รายงานวิจัยฉบับสมบูรณ์

โครงการประสิทธิภาพเชิงพลวัตในภาคการเกษตรของประเทศเปลี่ยนผ่านสาธารณรัฐประชาชนจีน

โดย ศาสตราจารย์ ดร. ศุภวัจน์ รุ่งสุริยะวิบูลย์

เดือน ธันวาคม ปี 2560

สัญญาเลขที่ RSA5980007

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คณะเศรษฐศาสตร์
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สนับสนุนโดยสำนักงานกองทุนสนับสนุนการวิจัย
และมหาวิทยาลัยธรรมศาสตร์

กิตติกรรมประกาศ

งานวิจัยเรื่อง “ประสิทธิภาพเชิงพลวัตในภาคการเกษตรของประเทศเปลี่ยนผ่าน สาธารณรัฐประชาชนจีน” ได้รับการสนับสนุนเงินทุนวิจัย “ทุนพัฒนานักวิจัย ประจำปี พ.ศ. 2559” จากสำนักงานกองทุนสนับสนุนการวิจัย ร่วมกับฝ่ายวิจัย มหาวิทยาลัยธรรมศาสตร์ และ คณะเศรษฐศาสตร์ มหาวิทยาลัยธรรมศาสตร์ ผู้เขียนจึงใคร่ขอขอบคุณสำนักงานกองทุนสนับสนุนการวิจัย ฝ่ายวิจัย มหาวิทยาลัยธรรมศาสตร์ และ คณะเศรษฐศาสตร์ มหาวิทยาลัยธรรมศาสตร์ ที่ได้กรุณาให้การสนับสนุนด้านเงินทุนในการวิจัยครั้งนี้

ผู้เขียนขอขอบคุณ คณะเศรษฐศาสตร์ มหาวิทยาลัยธรรมศาสตร์ ที่ให้การสนับสนุนผู้เขียนเป็นอย่างดีด้วยมาตลอดระยะเวลาในการดำเนินการวิจัยนี้

ผู้เขียนขอขอบคุณ Professor Dr. Thomas Glauben ผู้อำนวยการสถาบัน Institute of Agricultural Development in Central and Eastern Europe ประเทศสหพันธสาธารณรัฐเยอรมันนี ที่ได้เชิญให้ผู้เขียนไปบรรยายเกี่ยวกับแบบจำลองที่ได้พัฒนาขึ้นในงานวิจัยนี้ รวมถึงได้ให้ผู้เขียนนำเสนอผลการศึกษาที่ได้จากงานวิจัยนี้ให้แก่นักวิจัยและนักศึกษาระดับปริญญาเอกของทางสถาบัน ทำให้ผู้เขียนได้รับความรู้และข้อเสนอแนะที่เป็นประโยชน์ในการนำมาพัฒนางานวิจัยเป็นอย่างมาก

นอกจากนั้น ผู้เขียนขอขอบคุณ Dr. Yanjie Zhang จาก Institute of Agricultural Development in Central and Eastern Europe ประเทศสหพันธสาธารณรัฐเยอรมันนี ที่ได้ให้ความช่วยเหลือในการจัดเก็บรวบรวมข้อมูลการผลิตของประเทศ สาธารณรัฐประชาชนจีน ที่นำมาใช้ในงานวิจัยนี้ ตลอดจนให้ข้อเสนอแนะและคำแนะนำที่เป็นประโยชน์ต่องานวิจัยเป็นอย่างมาก

ผู้เขียนหวังว่าผลการศึกษาที่ได้จากงานวิจัยนี้จะทำให้ผู้อ่านสามารถเข้าใจถึงบริบทของการพัฒนาการผลิตภาคการเกษตรของ สาธารณรัฐประชาชนจีน เพื่อนำมาใช้เป็นข้อมูลที่สำคัญในการกำหนดแผนเชิงนโยบายที่เหมาะสมสำหรับพัฒนาการผลิตภาคการเกษตรให้เป็นไปอย่างยั่งยืนต่อไป หากงานวิจัยนี้มีข้อผิดพลาดประการใด ผู้เขียนยินดีน้อมรับคำแนะนำเพื่อนำมาปรับปรุงใช้ในการพัฒนางานวิจัยต่อไปในอนาคต

