1769
	二年级	700	3000	1500	5200	12514	1685
	三年级	700	3000	1500	5200	11981	1604
	四年级	700	3000	1500	5200	11351	1528
	五年级	700	3000	1500	5200	10810	1455
	六年级	700	3000	1500	5200	10295	1386
初中	初一	1480=200*2+30 补习*36 周	5000=400*12+200（校服）	2000	8480	15990	2791
	初二	1480	5000	2000	8480	15229	2658
	初三	1480	5000	2000	8480	14503	2531
高中	高一	3400=800*2+50 补习*36 周	7700=600*12+500（服装）	2000	13100	21339	5538
	高二	3400	7700	2000	13100	20322	5273
	高三	3400	7700	2500	13600	20094	5024
大学	大一	5500	11800=1200*9+1000（服装）	3000	20300	28564	8086
	大二	5500	11800	3000	20300	27204	7371
	大三	5500	11800	3000	20300	25909	7020

	大四	5500	11800	5000	22300	27106	6685
合计		42040	115300	39000	197840	341290	65749
研究生	研一	8000	12800=1300*9+1100（服装）	5000	25800	29866	9261
	研二	8000	12800	5000	25800	28444	8820
	研三	8000	12800	5000	25800	27090	8400
合计		66,040	153700	54000	275240	426690	92230

从表 1 可见，父母把孩子培养成大学生，23 年来的总投资静态值为 197840 元，其中教育费用为 42040 元，约占总投资的 21.25%。如果父母把孩子培养成研究生，26 年来的总投资静态值为 275240 元，其中教育费用为 66040 元，约占总投资的 23.99%。为了计算上的精确起见，需要考虑各年的利率，计算方法采用复利终值公式来计算 26 年来的父母对子女的总投资动态值。计算公式为：

$F=P*(1+i)^n$

其中：P—各年现金流、i 一利率、n 一年数、F 一终值。

由于二十多年来银行贷款年利率多次调整，根据中国人民银行发布的 2018 年 6 月起最新贷款基准利率，一年以内（含一年）为 4.35%，一至五年（含五年）4.75%，五年以上 4.90%，本文按历年来利率平均值大约为 5％带入终值公式计算。通过问卷调查及综合统计，福州大学 2017 届硕士研究生"父母对孩子成长投资费用"如表 1 所示，所需时间为 26 年，按复利算得的总投资费用终值为 426690 元，总教育费用终值为 92230 元（见表 1），教育费用约占总费用的 21.62%，如果只接受完本科教育的本科生，所需时间为 23 年，按复利算得的总投资费用终值为 341290 元，总教育费用终值为 65749 元，由上述数据可见父母培养一个大学生或者研究生的不易！

2. 家庭投资回收期计算

根据 BOSS 直聘研究院发布的《2018 中国性别薪酬差异报告》：中国女性劳动力的参与率和女性专业技术人员的比例始终保持在一个较高水平，然而，从男女所获得的薪酬来看，依然存在较大差距。只有 1 年以下工作经验的男女劳动者，薪资差距为 8.5%，随着工作年限增长，薪酬差距被逐渐拉大。工作经验达到 5 年以上时，女性由于婚育、家庭等因素，面临更大的职场晋升难度和职业生涯连续性的挑战，薪资差距升至 15%以上，而且这种分化会随着年龄增长进一步加快。从女性接受的教育程度来看，中专及以下学历的女性比相同学历男性的平均薪酬低 26.5%，到了本科阶段，下降至 18.3%。博士阶段则下降至 14.2%，可见，接受高等教育，有利于女性的职业发展，同时，教育依然是女性提高收入的重要方式。

下文，我们想通过女性接受高等教育投资回收期的计算，理性判断投资是否划算。投资回收期是指以投资项目经营净现金流量抵偿原始总投资所需的时间。投资回收期的计算公式为：

$r=1/（1+i）^n$

$R=P*r$ (结果皆保留四位小数）

其中"贴现值 R"指的是货币未来值的现值，P 指的是各年可剩余存款，"贴现率 r"是指将未来资产折算成现值的利率。

假设女性就读研究生三年无收入，本科毕业后就进入劳动力市场工作。根据对福建省各大高校 2015 届 200 名女性本科毕业生就业质量调查问卷显示，2015 年女性本科生平均月收入为 3，629 元，年收入为 43，548 元。根据调查预估，除去日常开销，一年可剩余存款为 25，000 元，则培养一名女硕士的机会成本为 75，000 元，据表 1 可计算得出父母对子女研究生三年的投资总费用为 77,400 元，可见，父母投资三年硕士研究生教育的总投资成本为 152，400 元。而利率以 2017 年中国人民银行三年以上存款年利率 i=2.75％计算，以此计算出家庭对女研究生投资总费用的投资回收期，结果如表 2 所示。

假设女性在高中毕业后就进入劳动力市场工作，据调查统计得出，福建省 2015 届高中毕业生中女

性平均月收入为 2，500 元，则年收入为 30，000 元，除去日常开销，每年可剩余存款为大约 15，000 元，同理可知，培养一名女本科生的机会成本为 60，000=15000*4 元，由表 1 可计算得出本科四年教育投资总费用为 83，200 元，那么可算出总投资成本为 143，200 元。同样以年利率 i=2.75％计算，以此出计算家庭对女本科生投资总费用的投资回收期，结果如表 3 所示。

表 2 一名女硕士研究生教育的总投资费用（含机会成本）回收期

年限 n	各年可剩余存款 P(单位：元)	贴现系数 r	贴现值 R (单位：元)	累计值 W (单位：元)
O	-152400	1	-152400	-152400
l	25000	0.9732	24330	-128070
2	25000	0.9472	23680	-104390
3	25000	0.9218	23045	-81345
4	25000	0.8972	22430	-58915
5	25000	0.8732	21830	-37085
6	25000	0.8498	21245	-15840
7	25000	0.8271	20677	**4837**

表 3 一名女本科生教育的总投资费用(含机会成本）回收期

年限 n	各年可剩余存款 P(单位：元)	贴现系数 r	贴现值 R (单位：元)	累计值 W (单位：元)
O	-143200	1	-143200	-143200
l	15000	0.9732	14598	-128602
2	15000	0.9472	14208	-114394
3	15000	0.9218	13827	-100567
4	15000	0.8972	13458	-87109
5	15000	0.8732	13098	-74011
6	15000	0.8498	12747	-61264
7	15000	0.8271	12406.5	-48857.5
8	15000	0.8049	12613.5	-36244
9	15000	0.7834	11751	-24493
10	15000	0.7624	11436	-13057
1l	15000	0.7420	11130	-1927
12	15000	0.7221	10831.5	**8904.5**

由表 2、表 3 可见，女研究生教育投资回收期为 7 年，女本科生教育投资回收期却需要 12 年，是女研究生投资回收期的近两倍。如再考虑结婚购房等因素，投资回收期将更长！假设正常情况下，一名本科生 23 岁毕业工作，硕士生 26 岁毕业工作，均到 60 岁退休。硕士研究生大概在 33 岁后，就能享受投资硕士研究生带来的纯收益，投资回收相对更快。而本科生虽然能享受 23 岁到 26 岁三年工作带来的收益，但却需要大概到 35 岁才能偿还教育投资成本。硕士研究生只要度过较为拮据的 7 年，未来还有 27 年的时间可享受比本科生更高的投资回报。因此从长远角度和经济学角度，家长应该加大对女性的教育投资力度，使女生接受更多教育机会，以便于缩短回收期，同时得到更多的投资回报，投资女性接受硕士研究生的教育是非常值得投资的，教育回报值更大。

我们再假设男性在高中毕业后就进入劳动力市场工作，据调查统计可知，福建省 2015 届高中毕业

生中男性平均月收入为 3，000 元，则年收入为 36，000 元，除去日常开销，每年可剩余存款大约为 20，000 元，同理可知，培养一名男本科生的机会成本为 80，000 元，由表 1 可计算得出本科四年教育投资总费用为 83，200 元，那么可算出总投资成本为 163，200 元。同样以年利率 i=2.75％计算，计算出男本科生投资总费用的投资回收期，结果如表 4 所示。

表 4 一名男本科生教育的总投资费用（含机会成本）回收期

年限 n	各年可剩余存款 P(单位：元)	贴现系数 r	贴现值 R (单位：元)	累计值 W (单位：元)
O	-163200	1	-163200	-163200
l	20000	0.9732	19464	-143736
2	20000	0.9472	18944	-124792
3	20000	0.9218	18436	-106356
4	20000	0.8972	17944	-88412
5	20000	0.8732	17464	-70948
6	20000	0.8498	16996	-53952
7	20000	0.8271	17442	-36510
8	20000	0.8049	16098	-20412
9	20000	0.7834	15668	-4744
10	20000	0.7624	15248	**10504**

由表 3、表 4 可见，培养一名女本科生教育投资回收期为 12 年，培养一名男本科生教育投资回收期只需要 10 年，比女本科生提前两年回收教育投资成本。而根据上述男女平均薪资可知，男性月平均薪资高于女性，这让我们意识到，男女本科生平均薪资差异是女本科生之所以投资回收期比男本科生长的原因所在。通过分析可知，是由于男性多从事房地产类、工程类、软件设计类等高压、高强度工作，所以，薪资往往会高于女性，而事实上，新时代女性事业心也不亚于男性，她们也能够胜任高压工作，因此，用人单位应尽可能保证男女同工同酬，减少家庭对女性高等教育投资的风险及女性就业面临的风险。同时，结合表 2、表 4 可知，女研究生投资回收期比男本科生少三年，这也让我们意识到，对女性的高等教育投资也是很值得的，如果女性有能力且爱读书，家长应鼓励与支持。

三、女性接受高等教育风险分析

通过上文教育投资——成本分析，我们发现人力资本的投资回收期较长，女性接受本科教育的投资回收期为 12 年；可见，女性高等教育投资存在一定的风险，因此下文将从社会政策、人才使用以及个人承担视角分析高等教育所存在的风险。

1. 社会政策风险

由于产业政策调整将导致社会对各产业人力需求量的变化，我国目前正处于转型期，产业结构处于变动之中，加之市场信息不确定和社会对人才需求的变幻莫测，大学生的就业形势也越发严峻。又如，大学生的扩招政策将精英教育变成了大众教育，由于毕业生增加过快而造成的“人才过剩”，加之，有的用人单位认为大学生所学知识与工作单位的要求存有距离，为了节约职业教育培训的投资成本，宁可使用有经验的人才，导致大学生们就业困难。

2. 人才使用风险

在多数公共领域，男性相比女性更多从事有价值的社会劳动，而传统女性劳动多处于家庭内部的私人领域，这使得男性在在公共领域处于领导地位，女性则多处于从属地位。由于女性在工作中难以融入男人的人际交往圈，影响了女性才华的充分施展，长此以往，使得一些女性无法将所学知识用于工作实际，人力资本含量也将随着岁月的流逝日渐衰减，能力的下滑又使得收入差距日益悬殊。

3. 个人承担风险

第一，个性风险。由于人力资本具有异质性，同样的人力资本投资，因人的禀赋不同，效果也不同。女性教育程度的提高也使得她们对工作岗位期望增高，但有的工作岗位对胜任力的要求更为多元，并非完全依学历而论。有的用人单位认为女生动手能力差，若男女在应聘时所拥有的文凭相当，用人单位则更倾向于将工作机会留给男性，这就造成在同等条件下，加大了女大学生的就业难度。

第二，生育风险。女性婚后面临生育休假以及生理周期，使得工作也容易出现间断，特别是当前我国全面放开二胎政策，多省份施行延长女性产假等政策引导之下，导致用人单位更倾向于选择男性，有些用人单位在录用女性，在签订就业合同中明文规定在工作几年之内不许结婚和生育，这无疑增加了女性因婚期孕期而单位不接纳的风险。

第二，意外风险，因为遇到不可抗力因素导致的人力资本损失，如遇车祸死亡或残疾；另一方面是因为长期不注意身体锻炼，致使身体健康状况欠佳，影响了人力资本作用的有效发挥。

通过上文调查数据显示，同一学历下，女性平均薪资少于男性导致女性高等教育投资回收期比男性长，且女性又面临社会政策、人才使用、个人承担等风险诸多挑战，因此，倘若政府、用人单位、高校及女性家庭在女性接受高等教育上不做出努力，那不仅导致女性投资回收期更长，更会使女性社会贡献率降低。

四、促进女性接受高等教育的策略

在女性人口近乎据半的中国，受过高等教育的女大学生是人力资源总量中的不可或缺的元素，女性接受教育程度的提升有利于我国经济和社会的全面发展。为了防范女性人力资本投资的风险，实现女性接受高等教育效用最大化，国家政府、用人单位、高等学校、家庭都应该采取相应的措施，为家庭投资女性教育提供支撑。

（一）政府对女性接受高等教育的政策导向

1、 拒绝性别歧视，树立正确的性别意识

性别平等的观念不是与生俱来的，主要受后天教育和社会价值观的影响，要真正解决社会对女性就业性别歧视问题，切实承认和保障女性的社会合法地位，政府部门起着重要的作用[10]。著名经济学家海闻曾说，“性别歧视的存在和一个国家的民主法治进程有关，最大的责任还在政府”，如果政府没有在女性就业平等权上发挥正面示范作用，出现优先录用男公务员的现象，将会给其他用人单位以不良的示范作用。政府应正确引导全社会树立男女平等的性别意识，利用有效渠道向社会大众宣传正确的性别意识，树立平等的社会性别观，保障女性合法就业权益，提高公众的社会性别觉悟，让公众深切认识到女性接受高等教育也会给家庭带来较大的经济效益，才会激励家庭保障对女性的高等教育投资。

2、 修订相关政策，制定两性平等的法律

我国已有一些保障女性平等参与高等教育的政策法规，但仍存有对女性教育权益关注不够的现象。例如，在计划经济时期，毕业生分配制度为女性就业提供了确切的保障，而在市场经济背景下，人才市场选择的自由性导致性别歧视现象更加严重。因此，随着女性接受高等教育数量的增加，为确保女性在接受高等教育上拥有与男性平等的权利，合理地分配社会和教育等资源，增进社会公众及家庭对两性平等的认知，政府还需制定一套完整的性别平等教育法律[11]，在招工广告中不许限制性别的条款，避免两性偏见和歧视，对性别歧视单位加大惩罚力度，使招聘方为性别歧视行为付出更大成本。与此同时，为女性提供法律救济，当女性遭遇就业性别歧视时，要有专门的机构进行调解和处理，有法可依，执法必严，消除用工性别歧视，引导就业市场的良性发展[12]。