ศุภวัจน์ รุ่งสุริยะวิบูลย์
ธันวาคม 2560

บทคัดย่อ

รหัสโครงการ : RSA5980007

ชื่อโครงการ : ประสิทธิภาพเชิงพลวัตในภาคการเกษตรของประเทศเปลี่ยนผ่าน สาธารณรัฐประชาชนจีน

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ระยะเวลาโครงการ : 16 เดือน มิถุนายน พ.ศ. 2559 **ถึง** 15 เดือน ธันวาคม พ.ศ. 2560

ในแวดวงวรรณกรรมนั้น ค่าประสิทธิภาพการผลิตถือเป็นตัววัดที่มีความสำคัญ เพราะนอกจากจะนำมาใช้เปรียบเทียบผลการดำเนินการของหน่วยผลิตในอุตสาหกรรมแล้ว ยังสามารถนำมาใช้เป็นข้อมูลสำคัญสำหรับผู้กำหนดนโยบายของรัฐเพื่อนำมาวางแผนเชิงนโยบายที่เหมาะสมในการกำหนดทิศทางและยุทธศาสตร์การพัฒนาเศรษฐกิจของประเทศ เนื่องจากงานวิจัยที่ศึกษาถึงผลการดำเนินการทางการเกษตรของประเทศเปลี่ยนผ่าน รวมถึงของประเทศสาธารณรัฐประชาชนจีนนั้น ค่าประสิทธิภาพการผลิตที่ถูกวัดจากแบบจำลองนั้นถูกพัฒนาจากแนวคิดในการแก้ปัญหาเชิงสถิตย์ ส่งผลทำให้ค่าประสิทธิภาพการผลิตที่วัดได้เกิดความคลาดเคลื่อน

งานวิจัยชิ้นนี้ได้ท้าทายข้อบกพร่องดังกล่าวด้วยการพัฒนาแบบจำลองการวัดประสิทธิภาพเชิงพลวัต (dynamic efficiency model) สำหรับวัดค่าประสิทธิภาพของหน่วยผลิตภายใต้การตัดสินใจเลือกแบบข้ามเวลา แบบจำลองการวัดประสิทธิภาพเชิงพลวัตในงานวิจัยนี้ถูกนำมาวิเคราะห์กับฐานข้อมูลการผลิตภาคการเกษตรของประเทศสาธารณรัฐประชาชนจีนใน 3 มณฑล ได้แก่ Zhejiang, Hubei และ Yunnan ระหว่างช่วงปี ค.ศ. 2003 ถึง 2006 เพื่อเปรียบเทียบถึงผลการดำเนินการทางการเกษตรที่เกิดขึ้นหลังจากที่ประเทศได้มีการปฏิรูปเศรษฐกิจจากระบบรวมศูนย์มาเป็นระบบที่ขึ้นกับกลไกของตลาด ผลการศึกษาที่ได้แสดงให้เห็นว่าผลการดำเนินการทางการเกษตรในแต่ละมณฑลมีความแตกต่างกันอย่างมาก ค่าประสิทธิภาพการผลิตของมณฑล Zhejiang มีค่าสูงที่สุด ในขณะที่มณฑล Yunnan มีค่าประสิทธิภาพการผลิตต่ำที่สุด นอกจากนั้น ต้นทุนในการปรับค่าของปัจจัยทุนและที่ดินอยู่ในระดับสูง หน่วยผลิตต้องใช้ระยะเวลานานมากในการปรับการใช้ปัจจัยทั้งสองให้อยู่ในระดับดุลยภาพระยะยาว จากผลการศึกษาที่ได้นี้สามารถกล่าวได้ว่าผู้กำหนดนโยบายควรให้ความสำคัญกับการปฏิรูปตลาดปัจจัยการผลิตต่าง ๆ โดยรวม และสิทธิของเกษตรกรในการครอบครอง

ที่ดินควรมีการเพิ่มและขยายมากขึ้นเพื่อให้การครอบครองที่ดินของเกษตรกรมีความมั่นคงและปลอดภัยมากขึ้น

คำหลัก การเกษตรกรรม สาธารณรัฐประชาชนจีน ประสิทธิภาพเชิงพลวัต ประสิทธิภาพการผลิต ต้นทุนการปรับตัว วิธีต้นทุนเงา

Abstract

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Project Title : Dynamic Efficiency in Chinese Agriculture

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Production efficiency is an important measure because it can be used to describe and compare firm performance. In addition, it can be used as important information for policy makers in order to provide appropriate policy planning in determining the direction and strategy of economic development of the country. In the literature, agricultural performance is measured from models developed using the static context. As a result, the production efficiency obtained from the model is inaccurate. Previous studies of Chinese agricultural performance have also relied on conventional approaches and employed static frontier-based models. In addition, given that these studies mostly investigated the performance of Chinese farms based upon different data sets and time periods, it goes without saying that a cross-study comparison is precluded by the lack of a common basis.