3、 杜绝生育歧视，加强女性就业保护

繁衍后代的重任不应由女性独自承担，不应让女性因为生育后代而遭受用人单位不公正的待遇[13]。政府应根据我国经济发展的实际情况，积极探索多种方法解决女性生育补偿问题，例如，通过税收、采取社会统筹等措施使生育成本社会化，同时，政府应将女性重返工作岗位的培训费用纳入社会保障，减少用人单位的培训支出，从而使用人单位雇佣男女两性劳动力的成本趋同、利益均等，以此解除用人单位聘用女性的后顾之忧[14]。另外，政府应采取措施监管到位，确保男女两性同工同酬、提高女性在社

会、家庭中的地位，从而使家庭对女性教育投资的后期收益得到保障，进而加大女性教育投资的力度。

（二）高校对女性接受高等教育的政策鼓励

1、保证教育资金

如果家庭的支付能力有限，女性的教育投资多少都会受到阻碍，因此，高校可以寻求政府、社会各界的帮助，呼吁企业和社会爱心人士设立投资基金、奖学金制度等，使高等教育成本向社会化迈进，为女性获得平等高等教育机会提供财政扶持，以便加大教育经费的投入，与女性家庭共同分担高等教育成本，减少家庭经济负担，增加女性接受高等教育的机会。与此同时，高校对学生实行弹性学分制，使其能够自由安排学习时间，学生可提前修完总学分，便于他们接受教育的闲暇时间能够进入劳动力市场获得经济报酬，以此在教育投资上上实现教育成本独立，从而减少因家庭投资不足而造成的高等教育约束。

2、提供就业支持

高校在制定培养方案和设置专业之前需对未来就业市场人才需求及未来的就业趋势进行前瞻性预测，制定合理的人才培养计划，重视女大学生的科研和实践能力的培养，为女大学生成为专门人才创造条件。作为女大学生，应根据自身的职业生涯规划选择合适的选修课程，形成其自身的差异化优势，从而在劳动力市场上提高竞争力[15]。高校就业指导工作应从高学历女性的就业需求出发，对面试技巧、形象礼仪、自身权益等方面进行有针对性的就业指导，帮助女大学生顺利迈入劳动力市场。高校应与用人单位紧密合作，为女大学生提供更多就业选择，高校还可邀请心理专家对存有学习及就业压力的女大学生实施心理疏导，排除心中焦虑，正确认清自我职业兴趣与职业胜任能力等。

（三）单位对女性接受高等教育的政策支持

用人单位要认识现代女性所承担的社会及家庭角色，正确看待女性生育问题，承认女性的社会价值，在追求利益最大化的同时，勇于承担社会责任，给予女大学生平等的就业机会[16]。用人单位需充分认识女性特有的人力资源优势，做到知人善任、同工同酬，通过营造性别平等的企业文化环境，给与女性施展才华的机会。同时，用人单位的人力资源部应为女性提供法律救助，使女性有冤有地可申诉，以此规范企业内部文化氛围，引导企业性别文化的良性发展。

（四）家庭对女性接受高等教育的决策能力

家庭对女性的高等教育投资决策最终是由家庭成员做出的，家长应给予子女公平的教育机会，为了降低女性教育决策的个人承担风险，建议家长多了解国家相关政策，结合家庭以及受教育者的内心需求、兴趣特长，来做出教育投资决策。在专业选择过程中，应充分考虑到女性细腻周到、亲和力、协调沟通能力强的特点，合理选择学习专业，为未来成功就业奠定素质基础。

由于文化水平越高的女性，在家庭和社会中的地位越高，越来越多的女性渴望通过接受高等教育提高自己的学识、能力与修养，通过提高自身的综合素质来确保其经济地位和人格层次的独立，进而在求职中提高自身的竞争力，成就一番事业立于不败之地，成为众人艳羡的白领、骨干、精英“白骨精”的代表，使女性在获得劳动价值的同时彰显人生价值。

Analysis on the Motivation, Cost and Enlightenment of Higher Education Investment from Family in Female

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Abstract: This article aims to reveal the motivation, cost, risk and profit of family education investment in female, and through questionnaires, collecting and analysing the family investment costs in education as well as the basic income of their children after graduating from school, and estimate the family the total cost of higher education investment in women, and the payback period of higher education investment, so as to reveal the family investment in education of females' risk, and puts forward countermeasures from the four aspects,that are government, university, enterprise and family.

Key words: family education investment, women, cost, risk, enlightenment

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北京市农民工消费行为影响因素研究

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摘要：农民工是伴随着国家改革开放出现的特殊群体，占中国将近五分之一的人口，他们从事城市基础建设、制造行业以及部分服务业，为祖国经济发展做出巨大贡献。本文以消费这一普遍经济活动为切入点，对北京市农民工展开了实地问卷调查，从影响农民工消费行为的个体、经济、社会、心理四方面因素出发，通过多元线性回归方程分析影响农民工消费支出、医疗消费态度、消费意愿的具体因素，为保障农民工消费、引导农民工合理消费提供相关建议。

关键词：农民工；消费行为；影响因素

一、引言

农民工群体是伴随着我国改革开放出现的一个拥有特殊身份的群体。他们在国家实行家庭联产承包责任制后，从农村土地解放出来，就近走到发展迅速的本地城镇，或跨地区、跨省流动到沿海经济发达地区，期望依靠劳动改善生活。这个群体主要分布于建筑业、制造业、服务行业和其他劳动力密集型产业,他们大多从事体力劳动，每年给所在城市创造大量财富，对中国工业化、城镇化和现代化建设做出了巨大的贡献。尽管如此，进城务工的农民工仍然处在城市的中低端消费市场，无论是衣食住行等基础资料消费，还是医疗、教育、娱乐等发展享受资料消费都处在较低水平。本文以北京市农民工为参照，研究这部分人群的消费行为影响因素，其目的是了解农民工消费难题，从而提出合理对策，提高他们的生活质量。另外现阶段，中国经济正在由投资和外贸拉动为主转向扩大内需特别是扩大消费转型的新常态，个人和家庭的消费对中国经济的拉动作用越来越大，数量庞大的农民工蕴含巨大的消费潜力，值得我们去研究他们消费问题。北京作为首都和快速发展的特大城市，吸引了大量外来人员来京务工。据北京市统计年鉴，2016 年北京市常住外来人口达到 807.5 万人，接近 1978 年北京市总人口的水平。在这个与城市文明不断碰撞的过程中，农民工以“北京人”为参照，不断调整自己的生活方式和消费行为。

二、相关文献综述

国内学者从不同的角度出发，对影响农民工消费行为的因素进行探讨。钱雪飞（2003）和白暴力（2008）分别从微观调查和宏观数据分析两方面发现农民工收入水平低是制约其消费能力的主要因素。李隆玲[1]（2016）专门分析了收入变化对农民工食物消费的影响，结果表明，农民工的收入水平提高时，食物消费支出和各类食物消费量都会显著增加；且中等收入农民工的收入水平提高时，食物消费支出和各类食物消费量增长的幅度比高收入、低收入人群更大。邢海燕[2]（2012）以浙江省 5 个地区的农民工为研究对象，发现除收入外，文化程度和职业对农民工的消费有很大影响。刘伟[3]（2011）以东莞农民工为研究对象，通过加权最小二乘法回归分析，发现家庭状况、汇款也是影响农民工消费的重要因素。卢海阳[4]（2014）重点分析了社会保险对农民工家庭消费的影响，结果发现养老、医疗、失业保险对农民工消费有促进作用；总体看来，社会保险对中低收入的农民工家庭消费影响较大。秦晓娟[5]（2014）实证研究发现城镇化水平，自我市民身份认同、市民的示范消费对农民工消费水平具有显著正向影响。向国成[6]（2015）以农民工家庭为研究单位，发现农民工市民化后，能够通过社会保障作用，显著提高其边际消费倾向，改善其消费结构，持续推动家庭消费的增加。沈晖[7](2015)以中国社会科学院农村经济发展研究所 2014 年就业状态农民工的调查统计数据为研究对象，发现农民工人均消费状况和劳动权益保障有密切关系，消费水平越高劳动权益的保障程度越高。

在前人提出的影响农民工消费行为的具体因素上，本文将这些因素归纳为个体、经济、社会和心理四大类，并通过设计问卷的形式验证影响北京市农民工消费行为的各种因素。

三、北京市农民工数据来源及样本基本情况

根据本文的研究目的与研究思路，问卷设计采用结构式调查问卷，分为两部分内容：一是个人基本情况，包括被访者性别、年龄、在京工作年限、婚姻状况、教育程度、从事职业、收入等；二是消费行为调查，根据这些行为表现确定各因素对他们的消费的影响。取样的地点范围主要包括北京物资学院周边的建筑工地、餐馆、街头以及以及八里桥市场，还有部分数据样本是在通州区宋庄镇及周边村庄获得。发放调研问卷采用的方法主要是随机抽样和偶遇抽样，问卷按照是否在外地从事非农产业进行身份识别，

然后当面访问或者当面发放回收。前后共发放问卷 258 份，有效回收问卷 230 份，有效回收率为 94.2%。230 个有效研究样本的基本情况如下：

从性别上看，男性占 60.0%，女性占 40.0%，这说明男性依旧是外出务工的主力军。从年龄上看，在样本数据里新生代农民工占比 47.7%，第一代农民工占比 52.3%。从婚姻状况上看，调查的新生代农民工中，未婚占比 82.0%，已婚占比 16.4%，离异占比 1.6%。第一代农民工中，97.1%拥有婚姻家庭，离异和丧偶的各有 1 个。这也就决定了当问及存款目的时，有一半的未婚新生代农民工将娶妻生子当作头等大事，68.8%的已婚农民工将子女教育作为存款主要目标。

受教育程度方面，小学及以下文化程度的农民工集中在 36 岁以上农民工中；大部分农民工的学历水平处于初中和高中阶段；大专及以上学历农民工主要集中在新生代农民工，占比 86.7%。这说明新生代农民工，在九年义务教育的全面实施过程中取得良好效果，他们相较于第一代农民工拥有较为良好的受教育背景。从事行业方面，女性农民工在餐饮业居多，占比 80.0%；男性农民工在建筑业和快递配送行业占绝大多数比例，达到 85.3%；制造业和其他服务业男女比例差别不大。当问及打工原因时，尽管有超过一半的农民工回答是改善家庭状况，还有 22.3%和 13.8%的人表示是为了谋求个人发展和开阔眼界。这说明全社会生活水平的提高正在慢慢改变外出务工农民工的观念，他们由传统的“出来挣钱”向“体验生活、追求梦想”转变。

四、北京市农民工消费行为影响因素实证分析

4.1 变量设置

自变量方面，本文以个体因素、经济因素、社会因素和心理因素四大类影响因素为基础，对问卷里的各因素进行筛选整理，具体选取性别、年龄、文化水平、月收入、家庭经济状况、单位购买保险情况、消费权益维护、消费参照、收入预期和留城意愿（综合考虑留京意愿和是否在城里有买房打算两项内容）10 项因素作为自变量。婚姻状况没有进入备选自变量是因为婚姻状况与年龄有密切关系，与指标 x2 有重叠部分；行业没有进入备选自变量是因为行业对农民工消费行为的影响是通过收入和行业特征产生效果的，与指标 x5 有重叠部分；月储蓄情况没有进入备选自变量是因为无法对问卷中的“每月会有不定额储蓄”和“每月有定额储蓄”进行比较排序；价格因素没有进入自变量是因为短时间内物价水平保持不变。因变量方面，根据消费行为依次选取能够量化的在京月消费支出、医疗消费行为、主观消费意愿 3 项指标。在所有变量中，月收入、在京月消费支出为定距型变量，因此使用原始数据进入模型；其他变量均为定序型变量，需要进行变量赋值。为方便进行后文的数据分析，将这些变量处理为虚拟变量，具体赋值情况见表 4-1 和表 4-2：

表 4-1 自变量赋值

影响因素	变量名	变量赋值
个体因素	x1 性别	0=“男”；1=“女”
	x2 年龄分组	0=“35 岁及以下”；1=“36 岁及以上”
	x3 文化水平	1=“小学及以下”；2=“初中”；3=“高中（中专）”；4=“大专及以上”
经济因素	x4 月收入	
	x5 家庭经济状况	1=“贫穷”；2=“一般”；3=“较好”；4=“富裕”
社会因素	x6 单位购买保险情况	1=“没有”；2=“不清楚”；3=“购买部分”；4=“有”
	x7 消费权益维护	1=“不了解”；2=“听说过，没使用过”；3=“使用过”
心理因素	x8 消费参照	1=“身边打工老乡”；2=“身边城市居民朋友”；3=“广告电视”
	x9 收入预期	0=“没有”；1=“有”
	x10 留城意愿	1=“没有”；2=“不确定”；3=“有”

表 4-2 因变量赋值

消费行为	y1 月在京消费支出	
	y2 在京医疗消费态度	1=“扛过去”；2=“去药店买药”；3=“去私人诊所”；4=“去正规医院”
	y3 主观消费意愿	1=“放弃”；2=“等降价再买”；3=“从网上买”；4=“咬牙买下”

4.2 研究假说

根据上述自变量和因变量的选取，本文做出如下假设：

1.性别和北京市农民工月消费支出水平、在京医疗消费态度以及主观消费意愿这些消费行为之间无

明显相关性。

2.月收入水平是影响北京市农民工消费行为的主要因素。在其他条件不变的情况下，收入越高，月消费支出越多，主观消费意愿越强。

3.农民工参加社会保险对其在京医疗消费态度有积极作用。在其他条件不变的情况下，参加社会保险的农民工更容易接受到正规医院看病买药。

4.消费参照群体对北京市农民工消费行为有影响。参照消费水平高的群体，能够促进农民工在京消费支出增加，主观消费意愿增强。

4.3 实证分析

本文利用 SPSS 软件首先对所有变量做相关性分析，其结果见表 4-3：

4-3 相关性

			性别	年龄分组	学历	收入	家庭经济状况	单位购买保险情况	消费权益维护	消费参照	收入预期	留京意愿
肯德尔tau_b	在京消费支出	相关系数	.071	-.411**	.434**	.268**	.422**	.276**	.160*	.763**	-.056	.296**
		显著性（双尾）	.324	.000	.000	.000	.000	.000	.018	.000	.470	.001
		N	130	130	130	130	130	130	130	130	130	130
	医疗消费态度	相关系数	-.089	.038	.035	.201*	.172*	.157*	.064	.228**	.183*	.107
		显著性（双尾）	.286	.645	.659	.015	.034	.041	.411	.005	.028	.192
		N	130	130	130	130	130	130	130	130	130	130
	主观消费意愿	相关系数	-.167	-.286**	.290**	.194*	.228**	.245**	.221**	.414**	.174*	.266**
		显著性（双尾）	.061	.000	.000	.012	.004	.001	.005	.000	.033	.001
		N	130	130	130	130	130	130	130	130	130	130

从表中明显看出性别（x1）与北京市农民工在京月消费支出（y1）、在京医疗消费态度（y2）和主观消费意愿（y3）无明显相关关系。而在京月消费支出（y1）与自变量 x2，x3，x4，x5，x6，x7，x8，x10 相关性较强；在京医疗消费态度（y2）与自变量 x4，x5，x6，x8，x9 有较强相关性；主观消费意愿（y3）与除性别（x1）外的其他自变量都有较强的相关性。

然后对因变量 y1，y2，y3 和与之对应的相关性较强的自变量分别建立多元回归方程，并采用向后筛选策略，对自变量加以筛选和控制，最终得到三个模型的回归结果，分别命名为消费支出回归结果、医疗消费态度回归结果、消费意愿回归结果，三个模型的具体分析结果如下。

（一）消费支出回归结果

将 8 个自变量全部引入消费支出回归方程后，SPSS 经过五步自变量筛选，完成回归方程的建立。其中调整后的 R 平方等于 0.89，回归方程显著性检验的 P 值等于.000（α=0.05），DW 值等于 1.787，VIF 接近于 1。整体来看，建立线性模型是恰当的，其系数结果见表 4-4：

4-4 系数

模型	非标准化系数	标准系数	T	显著性	共线性统计

	B	标准错误	贝塔			容许	VIF
5 （常量）	.263	.341		.730	.262		
年龄分组	-.257	.124	-.086	-2.134	.001	.668	1.502
收入	.278	.053	.292	2.853	.006	.432	1.365
家庭经济状况	.302	.209	.130	2.298	.021	.625	1.683
消费参照	.826	.064	.328	6.076	.000	.612	1.923

a. 因变量：在京消费支出

最终的线性回归方程为：$y_1 = 0.263 - 0.257x_2 + 0.278x_4 + 0.302x_5 + 0.826x_8$

根据消费支出线性回归方程中自变量回归系数的大小，发现对受访农民工在京月消费支出影响从大到小的排序依次是消费参照、年龄、家庭经济状况、月收入水平。其中年龄与在京月消费支出呈负相关关系，即年龄每增加一个单位会使在京月消费支出减少 0.257 个单位，这验证了前文所说的新生代农民工在消费上更加大胆，而第一代农民工在消费上表现出较为谨慎的态度。月平均收入、家庭经济状况以及消费参照与在京月消费支出呈正相关关系，即收入每增加一个单位会使在京月消费支出就会增加0.278 个单位，家庭经济状况每增加一个单位会使在京月消费支出就会增加 0.302 个单位，消费参照每增加一个单位会使在京月消费支出就会增加 0.826 个单位。这表明消费参照对农民工在京消费支出的正向影响更大。

（二）医疗消费态度回归结果

同样的，将 5 个自变量引入医疗消费特征回归方程，经过五步自变量筛选，方程仅保留一个自变量。此时，调整后的 R 平方等于 0.725，回归方程显著性检验的 P 值等于.000（α=0.05），DW 值等于 2.011，VIF 接近于 1。整体来看，在京医疗消费态度线形回归模型的建立是恰当的，其系数结果见表 4-5：

4-5 系数

模型	非标准化系数		标准系数	t	显著性	共线性统计	
	B	标准错误	贝塔			容许	VIF
5 （常量）	1.575	.120		13.089	.000		
单位购买保险	.279	.045	.481	6.204	.000	.756	1.322

a. 因变量：医疗消费态度

最终的线性回归方程：$y_2 = 1.575 + 0.279x_6$

这里发现单位购买保险情况是影响受访农民工在京医疗消费态度的主要因素。其中单位购买社会保险的数量越多，他们对待医疗消费态度越积极。这是因为社会保险包含医疗保险、工伤保险等在内，这对于他们出现意外病患时在医院看病有巨大作用，能帮助农民工报销部分医疗消费支出，减轻生活负担。而没有社会保险的农民工会采取谨慎的医疗消费态度，他们宁愿扛过去或去药店买点药，也不愿意去大医院看病。

（三）消费意愿回归结果

将备选的 9 个自变量进入消费意愿回归方程，经过七步自变量筛选，得到最终回归方程。在该方程中，调整后的 R 平方等于 0.703，回归方程显著性检验的 P 值等于.000（α=0.05），DW 值等于 2.062，VIF 略大于 1。整体来看，符合建立线性回归方程的条件，其系数结果见表 4-6：

4-6 系数

模型	非标准化系数		标准系数	t	显著性	共线性统计	
	B	标准错误	贝塔			容许	VIF
7 （常量）	.424	.197		2.780	.030		
收入	.231	.063	.301	3.021	.001	.452	2.215
家庭经济状况	.476	.140	.299	3.398	.001	.562	1.779
消费参照	.231	.158	.159	1.462	.046	.368	2.720

a. 因变量：主观消费意愿

最终的回归方程为：$y_3 = 0.424 + 0.231x_4 + 0.476x_5 + 0.231x_8$

根据最终线性回归方程中自变量回归系数的大小，发现对受访农民工消费意愿影响程度从大到小的排序依次是家庭经济状况、消费参照和月收入水平。它们都与农民工消费意愿呈正相关关系，即家庭经济状况越好，消费参照消费水平越高，月收入水平越高，农民工的主观消费意愿会随之越强烈。家庭经济状况差的农民工的家庭重担大，个人收入不仅要维持自己的消费支出，还要兼顾整个家庭的消费支出，因而其主观消费意愿弱，即便有自己中意的商品也很可能放弃购买。反过来，高收入的刺激会给予农民

工消费信心，使他们在中意商品面前更加大胆地消费；身边城市居民衣食住行娱消费示范和网络电视广告宣传效果也会引导农民工见到许多之前没有接触过的新奇产品，从而增加其主观消费欲望。

五、结论及相关建议

本文根据实证结果分析的结果发现，性别和北京市农民工的月消费支出、医疗消费态度和主管消费意愿无显著相关性；月收入水平（x4）在消费支出回归方程和消费意愿回归方程都有出现，对北京市农民工消费行为产生正向影响，即随着收入的增加，月消费支出越多，主观消费意愿越强。消费参照（x8）也在上述两个回归方程中出现，对北京市农民工消费行为造成有影响，具体表现为仿效城市居民或广告电视消费会刺激农民工在京消费支出的增加，面对喜欢的商品更容易下定决心购买。此外，在医疗消费态度回归方程中，农民工单位社会保险（x6）的入保参与度越高，他的在京医疗消费态度就越积极、更开明，反之他们倾向于生病时少花钱或者不花钱。至此，以上本文提出的研究假设都得以证明。

基于以上结论，本文提出以下建议：（1）促进收入稳定和增长，提高农民工消费能力；一方面，要规范不同行业用工标准，实现农民工同工同酬、同职同权，尤其是在工资支付上一定要明确责任，对于已发生的欠薪事件，政府有关部门要多渠道介入，一旦发现情况属实，立即与其他部门多方联动，严厉惩处恶意拖薪行为。另一方面，政府部门应该加强与用人单位及培训机构的合作力度与扶持力度，为农民工提供专业的，具有针对性的，适合用人单位的职业技能培训项目，以此提高农民工收入水平。（2）转变农民工消费观念，倡导适度消费；新闻媒体应积极发挥舆论引导作用，帮助农民工树立正确的消费观。社会金融机构应和用工单位积极合作，举办专题讲座的形式，帮助农民工学会合理分配自己的工资收入。政府部门要以身作则，带动全市市民，树立可持续发展观念，着力构建节约型消费模式，在全社会引领厉行节约、反对浪费的风尚，以此带动农民工共同形成适度消费、理性消费的良好社会风气。（3）健全农民工社会保障制度，增强农民工消费信心；政府应尽快建立健全的社会保障体系，将农民工纳入体系，用法律规定用人单位必须为从事高危工作的农民工参加工伤保险和医疗保险，同时要尽快实现医疗保障制度在城乡之间有效对接，使农民工在家乡参加的合作医疗能在北京医院诊所能够使用，从而降低大家对未来消费的担忧。同时，还要帮助失业农民工就业，比如建立“公共劳动”形式的流动人口“最低生存保障”体制[8]，建立覆盖全市农民工就业信息平台，发布招工方面的相关讯息等，从而多途径就业，增强农民工消费信心。（4）加快市民化、城镇化步伐，优化农民工消费环境；就北京市情况而言，政府应跳出户籍改革形式上的条框，更加注重农民工市民化实质上的需求，分类有序推进市民化发展。在住房，医疗，子女教育等方面，为农民工开启绿色通道，减轻他们在京各项支出负担。另外，在顺应京津冀一体化战略，有序迁出劳动密集型产业的同时，做好农民工随厂外迁的安置工作，使他们的身份更容易转化为当地居民身份，从而在公共服务等方面享受当地社会保障，获得较为轻松的消费环境，实现农民工消费质量的提升。

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Cross-correlation between futures and spot markets in China during bull and bear from 2014 to 2016—A study based on the perspective of fractality

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Abstract

In allusion to the deficiency of existing research, we first optimize the fractal methods based on the perspective of fractality. And the cross-correlation between futures and spot markets during the bull-bear cycle from 2014 to 2016 is analyzed based on the CSI 300 high frequency data from three dimensions of cross- correlation level, multifractal feature and conduction direction. To sum up, three conclusions are obtained. First, from the long-term scales, the spot market in the bull market and bear market both showed a high level of cross-correlation, but there are still some differences between them. Meanwhile, whether in the bull or bear market, multifractal characteristics can be found in the cross-correlation between futures and spot markets with significant difference, which affects the long memory, risk and effectiveness between markets. Finally, whether in the short or long term, the transmission between futures and spot markets is bidirectional, and who is on the leading position in the bull market is distinct from that in the bear market.This study is of practical significance for the design of hedging strategies, the optimal allocation of assets and the formulation of market regulatory policies.

Key words: bull and bear markets; cross-correlation; cross- correlation level; multifractal feature ; conduction directions

During the period of 2015 to 2016, after a bull market Carnival, the three “Stock Market Crash” attacked China stock market as the big bear market arrived abruptly, leading to an adverse influence on the whole society and economy. Compared with the bull-bear cycle during the year of 2007 to 2008, a wider range, greater strength and more far-reaching trouble was made this time. In the meantime, the relationship between the stock index futures market and the stock market has become focus of the public in this bull-bear cycle, and the stock index futures market was even considered to be an arch-criminal of the "Crash".

As a hedging financial instrument, CSI 300 Index（Shanghai-Shenzhen 300 Stock Index） futures contract has been developing rapidly although started late in 2010, which has its trading volume grown to the top few of the global stock index futures markets in less than 7 years since launched. It has not only provided investors with an effective tool for risk management, but also helped to purify the operating environment of China's stock market. In addition, it also helps improve the system of derivative instruments as well as promotes the reformation and development of the stock markets[1].

Based on the perspective of fractality, we take CSI 300 index futures as the research object, having a more comprehensive study on the cross-correlation between future and spot markets in the bull-bear cycle during 2014~2016 from the three dimensions of cross-correlation, multifractal characteristics and conduction direction. the complex relationship and conduction mechanism between the two markets are investigated to provide financial market stakeholders with a completely new insight perspective. This research is of theoretical reference value and practical significance to the design of hedging strategy, the optimal allocation of assets, the pricing of derivatives as well as the establishment of market regulatory policies and so on.

A large number of empirical studies indicate that the relationship between stock index futures and spot is the key to understanding the complex dependence structure of financial markets, which can reveal the digestion, diffusion and dissemination of market information[2-5] . Many scholars have conducted quite a few researches on the relationship between CSI 300 Index futures and spot markets. For instance, Yang et al.[2] found a strong bidirectional dependence between futures and spot markets in their intraday volatility by using asymmetric ECM-GARCH model. Yang & Steven [3] had an analysis on the impact that the futures may have on the spot based on AR-GJR-GARCH-M model and VECM–GARCH-M model, and they found the futures market intensifies positive feedback trading on the spot market which is detrimental to the informational efficiency. Chen & Dong[4] further explored the dynamic relationship between the two markets based on GARCH family model and VAR model. Results showed that stock index futures lead to a greater volatility in stock market in the short term. while the impact is gradually weak in the long term. Yao & Lin [5] employed Granger Causality and conditional Granger Causality model to estimate information flow and direct information flow between futures and spot markets. The results revealed that the information flow between the two markets is bidirectional, and the information flows from futures to stocks are slightly greater than those in the reverse direction, while the direct information flows from stocks to futures are significantly greater than those in the reverse direction.

The mentioned above researches failed to fully describe and accurately measure the complex and nonlinear dependence structure of financial markets whose reason was that these reseaches were all conducted based on the Efficient Market Theory which are proposed in the premise of "linearity and normality". Therefore, the Copula function family was introduced into the study of the complex linkage between the futures and spot markets by relevant scholars. For instance, Tong et al.[6]'s research based on Copula-GARCH model revealed that dependences between each pair of overnight (daytime) returns are time-varying, which decreases substantially after the creation of the CSI 300 index futures. Gong et al. [7] revealed a significant nonlinear dependence between the bid-ask spreads and returns which can greatly change in extreme cases by adopting the copula-MIDAS model.

However, the requirement that time series must be independent and identically distributed while using Copula has limited the application of Copula [8]. While fractal theory can not only overcome the defects of traditional efficient market theory and Copula model, but also make full use of the value of multiple time scales. Thus, Detrended Cross-correlation Analysis (DCCA)[9], Multifractal Detrended Cross-correlation Analysis (MF-DCCA)[10] and other research methods based on fractal theory have been proposed to apply to the study of the relationship between the CSI 300 index futures and spot markets widely[11-13]. For instance, by using MF-DCCA and MF-ADCCA methods, Ruan et al.[11] examined the cross-correlation properties of Baltic Dry Index (BDI) and crude oil index. They found a multifractality in their cross-correlation and cross-correlations of all kinds of fluctuations are persistent in the short time while cross-correlations of small fluctuations are persistent and those of large fluctuations are anti-persistent in the long term. Moreover, the multifractality of cross-correlation between them should be attributed to persistence of fluctuations of time series and fat-tailed distributions. Again, Ruan et al. [12] studied the price-volume relationship of the gold futures and spot market by adopting MF-DCCA methods. The empirical results indicated that for both spot and futures markets, the cross-correlations are anti-persistent in general. In the short term, the cross-correlation shows obvious fluctuations due to exogenous shocks, while in the long term, the relationship tends to be at a metastable level due to the dynamic mechanism. Xie et al. [13] conducted a study on the cross-correlation of the yuan-dollar exchange rate between onshore and offshore to find an anti-persistence and multifractal behavior in their cross-correlation. Based on AMF-DCCA and MF-DCCA , Cao et al.[14] investigated the cross-correlation of stock markets between China and America by using different risk conduction effect models from the perspective of China stock market. Empirical results indicated the existence of a bidirectional conduction effect between domestic and foreign stock markets, and the greater influence degree from foreign countries to domestic market compared with that from the domestic market to foreign countries. The above researches also demonstrate the feasibility and advantages of fractal theory in studying the cross-correlation between financial markets.