To fill these gaps, the main purpose of the study is to understand the state of adjustment processes and dynamic structure in Chinese agriculture, this paper proposes a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making. Using a panel data set of 4,201 Chinese farms from three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006, this is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. The findings show that the adjustment of quasi-fixed inputs is rather sluggish, implying that adjustment costs are considerably high on Chinese farms. The relatively low levels of allocative and technical efficiencies indicate that most of farms are unable to catch up with the production frontier under the existing production technology and that they are unable to use various inputs in the appropriate proportion given their respective prices.

Keywords: Chinese agriculture, dynamic efficiency, adjustment cost, shadow cost approach

Executive Summary

ค่าประสิทธิภาพการผลิตถือเป็นตัววัดที่มีความสำคัญ เพราะนอกจากจะนำมาใช้เปรียบเทียบผลการดำเนินการของหน่วยผลิตในอุตสาหกรรมแล้ว ยังสามารถนำมาใช้เป็นข้อมูลสำคัญสำหรับผู้กำหนดนโยบายของรัฐเพื่อนำมาวางแผนเชิงนโยบายที่เหมาะสมในการกำหนดทิศทางและยุทธศาสตร์การพัฒนาเศรษฐกิจของประเทศ เนื่องจากงานวิจัยที่ศึกษาถึงผลการดำเนินการทางการเกษตรของประเทศเปลี่ยนผ่าน รวมถึงของประเทศสาธารณรัฐประชาชนจีนนั้น

ค่าประสิทธิภาพการผลิตของหน่วยผลิตถูกพัฒนาขึ้นอย่างต่อเนื่องหลังจากที่แนวคิดเรื่องการวิเคราะห์เส้นพรมแดนการผลิตถูกนำเสนอในช่วงปลายทศวรรษที่ 1970 อย่างไรก็ตาม แบบจำลองที่ได้มีการนำเสนอในแวดวงวรรณกรรมถูกพัฒนาขึ้นจากพื้นฐานแนวคิดในการแก้ปัญหาเชิงสถิตย์ นั่นคือ การตัดสินใจของหน่วยผลิตในการผลิตไม่ได้คำนึงถึงผลของเวลาที่เกิดขึ้น การเพิกเฉยต่อผลของช่วงเวลาที่เกิดขึ้นในอนาคตต่อการตัดสินใจของหน่วยผลิตจะส่งผลทำให้ค่าประสิทธิภาพและการเติบโตผลิตภาพที่วัดได้จากแบบจำลองมีความไม่ถูกต้อง

งานวิจัยชิ้นนี้ได้ท้าทายข้อบกพร่องดังกล่าวด้วยการพัฒนาแบบจำลองการวัดประสิทธิภาพเชิงพลวัต (dynamic efficiency model) สำหรับวัดค่าประสิทธิภาพของหน่วยผลิตภายใต้การตัดสินใจเลือกแบบข้ามเวลาเพื่ออธิบายถึงพฤติกรรมของหน่วยผลิตที่ต้องการแสวงหาต้นทุนต่ำสุดจากการผลิต แบบจำลองเชิงพลวัตนี้สามารถนำไปประยุกต์ใช้ได้กับกระบวนการผลิตที่มีการใช้ปัจจัยกึ่งคงที่หลายชนิดเพื่อผลิตสินค้าเพียงชนิดเดียว นอกจากนั้น แบบจำลองยังสามารถอธิบายความแตกต่างของการผลิตแยกตามลักษณะภูมิศาสตร์ เทคโนโลยีการผลิต และลักษณะเฉพาะของการผลิต แบบจำลองการวัดประสิทธิภาพเชิงพลวัตสามารถวัดและแยกค่าประสิทธิภาพต้นทุนออกเป็นประสิทธิภาพประเภทต่างๆ รวมทั้งสามารถอธิบายถึงต้นทุนในการปรับค่าของปัจจัยกึ่งคงที่ที่เกิดขึ้นในกระบวนการผลิตของหน่วยผลิต