The above literature based on fractal methods such as DCCA and MF-DCCA focus on the confirmation of persistent cross-correlation and its multifractal features between the futures and spot market, while the relationship between CSI 300 stock index futures and the spot market in the bull bear cycle has never been studied, let alone the complex mechanism in them. Gunay[18] believes that there are significant differences in the complexity of the financial markets in the bull and bear periods, besides, the bull-bear cycle during 2014~ 2016 is of more value for research than before.

Compared with the previous literature, the innovation of this paper lies in two aspects: (1) on the premise of nonlinearity and non normality, and based on the optimized fractal research methods, a more comprehensive study of the cross-correlation between the CSI 300 index futures and spot market in the bull-bear cycle during 2014 to 2016 is conducted from three aspects of cross correlation level, multiple fractal characteristics and conduction direction, revealing the complex mechanism and running rules between the two markets; (2) the conducting direction of the two markets in the bull bear cycle is studied in the scales of short and long term, and which one takes the leading position in their relationship is further analyzed, completing the current researches. All of these studies are rarely involved in previous literature.

2. Methodology

2.1 Optimized MF-DCCA

MF-DCCA method is mainly used for investigating the cross correlation and multifractal characteristics of two non - stationary time series, but a large drawback still exist in the method——the non-overlapping of segment when dividing the time series can result in the lack of continuity in the fitting of the adjacent interval polynomial, which may lead to deviations of results because a new pseudo-fluctuation will be introduced[19]. Therefore, an optimized MF-DCCA was proposed by Zheng & Wang[20] to mitigate the deviation caused by pseudo-fluctuations. Based on their idea, this paper optimizes MF-DCCA methods by using overlapped sliding window technology. Let *x* (*i*) and *y* (*i*) be the time series of length N. Then the optimized MF-DCCA method can be described as follows:

Step1*:* We determine the accumulated deviation *xx (i)* and *yy (i)* of the time series *x (i)* and *y (i)* for i = 1, . . . , N:

$$xx(i)=\sum_{k=1}^{i}[x_k-\bar{x}] \qquad yy(i)=\sum_{k=1}^{i}[y_k-\bar{y}] \tag{1}$$

where $\bar{x}$ and $\bar{y}$ denote the mean of the time series *x (i)* and *y (i)* respectively.

Step2: Divide series *xx*(i) and *yy*(i) into $N_s=[(N-s)/(s-l)]$ segments of equal length s, where "[]"denotes the function which gives the integer part of a real number and *l* is the overlap length which is defined as $l=\frac{s}{3}$ according to(in reference of) the Ref. [20]. In order to make full use of the information included in the series, we repeat the same procedure starting from the end of the profile and obtain this 2Ns segments. Step2 is the only distinction between the optimized and traditional MF-DCCA, which was considered an effective way to alleviate errors caused by pseudo-fluctuations according to Zheng &Wang[20].

Step3: For each segment *v* where $v=1,2,...,2N_s$, the least square method is used to fitting the local trend which is named as $\tilde{XX}(i)$ and $\tilde{YY}(i)$. By eliminating the local trend of each segment we obtain the residual sequence given by following formulas：

$$f^2{}_v(s)=\frac{1}{s}\sum_{i=1}^{s}\left|xx_v(i)-\tilde{XX}_v(i)\right|\left|yy_v(i)-\tilde{YY}_v(i)\right| \tag{2}$$

Step4: Given the variances, We then obtain the q-th order fluctuation function：

$$\begin{aligned}F_{xy}(q,s)&=\{\exp\{\frac{1}{4N_s}\sum_{v=1}^{2N_s}\ln\left(f_v^2(s)\right)\},\ q=0\\ F_{xy}(q,s)&=\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}\left(f_v^2(s)\right)^{q/2}\}^{1/q},q\neq 0\end{aligned} \tag{3}$$

Step5: If the Power- law correlation is presented in the series $\{x_i\}$ and $\{y_i\}$, the function $F_{xy}(q,s)$ will behave as following scaling:

$$F_{xy}(q,s)\sim s^{h_{xy}(q)} \tag{4}$$

Generally the exponent $h_{xy}(q)$ is a function depending on the variable *q.* When q<0 or q>0, $h_{xy}(q)$ describe the scaling behavior of small fluctuation and large scale respectively. When q=2, the MF-DCCA method corresponds to the DCCA method, while $h_{xy}(2)$ become a standard Hurst exponent. When $h_{xy}(q)=0.5$, cross-correlation without long memory can be found between the two series, whereas $h_{xy}(q)>0.5$, we say that there is a long range cross correlation between the two time series, which means that there is not only significant autocorrelation in each sequence, but also a significant long memory between the two time series. If $0<h_{xy}(q)<0.5$, then we say that antipersistent cross-correlation exists in the two series, which means a significant antipersistent exists in each sequence as well as between the two series. In addition, when $h_{xy}(q)$ is a constant independent of q, the series present single fractal; whereas the series are multifractal when $h_{xy}(q)$ depends on q.

In order to quantify the multifractal degree of cross-correlation , Δh is defined according to Ref. [21] as

$$\Delta h = h_{\max}(q) - h_{\min}(q) \qquad (5)$$

where Δh can quantitatively characterize the market volatility. It can not only measure the multifractal degree of the cross-correlation of the two sequences, but also measure the risk of cross-correlation between the two time series [15]. A larger Δh means that the greater multifractal intensity, the greater the risk of cross market is, with the increasing infection of risk [8]. When the two time series are the same time series, that means $\{x_i\}=\{y_i\}$, the MF-DCCA method is transformed into the MF-DFA method.

Thus, let step size of q be t, the validity measurement model based on MF-DCCA method is given as

$$DME = \frac{1}{[(q_{\max} - q_{\min})/t]+1} \sum_{q=q_{\min}}^{q_{\max}} \left| h(q) - 0.5 \right| \qquad (6)$$

Proposed by Wang et al[21], this model reflects the market efficiency level by measuring fluctuations of various amplitudes. When DME approaches zero, the market shows high efficiency and effectiveness become stronger. While with the DME increasing, the market efficiency and effectiveness will become weaker.

The above optimization for MF-DCCA method applies equally to the methods of 2.2and 2.3.

2.2 DCCA coefficient

Proposed by Zebende[22], DCCA coefficient method is a nonlinear correlation measurement method which is mainly used to measure the cross-correlation level of two non-stationary time series at different time scales. The first three steps of the DCCA coefficient method correspond to those of the MF-DCCA method, thus, we begin with Step4.

Step4: We first calculate the fluctuation function of detrended covariance $F^2_{x,y;DCCA}$:

$$F^2_{x,y;DCCA} = \frac{1}{2N_s} \sum_{v=1}^{2N_s} f_v^{\,2}(s) \qquad (7)$$

When $\{x_i\}=\{y_i\}$, $F^2_{x,y;DCCA}$ turn into $F^2_{x;\mathrm{DFA}}$ or $F^2_{y;\mathrm{DFA}}$.

Step5: Next we calculate $\rho_{DCCA}(s)$ with following formulas:

$$\rho_{DCCA}(s) = \frac{F^2_{DCCA}(s)}{F_{x;DFA}(s) \cdot F_{y;DFA}(s)} \qquad (8)$$

Where $\rho_{DCCA}(s)$ range from -1 to 1. $\rho_{DCCA}(s)=1$ and $\rho_{DCCA}(s)=-1$ indicate the perfect cross-correlation and perfect anti-cross-correlation respectively, and $\rho_{DCCA}(s)=0$ implies that no cross-correlation exists between the two time series.

2.3 DCCA based on time delay

As a method to examine the linear causality, traditional Granger causality test fail to apply to the nonlinear market environment, therefore, a nonlinear Granger causality test was proposed to solve the problem. However, the nonlinear Granger causality could only determine whether the two sequences are Granger causality, and fail to measure the impact of one on another. While the DCCA method based on time delay proposed by Lin et al.[23] can calculate the degree of impact concretely other than determine the nonlinear causality between two markets, which overcomes the defects of previous methods. Then the method can be described as follows:

Step1: We suppose two time series $\{x(t)\}$ and $\{y(t)\}$, and defined a new series $\{y(t+\Delta T)\}$ by lagging $\{y(t)\}$ with ΔT. Then new time series are built:

$$x(m)=\sum_{t=1}^{m}(x(t)-\bar{x}), m=1,2,\cdots,N-\Delta T \quad (9)$$

$$y(m)=\sum_{t=1}^{m}(y(t+\Delta T)-\bar{y}), m=1,2,\cdots,N-\Delta T \quad (10)$$

Where $\bar{x}=\frac{1}{N-\Delta T}\sum_{t=1}^{N-\Delta T}x(t)$ and $\bar{y}=\frac{1}{N-\Delta T}\sum_{t=1}^{N-\Delta T}y(t+\Delta T)$.

Step 2 to step4 are consistent with those of MF-DCCA method, hence we start from **step5**:

When there exists cross-correlation between the series $\{x(t)\}$ and $\{y(t+\Delta T)\}$, the function $F_{xy}(s)$ will behave as following:

$$\Delta H_{\Delta T}^{S-F}=Hurst_{S\Delta T}-Hurst_{F\Delta T} \quad (11)$$

Where Hurst exponent tests power-law correlation between the time series, especially measure the influence of Futures (spot) on their different lag stages. In order to determine which market is more influential, we defined $\Delta H_{\Delta T}^{S-F}$ in reference of [16]:

$$\Delta H_{\Delta T}^{S-F}=Hurst_{S\Delta T}-Hurst_{F\Delta T} \quad (12)$$

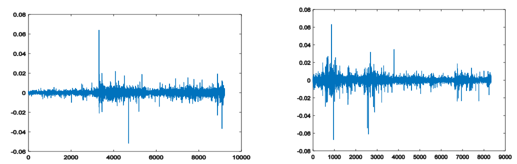
Where $S\Delta T$ and $F\Delta T$ stand for the lag stage of spot and futures respectively. $\Delta H_{\Delta T}^{S-F}>0$ indicates that futures has a greater impact on spot and takes the leading position in their relationship, otherwise, $\Delta H_{\Delta T}^{S-F}<0$ indicates a contrary situation.

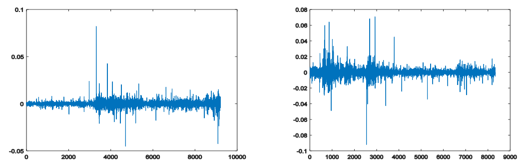
3 Empirical analysis

3.1 Data

This paper chooses CSI 300 index futures contracts of spot month and CSI 300 index as the research object. For abundant information is contained in the high frequency data, we use 5 minutes closing price during 2014-8-20 to 2016-3-1 as the sample. Here we use “futures” and “spot” for short. We have 17712 data for futures and spot respectively after excluding their overlapping parts in transaction time. The data are taken from Wind database.

Gunay[18] argues that bull and bear markets should be bounded by peaks within the sample range, with the section from trough to crest on the left being bull and the section from crest to trough on the right being bear. In our sample, the futures peak appears on 2015-6-8 while the spot peak appears on 2015-6-9. Taking into account that CSI300 index futures has a strong price discovery function, and is more sensitive to the change of market, we take futures as the standard to determine the bound of bull and bear periods. Hence, this paper selects the data during the period from 2014-8-20 to 2015-6-8 as the bull section, and data during the period from 2015-6-9 to 2016-3-1 as bear section, 9312 data and 8400 data are contained in the bull section and bear section respectively; by calculating logarithmic difference of the 5 minutes closing prices, we obtain the returns series:





Bull Bear Bull

Bear

Fig. 1 Returns series for futures Fig. 2 Returns series for spot

Table 1

Statistics of returns for futures and spot markets

		Mean	Minimum	Maximum	Std.dev	Skewness	Kurtosis	*JB* statistic	*ADF*
Bull	futures	0.0000882	-0.045166	0.082084	0.002821	2.084742	105.4030	4030382***	-97.71***
	spot	0.0000886	-0.051818	0.064080	0.002684	0.201725	63.02388	1382512***	-72.68***

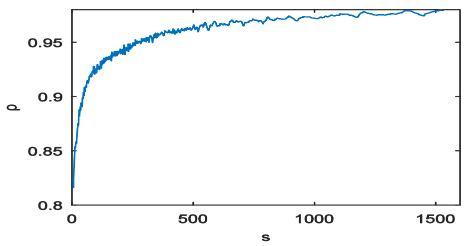
Bear	futures	-0.000079	-0.091936	0.070832	0.004826	0.384149	45.1237	616515.5***	-95.43***
	spot	-0.000075	-0.067348	0.063203	0.0003928	-1.47480	40.45834	489182.2***	-96.65***

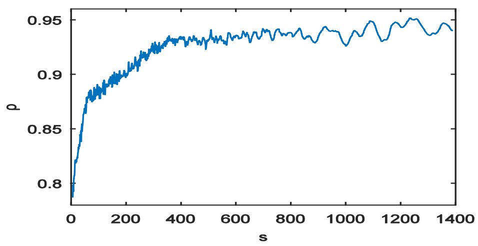
Attention: *, **and *** indicates they were significant at 10%, 5% and 1% levels respectively. The original assumption of JB statistic is that the sample sequence obeys the normal distribution。 $Q(n)$ stands for $Ljung-box\ Q$ statistic with q-th lag.The results of the three tests ADF are consistent, Only the test results containing constant and trend items are given here,which is obtaied by determining optimal test order by the AIC rule.

As is shown in Figure1 and Figure 2, the futures and spot returns fluctuate violently in both bull and bear markets, which demonstrate the clusters of small and large fluctuations. Table 1 suggests a fat tail of returns series whose skewness and kurtosis aren't consistent with normal distribution. Furthermore, the Jarque–Bera test results' rejecting the null hypothesis of the normal distribution at 1% significance level confirms that the futures and spot returns in both bull and bear markets are not Gaussian. In the meantime, the autocorrelation of each series is significant in the range of 20 orders of delay. Augmented Dickey–Fuller test results show that all series are stationary.