แบบจำลองการวัดประสิทธิภาพเชิงพลวัตในงานวิจัยนี้ถูกนำมาวิเคราะห์กับฐานข้อมูลการผลิตภาคการเกษตรของประเทศสาธารณรัฐประชาชนจีน โดยอาศัยฐานข้อมูลจากหน่วยงาน Research Center for Rural Economy (RCRE) of the Ministry of Agriculture, China ในการจัดทำข้อมูลการผผลิตภาคการเกษตรของสาธารณรัฐประชาชนจีนใน 3 มณฑล ได้แก่ Zhejiang, Hubei และ Yunnan ระหว่างช่วงปี ค.ศ. 2003 ถึง 2006 เพื่อเปรียบเทียบถึงผลการดำเนินการทางการเกษตรที่เกิดขึ้นหลังจากที่ประเทศได้มีการปฏิรูปเศรษฐกิจจากระบบรวมศูนย์มาเป็นระบบที่ขึ้นกับกลไกของตลาด ซึ่งข้อมูลที่นำมาใช้ในการวิเคราะห์จะประกอบไปด้วย ข้อมูลปริมาณการผลิตพืชผล (crop) และปัจจัยการผลิตต่างๆ ได้แก่ ปัจจัยที่ดิน ปัจจัยทุน ปัจจัยแรงงาน และ ปัจจัยการผลิตขั้นกลาง (intermediate input) เป็นต้น

ผลการศึกษาที่ได้แสดงให้เห็นว่าผลการดำเนินการทางการเกษตรในแต่ละมณฑลมีความแตกต่างกันอย่างมาก ค่าประสิทธิภาพการผลิตของมณฑล Zhejiang มีค่าสูงที่สุด ในขณะที่ มณฑล Yunnan มีค่าประสิทธิภาพการผลิตต่ำที่สุด นอกจากนั้น ต้นทุนในการปรับค่าของปัจจัยทุนและที่ดินอยู่ในระดับสูง หน่วยผลิตต้องใช้ระยะเวลานานมากในการปรับการใช้ปัจจัยทั้งสองให้อยู่ในระดับดุลยภาพระยะยาว จากผลการศึกษาที่ได้นี้สามารถกล่าวได้ว่าผู้กำหนดนโยบายควรให้ความสำคัญกับการปฏิรูปตลาดปัจจัยการผลิตต่างๆโดยรวม และสิทธิของเกษตรกรในการครอบครองที่ดินควรมีการเพิ่มและขยายมากขึ้นเพื่อให้การครอบครองที่ดินของเกษตรกรมีความมั่นคงและปลอดภัยมากขึ้น

เนื้อหางานวิจัย

งานวิจัยของโครงการวิจัยนี้ได้นำเสนอในรูปแบบของบทความทางวิชาการ ชื่อบทความ "Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach"

ในแวดวงวรรณกรรมนั้น ค่าประสิทธิภาพการผลิตถือเป็นตัววัดที่มีความสำคัญ เพราะนอกจากจะนำมาใช้เปรียบเทียบผลการดำเนินการของหน่วยผลิตในอุตสาหกรรมแล้ว ยังสามารถนำมาใช้เป็นข้อมูลสำคัญสำหรับผู้กำหนดนโยบายของรัฐเพื่อนำมาวางแผนเชิงนโยบายที่เหมาะสมในการกำหนดทิศทางและยุทธศาสตร์การพัฒนาเศรษฐกิจของประเทศ เนื่องจากงานวิจัยที่ศึกษาถึงผลการดำเนินการทางการเกษตรของประเทศเปลี่ยนผ่าน รวมถึงของประเทศสาธารณรัฐประชาชนจีนนั้น ค่าประสิทธิภาพการผลิตที่ถูกวัดจากแบบจำลองนั้นถูกพัฒนาจากแนวคิดในการแก้ปัญหาเชิงสถิตย์ส่งผลทำให้ค่าประสิทธิภาพการผลิตที่วัดได้เกิดความคลาดเคลื่อน