3.2 Cross-correlation analysis

In order to test the cross-correlation between futures and spot markets of various time scales quantitatively, DCCA is used and according to Eq.(8), we obtain the level of cross-correlation in bull and bear markets of different time scales:





Bull

Bear

Fig.3 $\rho_{\mathrm{DCCA}}(s) \sim s$

Table 2

The description of $\rho_{\mathrm{DCCA}}(s)$

	Mean	Minimum	Maximum	Std. dev	Skewness	kurtosis	Jarque-Bera
Bull	0.961843	0.816012	0.979425	0.021864	-2.793032	12.98233	8341.753***
Bear	0.926323	0.787323	0.951630	0.024527	-2.524711	10.56434	4773.393***

Notes: the null hypothesis of Jarque-Bera is the return series are normally distributed, and *** indicates rejection of the null hypothesis at the 1% significance level.

In Figure3, we find that in short term, the cross-correlation between the two markets is not significant in both bull and bear markets. With the increasing of time scales, the cross-correlation increases rapidly and slows down when s=400, which indicates that their cross-correlation stays in a high level in the long term, consistent with the conclusion of Cao et al.[15]. Futures contract is a derivative product based on spot price, and futures market provides price information for spot market through price discovery function. Thus, even though the two markets are weakly linked in short term, they present a relatively high level of cross-correlation in the long term, which shows an inseparable relationship between them.

In the meantime, attention should be paid to the remarkable difference in the cross-correlation between the bull and bear market. We quantify their difference by calculating $\rho_{\mathrm{DCCA}}(s)$. As is shown in Table 3, the $\rho_{\mathrm{DCCA}}(s)$ in the bull market has a larger mean value in comparison with bear market, implying a higher level of cross-correlation in the former. In addition, futures and spot in the bull market presents a more stable cross-correlation for its lower standard deviation of $\rho_{\mathrm{DCCA}}(s)$, which provides regnant conditions for hedging, arbitrage as well as supervision. We have proved that the return series in the bull and bear market present a “fat tail” with a non-zero skewness and a kurtois larger than 3. In the same way, the $\rho_{\mathrm{DCCA}}(s)$ series reject the null hypothesis of the normal distribution at 1% significance level. Thus, we can conclude that the $\rho_{\mathrm{DCCA}}(s)$ series are not normally distributed in both bull and bear market.

3.3 Multifractal analysis

Optimized MF-DFA method and MF-DCCA method are adopted to explore the multifractal between the futures and spot markets and of themselves in this section. q 's value range from -10 to 10 with a step length of 2, and the scale s varies from 5 to N/6, as is defined in Ref.[16]. According to Eq. 4, Fig. 4and Fig. 5 are obtained:

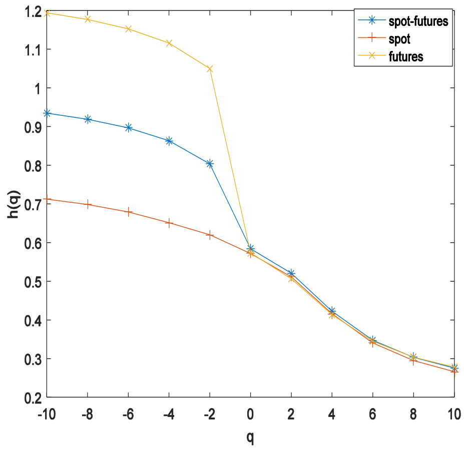


Fig. 4 $h(q) \sim q$ of bull market

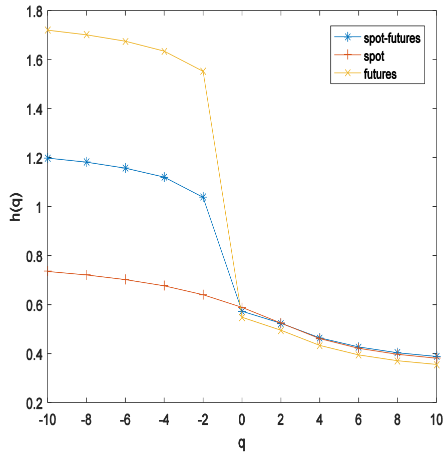


Fig. 5 $h(q) \sim q$ of bear market

As is shown in Fig. 4 and Fig. 5 , $h_{xy}(q)$ 、 $h_x(q)$ 、 $h_y(q)$, where x, y and xy denote spot, futures and spot-futures markets (we name it “cross-market”) respectively, decrease with q, having a non-linear dependency on q .Thus, we can firm that there exist multifractal cross-correlation features between futures and spot as well as in themselves in both bull and bear markets.

From Fig.4 and Fig.5 we could also observe that, the futures market in bull market, futures market and cross-market in the bear market have "jumping point" phenomenon. That is, when $q \le -2$, their $h(q) > 1$,which means small fluctuations are non-stationary processes with persistence[24], Whereas when $q \ge 0$, $h(q)$ jump into the range of 0~1 again. Thus, $h(q)$ has a substantial jump when q 's value ranges from -2 to 0. Bai et al.[19] argued that extreme volatility will dominate the market with persistence once this phenomenon occurs. In other words, the larger the jump, the more the market volatility and the greater the extreme risk. There is a “jump phenomenon” in $h(q)$ of futures markets in either bull market or bear markets , which implies that China's stock index futures market is faced as greater risk with a higher probability for extreme events to happen due to its high leverage and a high degree of market sensitivity. Investors will be confronted with great risk if they carry out one-way speculation. While the “jump phenomenon” exist in cross-market in bear market only, which indicates that compared with the bull market, the relation between futures and spot market has undergone extreme changes in the bear market. The interdependent structure between two markets is very unstable and it is difficult to grasp the relationship between them. While the “jump phenomenon” doesn’t occur in the spot market in either bull or bear market and it fluctuates more gently.

Complexity of financial market like long memory, market risk and effectiveness have been the focus and hot topic of academic circle. Many previous literature have proved that the multifractal theory is one of the best methods to study the complexity of financial markets. Therefore, in this chapter, the long memory, risk and effectiveness of futures and spot in the bull market and bear market will be analyzed and compared in the next three sections according to the multifractal features mentioned above.

3.3.1 Long memory analysis

According to Eq.4, we obtain the values of $h(q)$:

Table3

The $h(q)$ of cross, futures, and spot markets in the bull and bear periods

	bull			bear		
	futures	spot	cross	futures	spot	cross
-10	1.1940	0.7122	0.9347	1.7203	0.7356	1.1979
-8	1.1768	0.6982	0.9188	1.7013	0.7210	1.1809
-6	1.1525	0.6789	0.8966	1.6747	0.7020	1.1571
-4	1.1159	0.6513	0.8634	1.6347	0.6765	1.1199
-2	1.0502	0.6199	0.8032	1.5524	0.6399	1.0382
0	0.5735	0.5717	0.5838	0.5478	0.5884	0.5728
2	0.5062	0.5114	0.5208	0.4951	0.5245	0.5235
4	0.4237	0.4159	0.4225	0.4332	0.4613	0.4643
6	0.3487	0.3404	0.3475	0.3944	0.4215	0.4266
8	0.3036	0.2948	0.3032	0.3710	0.3971	0.4035
10	0.2779	0.2659	0.2756	0.3555	0.3808	0.3880

As we can see from Table 3, when $q<0$, the bull and bear markets will present a relationship as $0.5<h_y(q)<h_{xy}(q)<h_x(q)$, suggesting that the long memory exists in both markets as well as the historic market trend have an positive impact on the current trend. The market trend is persistent and is more difficult to reverse, thus, the investment strategy will perform as well in the future as they do in the current with relatively high probability. when $q=2$, the situation falls into two categories, where $0.5<h_x(q)<h_y(q)<h_{xy}(q)$ in bull market and $0.5<h_x(q)<h_{xy}(q)<h_y(q)$ in bear market， implying that the long memory of futures market is significantly weaker than that of cross market and spot market, closing to 0. At this point, the market tends to random walk, and it is difficult for investors to grasp the law of the futures market. The one-way speculative behavior in the futures market by means of historical information will bring disaster to investors. When $q>2$ with a large fluctuation, $h_y(q)<h_{xy}(q)<h_x(q)<0.5$ in both bull and bear markets, where either the two markets or the cross-market also present anti-persistence by mean reversion. The characteristic that large fluctuation can easily cause reversal is likely to provide investors on futures-spot markets with evidence to carry out related arbitrage activities.

Akerlof and Shiller [25] argued that investors tend to buy when the stock market rises and sell when the stock market declines. Their response to past price changes may be reflected in a larger price change in the same direction，and it will and maintain for a period，which called “feedback from price to price”. Futures, spot and cross market have long memory characteristics, sustainable ability in a slight fluctuation, this phenomenon is precisely " feedback from price to price " mechanism of the results. But the only thing is that the trend of supporting the bull market and the bear market is the expectation that prices will rise or fall, and this expectation won't last forever.In fluctuating sharply, the long memory of the above three markets gradually decay ,and finally become anti-persistent characteristics, which follows a mean-reverting process. this phenomenon is the expectations of investors and the result won't last forever.

3.3.2 Risk analysis

According to Eq.5, we obtain Table 4.

Table4

The Δh in bull and bear markets

	futures		spot		cross market	
	bull	bear	bull	bear	bull	bear
Δh	0.9161	1.3648	0.4463	0.3547	0.6591	0.8099

To analyze from table 4, we have some observation.

First, the Δh of futures is significantly higher in bear market than that in the bull market, which indicates that the Three “Crashes” have increased the market risk to a great extent. In the bear market, the spot market has witnessed thousands of stocks rising to daily limit and then fall to limit, thus leading to the frequent boom and bust of futures market, in which not only for long futures account, but also for short account is faced with the possibility of being forced liquidation, triggering panic among investors in the futures market.

Second, the Δh of cross-market is smaller in the bull market than that in the bear market, implying that cross-market is more multifractal in bear market, and thus is faced with higher risk, which further shows that the contagion effect between the futures and the spot market in the bear market is increasing. When formulating measures, the market regulators should take the two market as a whole, the effect of policies will be weakened or even invalid if we just pay attention to a single market and ignore the risk from external. In the meantime, the risk of cross-market is higher than that of spot market in either bull or bear market, but significantly lower than that of futures market, thereby the investors can reduce the risk through arbitrage between the two markets and improving SHARP ratio to reduce the probability of extreme events leading to loss.

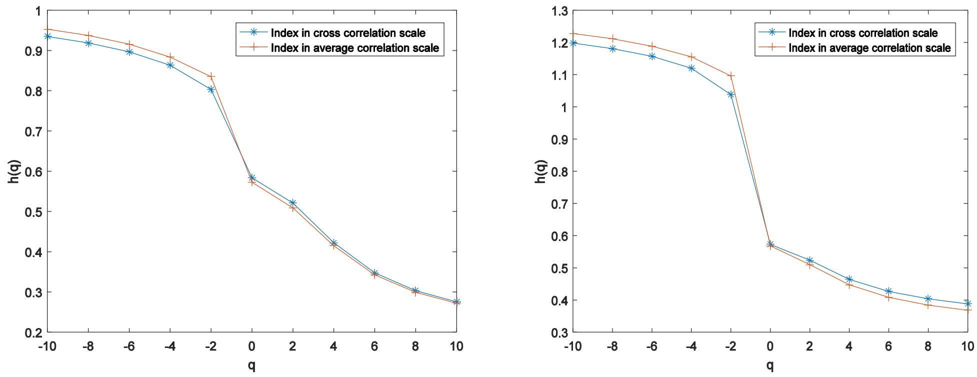
The above research on the risk between the two markets has proved that there exists market risk between futures and spot markets in whether bull or bear market, where the risk contagion is more pronounced in bear markets . However, few studies have referred to the problem whether small fluctuation or large fluctuation is the risk contagion way in this round of bull and bear cycle in China. Hence we try to further explore the risk contagion between futures and spot markets by comparing the values of $h_{xy}(q)$, $h_x(q)$ and $h_y(q)$. According to Jiang and Zhou[26], the relationship among the three $h(q)$ which are calculated by MF-DCCA method can be depicted as follows:

$$h_{xy}(q) = (h_x(q) + h_y(q))/2 \qquad (13)$$

Nevertheless, previous results implied that the Eq.13 did not work[14], for there is certain deviation between the $h(q)$ in cross-correlation scale and $h(q)$ in average auto correlation scale, which is of certain significance for understanding the complexity of futures and spot markets[26]. The deviation is defined as follows in reference to Ref.[27]:

$$Detrend(q) = \frac{h_{xy}(q) - (h_x(q) + h_y(q))/2}{(h_x(q) + h_y(q))/2} \qquad (14)$$

Jiang and Zhou et al.[26] argue that if $Detrend(q)$ between the two markets is above zero, it means the q'th order fluctuation of one market can be mainly attributed to the shock and risk contagion brought by another market, other than the market itself. Otherwise, q'th order fluctuation of one market should be attributed to itself. According to Eq.14, Fig. 6 is obtained:



(a) bull (b) bear

Fig. 6 Index in cross (average) correlation scale in the bull and bear markets

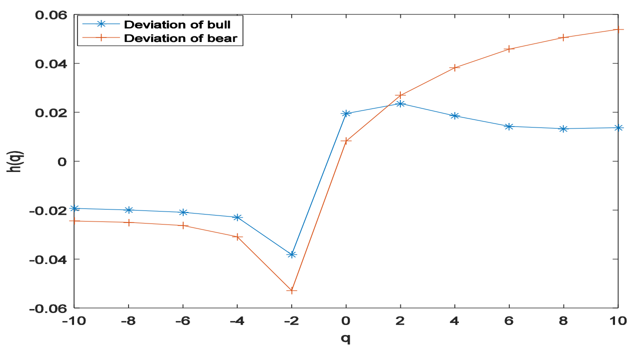


Fig. 7 Deviation between bull and bear market

Fig.6 and Fig.7 confirm that the Eq.13 is wrong in whether bull or bear market, which is consistent with the conclusion of Ref.[2]. When $q < 0$, cross-correlation exponents in futures and spot market are all below average scaling exponents, which indicates that the small fluctuation of the two market should be mainly attributed to the market itself, less affected by external facts. While when $q > 0$, cross-correlation exponents in two markets are all above average scaling exponents, indicating that the large fluctuation of one market should be caused by the risk contagion of another market, rather than itself [28]. For instance, the opening of Shanghai-Hong Kong Stock Connect program has significantly enhanced the open degree of spot market. Therefore，A sustained slump occurred in the main peripheral market led to a second Crash in China’s stock market in the late August 2015. The futures market was further infected for the cross-correlation between them, causing volatility in the futures market. The above results also showed that the risk contagion between China's futures and spot market mainly occurred with great fluctuation, while slight fluctuations are mainly due to its own factors.

From Fig.7 we could also observe that, there are some differences between the bull and bear market in the relative deviation, in which when $q > 0$, the deviation between cross-correlation and average auto correlation in bear market is greater than that in the bull market. Therefore, it is in bear market that a market with large fluctuation is more likely to be affected by the shock and risk contagion from another market.

Conclusion can be drew from above analysis that whether in the bull or bear market, the risk contagion between China’s stock and futures markets always occurred with large fluctuation, with a greater strength and larger range, bringing an even worse impact. Therefore, China's market regulators should strengthen the supervision and early warning of large fluctuations while supervising the stock index futures and stock market, and put the prevention and control of financial risks on a more important position to ensure no system risk, maintain the normal order of the market, and promote the healthy and sustainable development of China's financial market.

3.3.3 Market efficiency analysis

By calculating based on Eq.6, DME of bull and bear market are obtained in Table 5.

Table 5

The DME of bull and bear markets

	Spot		Futures		Cross-market	
	Bull	Bear	Bull	Bear	Bull	Bear
DME	0.1297	0.1479	0.3572	0.5711	0.2429	0.3279

As is shown in Table 5, the DME of the two markets and cross-market in the bull are all below that in the bear, implying a higher level of efficiency in the bull than the bear. The high efficiency of bull market attracts more social funds to take part in the investment activity. Whereas the bear market has a weaker efficiency for the reason that the three “Crash” has brought a series of great impacts on the market investors’ accounts as well as their confidence and has intensified herding behavior and other irrational phenomenon. An efficient market can attract more investors to join, optimize the allocation of resources and accelerate the flow of capital, playing an important role in the development and stability of economy, whereas a market of low efficiency is difficult to attract investors, which can be verified by the dramatic decline of trading volume in the bear market.

Although the market efficiency in the bull market is higher than the bear market, we found that the difference is not significant. To further analyze, we can attribute this to three facts. First, the Commission increased its efforts to crack down on irregularities and illegal activities and intensified its monitoring of market trends during “crashes”. Second, the China Securities Finance Corporation tried to intervene the market through a series of large-scale capital investment, alleviating the extreme fluctuation. Moreover, CFFEX (China Financial Futures Exchange) effectively curbed market speculation by adjusting relevant policies including raising the margin ratio and fees as well as limiting positions number. The above series of measures have stabilized the market sentiment and controlled the chaotic situation caused by “Crash” to a certain extent. For these reason, although the bear market has experienced several rounds of decline, the market efficiency is only slightly inferior to the bull market. This founding implies an enhancement of capacity of China’s market supervision authorities, which have adjusted themselves to the complex market environment.

3.4 Conduction direction analysis

The cross-correlation conduction direction between the spot and futures markets during the bull and bear periods is investigated by adopting the DCCA method based on time delay. The ΔT value in previous studies using high frequency data range from 1 to 48[15], which can only investigate the conductive direction in the short term[1], ignoring that of long term. Therefore, we carry on the correlation research from both the short-term and the long-term. We let the ΔT range from 1 to 48 in the short term, while range from 48 to 1096 in the long term with a step size of 48. By excluding break days ,there are 22 trading days per month, and 48 data can be obtained each day, equal to step length , thus, we can study the conductive direction for maximum lag of 22 days. According to Eqs.11-12, Figure5~10 are obtained, among which Figure 8~10 present the result in the short term, while Figure11~13 present the results in the long term.

(1) As is show in Figure8~9, the Hurst exponent is above 0.5 in both the bull and bear markets, which indicates that the cross-market expresses a long-range cross-correlation with either spot or futures lagging behind. With the lags increasing, $Hurst_{S\Delta T}$ and $Hurst_{F\Delta T}$ decrease gradually after a sharp rise. This can be attributed to the fact that with time going, people tend to judge the difference between two markets rationally, thus act irrationally with smaller probability, which in turn affects the cross-correlation between the two markets indirectly. The above results also show that the futures (spot) will be affected in the lag of spot (futures), implying that the

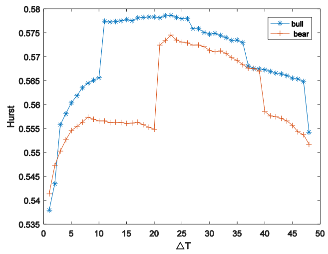


Fig.8 Hurst exponent in the lagged spot market

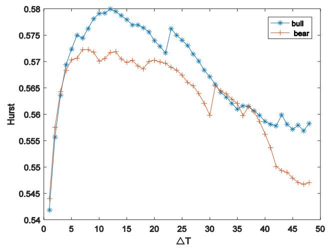


Fig.9 Hurst exponent in the lagged futures market

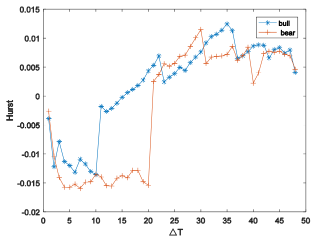


Fig.10 The difference in the Hurst exponent of the two markets

To analyze from the short-term perspective, we have two observation:

(1) As is show in Figure8~9, the Hurst exponent is above 0.5 in both the bull and bear markets, which indicates that the cross-market expresses a long-range cross-correlation with either spot or futures lagging behind. With the lags increasing, $Hurst_{S\Delta T}$ and $Hurst_{F\Delta T}$ decrease gradually after a sharp rise. This can be attributed to the fact that with time going, people tend to judge the difference between two markets rationally, thus act irrationally with smaller probability, which in turn affects the cross-correlation between the two markets indirectly. The above results also show that the futures (spot) will be affected in the lag of spot (futures), implying that the transmission direction between the two markets is two-way.

(2) As is show in Fig.10 , when $\Delta T < 10$, $\Delta H_{\Delta T}^{S-F}$ is below zero either in the bull or bear market, indicating that the spot market has a greater impact on futures markets in the same lag. However, with ΔT increasing, $\Delta H_{\Delta T}^{S-F}$ turns positive, suggesting that in the larger scale of lags, the futures market has a greater impact on the spot market. In the meantime, the futures market exerts a greater impact on the spot market in the bull market compared with the bear market.

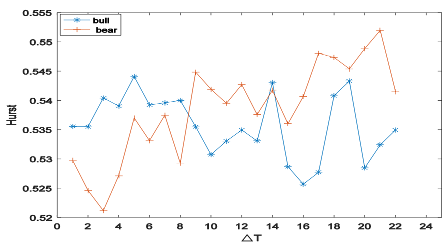


Fig.11 Hurst exponent in the lagged spot market

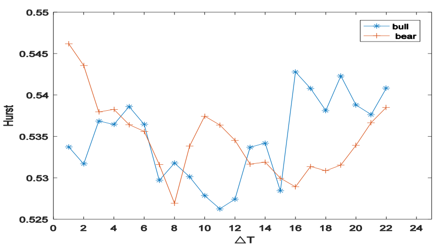


Fig.12 Hurst exponent in the lagged futures market

[1] One trading day contains 48 data, while ΔT range from 0~48, that is , they only studied the conduction direction behind one day actually.

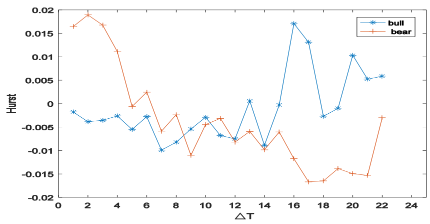


Fig.13 Difference in the Hurst exponent of the two markets

To analyze from the long-term perspective, we have two conclusion.

(1) As is show in Fig.11~12, *Hurst* exponent of the bull and bear are both above 0.5, manifesting the existence of long memory in the cross-market whether with the spot or futures lagging behind. $Hurst_{S\Delta T}$ and $Hurst_{F\Delta T}$ change with the increase of the lags, thus the transmission direction of the two markets is still two-way. However, compared with the short lag, $Hurst_{S\Delta T}$ and $Hurst_{F\Delta T}$ change more gently in the long-term delay, which implies that investors in the market are more susceptible to the impact of short-term information, while less sensitive to the impact of long-term information.

(2) As is show in Fig.13, when $\Delta T \leq 720$ (15 days lag), $\Delta H_{\Delta T}^{S-F}$ in the bull market are all below zero, implying the spot has a greater impact on the futures market, whereas $\Delta H_{\Delta T}^{S-F}$ are positive when $720 < \Delta T \leq 1056$ (15~22 days). The situation varies when it comes to the bear market, when $48 \leq \Delta T \leq 288$ (1~6 days), $\Delta H_{\Delta T}^{S-F}$ is above zero, indicating that futures affects more on the spot, whereas $\Delta H_{\Delta T}^{S-F}$ is below zero when $336 \leq \Delta T \leq 1056$ (7~22 days), implying an opposite situation. The futures is more sensitive to the changes in market direction due to its high leverage and liquidity. In this case, the futures gradually take the leading position with the increase of time delay in the bull market. While in the bear market, the rescue work is mainly carried out on the spot market, in which massive stock purchasing, crackdown of illegal behavior and other measures were carried out to improve the confidence of the market. In this way, with the increase of time delay, the spot gradually takes the leading place in the bear market.

4. Conclusion

Based on fractal theory, this paper conducts a comprehensive study of the cross-correlation between CSI 300 index futures and its spot markets in the 2014~2016 bull and bear cycle from the three aspects of cross-correlation level, multifractal and conduction direction by adopting optimized DCCA coefficient method, MF-DCCA method and DCCA method based on time delay. The findings are as follows.

First, whether in bull market or bear market, the cross-correlation between the futures and spot markets is weaker in the short-term scale than that in the long-term scale. Meanwhile, the cross-correlation of the bull market is higher and more stable in comparison with that of bear market, which indicates that the stakeholders in the bull market are more available to grasp the relationship between the spot and futures market so as to carry out hedging, arbitrage as well as market supervision more effectively. Next, we found the existence of multifractal cross-correlation between the futures and spot market as well as their differences between the bull and bear markets, which has a certain influence on long memory, market risk and effectiveness. Although there are difference in the market risk and effectiveness between the bull and bear markets, they are not significant, which can be attributed to the measures that China's market regulatory authorities have adopted to suppress the extreme fluctuations in the market during the three "crash" . Moreover, whether in the long-term or short-term, the cross-correlation of the futures and spot market is bidirectional conduction in both bull and bear markets. While the long-term cross-correlation of futures and spot markets in the bear market is different from others, in which the stock market gradually take the leading position in their relationship with the increase of lag. A wide range of powerful bailout behavior conducted by securities authorities should be account.

Further analyzing, some inspirations are obtained: (1) For one thing, the difference of cross-correlation level between the bull and bear market requires the stakeholders to take different views on them so as to better study the relationship between the futures and spot markets and carry out the effective investment and supervision activities. For another thing, the cross-correlation coefficient series present the characteristic of nonlinear and non normal in both the bull and bear market, suggesting that nonlinear method should be introduced into the pricing of derivatives, hedging strategy design to design the financial products that can depict the nonlinear dependence structure of markets more accurately. (2) The cross-correlation between the futures and spot markets has proved to be multifractal and different in the bull and bear market, implying that the two markets have a nonlinear complex dependent structure. Investors and market regulators should treat two markets as a whole, but differentiate their relationship in the bull and bear market. Since separately studying of the two markets will bring losses to the investors as well as make the market supervision invalid. This founding also provides a new perspective for China's financial market stakeholders to understand the relationship between the futures and spot markets. (3) There is a two-way transmission in the cross-correlation between the futures and spot market in the bull and bear market either in long term or short term, where who takes the leading position differs in the bull and bear market. Again, this requires the market regulators to take the two markets as a whole, and accurately grasp who takes the leading position in the bull and bear markets. Measures should be taken from the source to reduce policy delay, thus raising the effectiveness of policy. In this way, we can create a stable market environment to promote the development of China's financial markets.

Acknowledgments

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Marginal Effects of Public Employment on Unconditional Distribution of Wage Income in China

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Abstract

In this paper, the marginal effects of employment expansion in China's public sector on the unconditional distribution of wage income is investigated with the unconditional quantile estimation (uqe) suggested by Firpo, et al (2009) using the China Health and Nutrition Survey (CHINS) data. To get rid of the effects of Asia financial crisis on 1997 and the subprime financial crisis on 2008 on our empirical results, the whole sample is split into three sample periods, the first from 1989 to 1997, the second from 2000 to 2006 and the last from 2009 to 2011. The marginal effects of public employment on the unconditional distribution of wage income are summarized as follows. First, an expansion of employment in China's public sector has a significantly negative impact on the mean level of wage income in the first sample period and becomes significantly positive in the second and third sample periods. Second, an expansion of employment in China's public sector reduces the dispersion of wage income in three sample periods. This implies that an increment of the employment in public sector improves the income inequality in China. Third, the expansion of public employment makes the unconditional distribution of wage income from symmetric to be skewed to the left. The main conclusion of this paper is, without considering the inefficiency of state-owned firms, the expansion of employment in public sector is a suggestive policy strategy to improve income inequality.

Introduction

Market reform since the 1980s has fundamentally changed China's economy and has dramatically increased the economic growth. Simultaneously, the inequality of income distribution accompany with economic growth has become a cruel criticism globally. In China, the Gini coefficient increased to near 0.5 in 2008-2009 and decreased to 0.46 in 2015. Even though the income inequality is getting mild recently, however, the Gini coefficient of 0.46 is still relative high international-wise.

In literature, the income distributional gap in China has been explored in different aspects. The factors caused the income distributional gap could be classified into the differences in 1) national financial development (see Hu and Liu (2010), Sun (2012), and Yang and Ma (2014)), 2) educational levels (see Chen et al. (2010), and Yang (2015), 3) levels of urbanization (see Tsao et al. (2010), Sun and Wu (2012), and Lu (2016)), and etc. In addition, Chen and Gao (2010) finds that the income differences have been getting large among occupations. Deng(2011) finds that the income gaps are relative larger in big cities than in small cities. Also, Chen(2010) verifies that the inequality of occupations is an important factor causing the income differences.

Expanding employment in public sector could be a favorable policy to get elicit votes in political election campaign. And, it could be a fiscal policy tool for promoting income level. Using conditional quantile regression, Mueller (1998) compares the wage difference between public and private workers.

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Quadrini (2007) indicates that expansion of public-sector employment is taken as a fiscal policy tool in years of economic recession. To reduce the negative impact of the Global Financial Crisis of 2008 on economy, China's government expanded the employment of public sector strategically. The number of public-sector employment increased from 64.2 millions. It is interesting to know the effects of the employment expansion in public sector on the income distribution.

To explore the marginal effects of an expansion of public-sector employment on the income inequality, this paper conducts an empirical study using the unconditional quantile estimation of Firpo, et al (2009) and the surveyed data of CHNS (China Health and Nutrition Survey). Baltagi and Ghosh (2017) confirm the effects of unionization on US wage inequality during the period 1983–1985 for both conditional and unconditional quantile regressions as in Firpo, et al (2009). Our empirical results support the expansion of public-sector employment in China have the effect on reducing the income inequality. The rest of this paper is organized as follows. Section 2 summaries the roles of employment in public sector on economic development. In section 3, the unconditional quantile estimation of Firpo, et al (2009) is introduced. The empirical data of this paper, CHNS, is described in section 4. The empirical analyzes using unconditional quantile estimations are also provided in section 4. The last section provides empirical findings and conclusions.

Roles of Employment in Public Sector

Commonly, in advanced countries, the wages of government officers are determined by the principle of "equal pay" with worker of the private sector. In other words, the overall wage level of the public sector must be balanced with that of the private sector. One reason behind the equal pay principle is the perception of fairness from the viewpoint of nationals and citizens, though equal pay is also important for ensuring efficiency in the labor market. In practice, however, the wage structure of the public sector has often diverged from that of private sector. Usually, wages in the public sector are generally less dispersed in major countries. Morikawa (2016) finds out that the wages in public sector are relative higher at the lower end of the wage distribution and relative lower at the higher end in Japan.

Wages in the public sector tend to be higher at the lower end of the wage/skill distribution and lower at the higher end of the distribution. If the wage level is excessive for some worker types in the public sector, then in- efficient rationing is inevitable. In contrast, if the wage level of skilled workers is too low for some worker types in the public sector, the government has difficulty in hiring people with the necessary skills, which may negatively influence the quality of public services (Borjas, 2002; Nickell and Quintini, 2002).

Because wages are an important incentive for workers, irrespective of their sector, appropriate public sector wage levels and structures are essential to ensuring high-quality and efficient public services. Several empirical studies have indicated that the wage levels of public sector employees (Borjas, 2002; Nickell and Quintini, 2002; Dal Bo et al., 2013) and politicians (Besley, 2004; Gagliarducci and Nannicini, 2013; Mocan and Altindag, 2013) affect the quality of workers and services in the public sector.

Similarly to other advanced countries, the wages of government officials in Japan are determined by the principle of "equal pay" with those of the private sector. In other words, the overall wage level of the public sector must be balanced with that of the private sector. One reason behind the equal pay principle is the perception of fairness from the viewpoint of nationals and citizens, though equal pay is also important for ensuring efficiency in the labor market. In practice, however, the wage structure of the public sector has often diverged from that of private sector. As shown in the next section, wages in the public sector are generally less dispersed in major countries. Wages in the public sector tend to be higher at the lower end of the wage/skill distribution and lower at the higher end of the distribution. If the wage level is excessive for some worker types in the public sector, then in- efficient rationing is inevitable. In contrast, if the wage level of skilled workers is too low for some worker types in the public sector, the government has difficulty in hiring people with the necessary skills, which may negatively influence the quality of public services (Borjas, 2002; Nickell and Quintini, 2002).

Some studies have recently adopted quantile regression techniques to examine wage gaps at various points in the wage distribution (Mueller, 1998; Lucifora and Meurs, 2006; Gittleman and Pierce, 2012; Lewin et al., 2012). These studies generally found that wage premiums for public sector workers are greater at the bottom of the wage distribution and lower, or even negative at the top of the wage distribution.

In the literature, in China, the causes of income inequality have been verified by the development of finance (see Hu and Liu (2010), Sun (2012), and Yang and Ma (2014)), by education promotion(see Zhang

(2006), Chen et al. (2010), Yang et al. (2015)), and urbanization (see Cao et al. (2010), Sun and Wu (2012), Lv (2016)). The income gaps among occupations have been found to be larger by Chen and Gao (2012), and among cities by Deng (2011). Chen et al. (2010) studies the impact of earning inequality among occupations on the income gap and finds out that the urban-rural income gap is caused by occupational earning differences.

Unconditional Quantile Estimation

Denote $T(\mathrm{F}_Y)$ as the descriptive measure on a probability distribution function F_Y. Since $T(\mathrm{F}_Y)$ assigns a real number to each member of a class of functions, functions of functions, it is often referred to as a statistical functional, or simply a functional. Firpo, et al (2009) defines the *Recentered Influence Function* (RIF) as

$$RIF(y;\mathrm{T},\mathrm{F}_Y) = T(\mathrm{F}_Y) + \int IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)\Box_y(\mathrm{y}) = T(\mathrm{F}_Y) + IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y),$$

where $IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)$ denotes the *Influence Function* of the functional $T(\mathrm{F}_Y)$ evaluated at y. It is easy to have

$$E[RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)] = \int RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)\,\mathrm{dF}_Y(\mathrm{y}) = \int [T(\mathrm{F}_Y) + IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)]\,\mathrm{dF}_Y(\mathrm{y}) = T(\mathrm{F}_Y).$$

This indicates that any magnitude of interest can be seen as an expectation. Besides, by the fact of $F_Y(y) = \int F_{y|X=\infty} dF_X(\mathrm{x})$,

$$T(\mathrm{F}_Y) = \mathrm{E}\left\{E[RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)\,\middle|\,X = x]\right\},$$

the random variables X have been introduced through the law of iterative expectation.

Suppose F_X changes marginally in the direction of G_X. Assume $F_{Y|X}$ stays constant and let $\alpha(\mathrm{T})$ be the vector of partial effects on T of moving each coordinate of X separately as a location shift. Then (under some regularity)

$$\alpha(\mathrm{T}) = \int \frac{\mathrm{d}\,E[RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)\,|\,X = x]}{dx} dF_X(\mathrm{x}).$$

Let q_τ be the τ th quantile of Y (unconditional), i.e., $T(F_Y) = q_\tau$ and then the influence function is

$$IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y) = \frac{\tau - 1[\mathrm{y} \le \mathrm{q}_\tau]}{f_Y(\mathrm{q}_\tau)},$$

$$RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y) = T(\mathrm{F}_Y) + IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y) = \mathrm{q}_\tau + \frac{\tau - 1[\mathrm{y} \le \mathrm{q}_\tau]}{f_Y(\mathrm{q}_\tau)}. \qquad (1)$$

The derivations of $IF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)$ and $RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y)$ of q_τ can be found in Huber and Ronchett (2009).

AS $1[\mathrm{y} \le \mathrm{q}_\tau] = 1 - [\mathrm{y} > \mathrm{q}_\tau]$, (1) can be further rewritten as

$$\begin{aligned} RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y) &= [\mathrm{q}_\tau + \frac{\tau - 1}{f_Y(\mathrm{q}_\tau)}] + \frac{1}{f_Y(\mathrm{q}_\tau)} 1[\mathrm{y} > \mathrm{q}_\tau] \\ &= c_{2,\tau} + c_{1,\tau} 1[\mathrm{y} > \mathrm{q}_\tau], \end{aligned}$$

And then it is easy to have

$$RIF(\mathrm{y};\mathrm{T},\mathrm{F}_Y) = c_{2,\tau} + c_{1,\tau}\,\mathrm{P}[\mathrm{y} > \mathrm{q}_\tau\,|\,X = x].$$

Thus, the unconditional partial effect is

$$
\begin{aligned}
\alpha(\tau) &= \int \frac{dE[\mathrm{RIF} \mid X = x]}{dx} dF_X(\mathrm{x}) \\
&= \int \frac{d\left\{c_{2,\tau} + c_{1,\tau}\,\mathrm{P}[\mathrm{y} > \mathrm{q}_\tau \mid X = x]\right\}}{dx} dF_X(\mathrm{x}) \\
&= c_{1,\tau} \int \frac{d\left\{P[\mathrm{y} > \mathrm{q}_\tau \mid X = x]\right\}}{dx} dF_X(\mathrm{x}).
\end{aligned}
$$

Based on assumptions on the functional form of $P[\mathrm{y} > \mathrm{q}_\tau \mid X = x]$, for examples, linear probability model, Logit model and nonparametric model, Firpo, et al (2009) suggests three estimations for $\alpha(\tau)$. However, Firpo, et al (2009) and Su, et al (2015) suggest the estimation of $\alpha(\tau)$ based on assuming a Logit model for $P[\mathrm{y} > \mathrm{q}_\tau \mid X = x]$. This estimation is as follows.

By specifying a Logit model, given the estimated $\hat{q}_\tau$,

$$
P[\mathrm{y}_i > \hat{q}_\tau \mid X = x_i] = \frac{\exp(\mathrm{x}_i' \gamma)}{1 + \exp(\mathrm{x}_i' \gamma)},
$$

the marginal effect of the j th explanatory variable on $P[\mathrm{y}_i > \hat{q}_\tau \mid X = x_i]$

$$
\frac{dP[\mathrm{y}_i > \hat{q}_\tau \mid X = x_i]}{dx_{ij}} = \gamma_j \left[\frac{\exp(\mathrm{x}_i' \gamma)}{1 + \exp(\mathrm{x}_i' \gamma)}\right]\left[1 - \frac{\exp(\mathrm{x}_i' \gamma)}{1 + \exp(\mathrm{x}_i' \gamma)}\right].
$$

Denote $\hat{\gamma}$ as the MLE of the Logit model. Thus, the expectation

$$
\int \frac{d\left\{P[\mathrm{y} > \mathrm{q}_\tau \mid X = x]\right\}}{dx} dF_X(\mathrm{x})
$$

could be approximated by the sample mean of the estimated marginal effects

$$
\frac{1}{n}\sum_{i=1}^{n} \hat{\gamma}_j \left[\frac{\exp(\mathrm{x}_i' \hat{\gamma})}{1 + \exp(\mathrm{x}_i' \hat{\gamma})}\right]\left[1 - \frac{\exp(\mathrm{x}_i' \hat{\gamma})}{1 + \exp(\mathrm{x}_i' \hat{\gamma})}\right]
$$

Then, the j th element in $\alpha(\tau)$ can be estimated by

$$
\hat{\alpha}_j(\tau) = \frac{1}{\hat{f}_Y(\hat{q}_\tau)} \left\{\frac{1}{n}\sum_{i=1}^{n} \hat{\gamma}_j \left[\frac{\exp(\mathrm{x}_i' \hat{\gamma})}{1 + \exp(\mathrm{x}_i' \hat{\gamma})}\right]\left[1 - \frac{\exp(\mathrm{x}_i' \hat{\gamma})}{1 + \exp(\mathrm{x}_i' \hat{\gamma})}\right]\right\}
$$

This method is called the RIF-LOGIT estimation.

Empirical Studies

The empirical data used in this paper is from China Health and Nutrition Survey (CHINS) from 1989 to 2011. Since it has been well demonstrated that the wage gap between the public and non- public sectors before 2000 is large resulting from the significant differences of non-money benefit in wage including the subsidies of residence, medical care, etc. The differences of non-money benefit in wage have been reduced after 2000. To get rid of the influences of financial crises in 2008, the sample after 2000 is split into two periods: 2000 to 2006 and 2009 to 2011. There are 3024, 4293, and 4759 observations in each of the sample periods, 1989 to 1997, 2000 to 2006, and 2009 to 2011, respectively.

The classification of employments in public and non-public sectors in China has been arguable in literature, typically on the employments of the state-own firms. Chang (2012) and Jiang et al (2012) classify the employments of the state-own firms into public but In and Gan (2009) and Jiang and Qian (2012) into the non-public sector on the other hand. The four surveys of CHNS in the years after 2000 defined the public sector including government offices, state-own firms and research institutes, state-own enterprises. Following CHNS's definition after 2000, we take the state-own enterprises as in public sector. Based on the definition of employment in public and non-public sectors, there are 66.35 of sampled individuals are working in the public sector in the sample periods 1989 to 1997, 2000 to 2006, and 2009 to 2011, respectively. It is obvious that the proportion of public employment in China is getting decrease as the development of economy. This is also known as the “privatization” of China’s economy.

Table 1. Sample Averages of Variables

Years	1989-1997	2000-2006	2009-2011
lnIncome	4.5380	6.4171	7.2082
Public	0.6635	0.3823	0.3646
Sex	0.6019	0.6026	0.5793
HighEdu	0.0728	0.0948	0.2112
Rural	0.4048	0.5707	0.5257

The salary system of employed workers in China is monthly based. There are two sources of income for employees from employers. The first is the monthly-based incomes including month salary, subsidies for housing fund, supplementary food, medical care, books and newspapers, and etc. And, the second is the annual-based incomes including the year-end bonus which is not productivity base, performance bonus, and children's educations. The averaged monthly income we considered is calculated as the sum of monthly-based incomes plus the annual-based incomes divided by 12. Since the averaged monthly income is obtained monthly, we define it as the "wage income", the dependent variable considered in this paper is the wage income taken in natural logarithm and denoted as ln(wage income).

The summary statistics of the wage income for our sample years are provided in Table 1. The means of wage income in both public and non-public sectors increase annually, however at different growth rates. It is obvious that means of the wage income in public sector are lower than the ones in non-public sector in years before 2000. On the contrary, the means of averaged monthly wages in public sector become higher in years after 2000. From Fig. 4, the distributions of wage incomes in both public and non-public sectors are skewed to the right at earlier years, 1989 – 1997, and the become less and less skewed later on. The mean of wage incomes in public is similar to the mean in non-public sectors for years 1989 – 1997, and becomes greater in years 2000 – 2006 and 2209 – 2011. In addition, the dispersions of the distribution of wage incomes in public sector are smaller than the ones in non-public sector for all years.

Table 2. Summaries of Averaged Monthly Incomes for Year

year	sector	mean	10 %	25 %	50 %	75 %	90 %
1989	Public	49.211	29.801	36.126	44.235	55.390	70.181
	Non-public	57.526	26.632	33.739	43.426	59.191	90.762
1991	Public	70.458	44.401	53.081	65.100	82.627	101.823
	Non-public	75.724	38.392	50.077	65.100	85.381	119.683
1993	Public	115.841	60.511	76.212	100.086	138.468	179.053
	Non-public	141.637	56.654	80.161	117.900	176.462	247.920
1997	Public	508.944	249.296	343.113	472.402	633.185	820.488
	Non-public	546.963	251.948	356.374	460.800	638.157	861.927
2000	Public	699.723	285.617	391.295	575.994	817.182	1047.262
	Non-public	603.869	269.749	371.302	476.028	666.440	952.057
2004	Public	1032.995	428.426	647.399	920.322	1190.071	1618.496
	Non-public	809.897	285.617	437.946	618.837	952.057	1332.879
2006	Public	1293.224	522.128	783.191	1074.969	1443.529	1904.230
	Non-public	1019.229	368.561	506.771	737.121	982.828	1766.020
2009	Public	1718.435	668.856	1003.284	1532.794	2020.502	2619.685
	Non-public	1383.466	501.642	668.856	919.677	1337.712	2090.174
2011	Public	2372.610	844.684	1366.852	1919.736	2623.640	3839.472
	Non-public	1795.626	652.710	921.473	1324.618	1919.736	3071.578

Empirical Marginal Effects on Unconditional Distribution of Averaged Monthly Income

The regression model considered in this paper is

$$\text{lnIncome} = \beta_1 + \beta_2\,\text{Public} + \beta_3\,\text{Sex} + \beta_4\,\text{HighEdu} + \beta_5\,\text{Exper} + \beta_6\,\text{Exper}^2 + \beta_7\,\text{Rural} + \text{error}.$$

For comparisons, the mean regression estimated by OLS and the unconditional quantile regressions at quantiles 0.1, 0.25, 0.5, 0.75, and 0.9 are considered. Robust standard errors for OLS estimations and bootstrapped standard errors (1000 replications) for RIF-LOGIT estimations are used for computing the t-values which are in parentheses. These estimations are conducted with R-3.2.5. The package "ks" is used to estimate the density function and package "boot" is to do the bootstrapping. The R codes and empirical data are available from authors upon request The empirical estimated results from the first sample period from 1989 to 1997 are shown in Table 3. All estimated coefficients from the OLS regression are significant at 5 %. The coefficient of "Public" is -0.036 with t-value -2.810 and indicates the marginal effect of "Public" is negative on the conditional and unconditional mean of salary income. This indicates that expansion of employment in public sector decreases the conditional and unconditional mean of salary income at the time from 1989 to 1997. However, the marginal effects of "Public" on the unconditional income distribution at 10 %, 50 %, and 75 % quantiles are significant at 5 % level but are not significant at 25 % and 90 % quantiles. The marginal effects are different in values at quantiles. For examples, the marginal effect is 0.069 which is significantly positive at quantile 10 % but is -0.211 which is significantly negative at quantile 75 %.

Table 3. Estimation Results from OLS and Unconditional Quantile Regressions

	OLS	10 %	25 %	50 %	75 %	90 %
1989-1997						
Public	-0.036	0.069	0.022	- 0.050	-0.211	0.067
	(-2.810)	(3.409)	(1.266)	(-2.461)	(-5.778)	(1.729)
Sex	0.127	0.074	0.098	0.128	0.211	0.090
	(11.089)	(4.303)	(6.490)	(7.353)	(5.975)	(2.703)
HighEduc	0.152	0.355	0.166	0.177	0.035	0.274
	(6.925)	(4.698)	(5.255)	(6.183)	(0.536)	(4.577)
Exper	0.020	0.016	0.019	0.019	0.031	0.008
	(9.261)	(4.235)	(6.108)	(5.740)	(4.225)	(1.035)
$Exper^2$	-0.022	-0.005	-0.011	-0.014	-0.059	-0.002
	(-4.468)	(-0.578)	(-1.518)	(-1.978)	(-3.716)	(-0.115)
Rural	-0.092	-0.084	-0.079	-0.087	-0.146	-0.071
	(-7.942)	(-4.678)	(-5.037)	(-5.052)	(-4.179)	(-2.171)

Note: *t*-values are in parentheses.

For the sample period from 2000 to 2006, the estimated coefficient of "Public" from OLS is 0.168 with t-value 8.143 which is significant statistically. This result is oppositely different from the one for the sample period from 1989 to 1997. The marginal effect of "Public" on the conditional and unconditional means of wage income becomes significantly positive which implies that an expansion of employment in public sector increases the means of wage income. In addition, the marginal effect of "Public" on the unconditional income distribution at 10 % (0.184), 25 % (0.176), 50 % (0.254), 75 % (0.140) and 90 % (0.027) quantiles are all positive and significant at 5 % level. These results indicate that an expansion of employment in public sector make the conditional and unconditional means larger and moves the unconditional income distribution to the right.

Table 4. Estimation Results from OLS and Unconditional Quantile Regressions

	OLS	10 %	25 %	50 %	75 %	90 %
2000-2006						
Public	0.168	0.184	0.176	0.254	0.140	0.027
	(8.143)	(5.657)	(6.653)	(10.364)	(6.029)	(0.559)
Sex	0.259	0.205	0.266	0.274	0.203	0.306
	(13.608)	(7.067)	(11.528)	(11.567)	(8.355)	(6.219)
HighEduc	0.306	0.280	0.230	0.327	0.300	0.424
	(9.100)	(3.156)	(4.397)	(7.460)	(9.372)	(6.828)
Exper	0.019	0.017	0.015	0.021	0.020	0.033
	(5.717)	(3.556)	(3.480)	(4.856)	(4.727)	(4.066)
$Exper^2$	-0.050	-0.050	-0.046	-0.054	-0.042	-0.071
	(-6.535)	(-4.529)	(-4.715)	(-5.528)	(-4.630)	(-3.889)
Rural	-0.113	-0.117	-0.070	-0.098	-0.093	-0.148
	(-5.825)	(-3.79)	(-3.130)	(-4.389)	(-4.413)	(-3.689)

Note: *t*-values are in parentheses.

As for the sample period from 2009 to 2011, the estimated coefficients of OLS (0.134) and the marginal effects of "Public" on the unconditional income distribution at 10 % (0.112), 25 % (0.257), 50 % (0.267), and 75 % (0.143) quantiles are all positive and significant at 5 % level. However the estimated coefficient at quantile 90 % is -0.047 which is insignificant at 5 % level. These results also indicate that an expansion of employment in public sector make the conditional and unconditional means larger and moves the unconditional income distribution to the right. It is clear that know that the marginal effects of an expansion of the employment in public sector are more and more significantly positive on the unconditional income distribution.

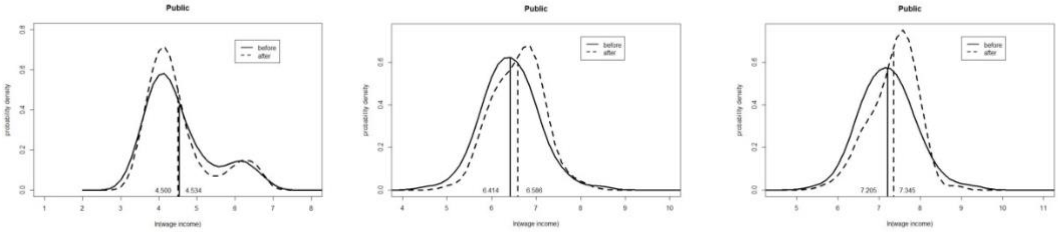
Table 5. Estimation Results from OLS and Unconditional Quantile Regressions (continued)

	OLS	10 %	25 %	50 %	75 %	90 %
2009-2011						
Public	0.134	0.112	0.257	0.267	0.143	-0.047
	(6.926)	(3.259)	(9.689)	(10.693)	(4.476)	(-1.207)
Sex	0.310	0.345	0.294	0.323	0.304	0.242
	(17.825)	(10.900)	(12.643)	(13.531)	(10.750)	(6.063)
HighEduc	0.430	0.365	0.437	0.458	0.464	0.555
	(17.280)	(4.879)	(9.518)	(13.021)	(13.512)	(11.090)
Exper	0.019	0.009	0.008	0.021	0.027	0.033
	(5.847)	(1.620)	(2.074)	(5.199)	(5.674)	(4.783)
$Exper^2$	-0.047	-0.037	-0.030	-0.049	-0.057	-0.064
	(-7.061)	(-3.413)	(-3.609)	(-5.741)	(-5.623)	(-4.259)
Rural	-0.093	-0.029	0.026	-0.078	-0.176	-0.184
	(-5.323)	(-1.050)	(1.295)	(-3.617)	(-6.764)	(-4.946)

Note: *t*-values are in parentheses.

Marginal Effect of an Employment Expansion in Public Sector on Unconditional Income Distribution

To explore the marginal effects of "Public" more detail, we compare the estimated density functions of the wage income "before" and "after" a unit change of "Public" variable. Denote $\hat{q}_\tau$ as the τ th sample quantile and $\hat{\alpha}_\tau$ (*Public*) as the estimated marginal effect of factor "Public" on the τ quantile of unconditional wage income at quantile τ. Consider τ = 0.01 to 0.99 at an increment 0.01, there are 99 $\hat{q}_\tau$ and $\hat{q}_\tau + \hat{\alpha}_\tau$ (*Public*) calculated. Using the kernel smoothing density estimator, the density estimations with $\hat{q}_\tau$ and with $\hat{q}_\tau + \hat{\alpha}_\tau$ (*Public*) are the estimated density functions of "before" and "after", respectively. The estimated density function of "before" is nothing but the estimated sample quantile of unconditional wage income. The estimated density function of "after" is the estimated sample quantile of unconditional wage income after an expansion of the employment in public sector. The estimated "before" (denoted as solid line) and "after" (denoted as dotted line) density functions using the empirical data from 1989-1997, from 2000-2006, and from 2009-2011 are represented as figures in panels (a), (b), and (c) of Figure 1, respectively.



(a) 1989 to 1997 (b) 2000 to 2006 (c) 2009 to 2011

Figure 1: Marginal Effect of “Public” on Unconditional Averaged Monthly Income

For the first sample period from 1989 to 1997, the estimated “before” density function (solid line in panel (a) of Figure 1) has the mean at 4.534 and has a shape with two modes around 4.1 and 6.2. The estimated “after” density function (dotted line) has the mean at 4.5 and also has a shape with two modes around 4.1 and 6.3. It is clear that the mean of estimated “before” density functions is mild smaller than the one of estimated “after” density functions. This finding is consistent with the negative estimated coefficient of “Public” from the OLS which is -0.036. And, the first modes of these two estimated density functions are similar and the second mode of “after” is mild larger than the one of “before”. In addition, it is found that the estimated “after” densities are higher than the ones of “before” around the first mode, but on the contrary, the “after” densities are smaller than the “before” ones for the other levels of wage income. These results conclude that an expansion of public employment decreases the mean level and the dispersion of wage income. This implies that the expansion of employment in public sector not only decreases the mean level but also reduces the inequality of wage income.

Rather than two modes for the two density functions from sample period from 1989 to 1997, there is only one mode for each density functions estimated from sample period from 2000 to 2006 which are shown as the figures of panel (b) in Figure 1. The estimated density function of “before” (denoted as solid line) is in a bell shape symmetric at the mean 6.414 and the one of “after” (denoted as dotted line) is skewed to the left with the mean 6.586. This finding can be verified with the positive OLS coefficient of “Public” which is 0.168 and statistically significant as shown in Table 3. This result implies that the mean level of wage income is increased as an expansion of the employment in public sector. Since the “after” density function becomes skewed to the left, an expansion of public employment has significant improvement of wage incomes. In addition, it is obvious that the dispersion of the “after” density function is moderate smaller than the one of “before” density function. This result indicates that an expansion of employment in public sector will reduce the dispersion of the distribution of wage income. To a summary, an expansion of employment in public sector not only moves the distribution of the wage income to the right but also reduces the inequality of wage income.

The “before” and “after” density functions estimated from the sample period from 2009 to 2011 are presented in the panel (c) in Figure 1. Similar to the ones estimated from sample period 2000 to 2006, there is one mode for each density functions. In addition, the estimated density function of “before” (denoted as solid line) is in a bell shape symmetric at the mean and the one of “after” (denoted as dotted line) is skewed to the left. The mean of the “after” density function is 7.345 which is larger than the one of “before” density function, 7.205. This finding is consistent with the positive OLS coefficient of “Public” which is 0.134 and statistically significant as shown in Table 4. This result also implies that the mean level of wage income is increased as an expansion of the employment in public sector. Since the “after” density function is also skewed to the left, an expansion of public employment also has significant improvement of wage incomes. In addition, it is obvious that the dispersion of the “after” density function is moderate smaller than the one of “before” density function. This result indicates that an expansion of employment in public sector will reduce the dispersion of the distribution of wage income. To a summary, an expansion of employment in public sector not only moves the distribution of the wage income to the right but also reduces the inequality of wage income. It worths of noticing that an expansion of employment in public sector improves the inequality of wage income more and more from the second sample period (2000 to 2006) to the third (2009 to 2011).

To a summary, the marginal effect of an expansion of employment in public sector on the mean of wage income is significantly negative on the sample period from 1989 to 1997 and becomes significantly positive on the sample periods from 2000 to 2006 and from 2009 to 2011. However, the positive marginal effect on sample period from 2006 to 2006 is larger than the one on sample period from 2009 to 2011. For the sample periods from 2000 to 2006 and 2009 to 2011, an expansion of employment in public sector have the following effects on the unconditional distribution of wage income:

1.an expansion of employment in public sector increases the mean level of the unconditional distribution of wage income;

2.an expansion of employment in public sector decreases the dispersion of the unconditional distribution of wage income;

3.an expansion of employment in public sector makes the unconditional distribution of wage income from symmetric to skewed to the left.

Conclusions and Suggestions

This paper investigates the marginal effect of an expansion of employment in public sector on the unconditional distribution of logarithm of wage income in China. The unconditional quantile estimation of Firpo et al. (2009) is implemented. The empirical data used in this paper is from China Health and Nutrition Survey (CHINS) in 1989 to 2011. To grid of the effects of the possible structural changes caused by the Asia financial crisis on 1997 and the subprime financial crisis on 2008 on our empirical results, the whole sample is split into three sample periods, from 1989 to 1997, from 2000 to 2006, and from 2009 to 2011.

Our empirical studies suggest the following findings:

1. The marginal effect of "Public" on the mean level of wage income is significantly negative originally for the first sample period 1989 to 1997 and then becomes significantly positive later for sample periods 2000 to 2006 and 2009 to 2011.
2. For the sample periods from 2000 to 2006 and from 2009 to 2011, an expansion of employment in public sector decreases the dispersion of the unconditional distribution of wage income. That is the inequality of income could be improved by an expansion of employment in public sector.
3. An expansion of employment in public sector in the sample periods from 2000 to 2006 and from 2009 to 2011 makes the unconditional distribution of wage income from symmetric to skewed to the left.
4. Above marginal effects of an expansion of employment in public sector on the unconditional distribution of wage income are larger in sample period from 2006 to 2008 than the ones in sample period from 2009 to 2011.

Given these finding and without considering the inefficiency of state-owned firms, an expansion of employment in public sector could be a good political strategy for China to improve the income inequality.

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