งานวิจัยชิ้นนี้ได้ท้าทายข้อบกพร่องดังกล่าวด้วยการพัฒนาแบบจำลองการวัดประสิทธิภาพเชิงพลวัต (dynamic efficiency model) สำหรับวัดค่าประสิทธิภาพของหน่วยผลิตภายใต้การตัดสินใจเลือกแบบข้ามเวลาเพื่ออธิบายถึงพฤติกรรมของหน่วยผลิตที่ต้องการแสวงหาต้นทุนต่ำสุดจากการผลิต แบบจำลองเชิงพลวัตนี้สามารถนำไปประยุกต์ใช้ได้กับกระบวนการผลิตที่มีการใช้ปัจจัยกึ่งคงที่หลายชนิดเพื่อผลิตสินค้าเพียงชนิดเดียว นอกจากนั้นแบบจำลองยังสามารถอธิบายความแตกต่างของการผลิตแยกตามลักษณะภูมิศาสตร์ เทคโนโลยีการผลิต และลักษณะเฉพาะของการผลิต แบบจำลองการวัดประสิทธิภาพเชิงพลวัตสามารถวัดและแยกค่าประสิทธิภาพต้นทุนออกเป็นประสิทธิภาพประเภทต่าง ๆ รวมทั้งสามารถอธิบายถึงต้นทุนในการปรับค่าของปัจจัยกึ่งคงที่ที่เกิดขึ้นในกระบวนการผลิตของหน่วยผลิต

แบบจำลองการวัดประสิทธิภาพเชิงพลวัตในงานวิจัยนี้ถูกนำมาวิเคราะห์กับฐานข้อมูลการผลิตภาคการเกษตรของประเทศสาธารณรัฐประชาชนจีนใน 3 มณฑล ได้แก่ Zhejiang, Hubei และ Yunnan ระหว่างช่วงปี ค.ศ. 2003 ถึง 2006 เพื่อเปรียบเทียบถึงผลการดำเนินการทางการเกษตรที่เกิดขึ้นหลังจากที่ประเทศได้มีการปฏิรูปเศรษฐกิจจากระบบรวมศูนย์มาเป็นระบบที่ขึ้นกับกลไกของตลาด ผลการศึกษาที่ได้แสดงให้เห็นว่าผลการดำเนินการทางการเกษตรในแต่ละมณฑลมีความแตกต่างกันอย่างมาก ค่าประสิทธิภาพการผลิตของมณฑล Zhejiang มีค่าสูงที่สุด ในขณะที่ มณฑล Yunnan มีค่าประสิทธิภาพการผลิตต่ำที่สุด นอกจากนั้น ต้นทุนในการปรับค่าของปัจจัยทุนและที่ดินอยู่ในระดับสูง หน่วยผลิตต้องใช้ระยะเวลานานมากในการปรับการใช้ปัจจัยทั้งสองให้อยู่ในระดับดุลยภาพระยะยาว จากผลการศึกษาที่ได้นี้สามารถกล่าวได้ว่าผู้กำหนดนโยบายควรให้ความสำคัญกับการปฏิรูปตลาดปัจจัยการผลิตต่าง ๆ โดยรวม และ

สิทธิของเกษตรกรในการครอบครองที่ดินควรมีการเพิ่มและขยายมากขึ้นเพื่อให้การครอบครองที่ดินของเกษตรกรมีความมั่นคงและปลอดภัยมากขึ้น

Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach

Abstract

To understand the state of adjustment processes and dynamic structure in Chinese agriculture, this paper proposes a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making. Using a panel data set of 4,201 Chinese farms from three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006, this is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. The findings show that the adjustment of quasi-fixed inputs is rather sluggish, implying that adjustment costs are considerably high on Chinese farms. The relatively low levels of allocative and technical efficiencies indicate that most of farms are unable to catch up with the production frontier under the existing production technology and that they are unable to use various inputs in the appropriate proportion given their respective prices.

Keywords: Chinese agriculture, dynamic efficiency, adjustment cost, shadow cost approach

JEL codes: D21, D61, Q12

1. Introduction

China's agricultural development has been remarkable over the past four decades. The rural reform that began in the late 1970s improved farmers' incentives and had a huge impact on China's agricultural productivity, growth, and output. The value of agricultural output increased enormously, from 139.7 billion Chinese yuan in 1978, to 10,222.6 billion yuan in 2014.[1] Agricultural total factor productivity (TFP) has also grown extremely fast—by 4% per annum on average from 1979 to 2008 (Zhang and Brümmer, 2011). The great achievement of China's agricultural production has so far come almost entirely from smallholder farming, represented by about 200 million small-scale farms.

Despite great successes, many challenges remain or have even increased over the last decade. For instance, the continued rising opportunity costs of agricultural labour will lead to the gradual loss of China's competitive labour advantage. Further, household rights to land are still incomplete after several waves of land tenure reforms (Ma et al., 2015). This induced land insecurity reduces the incentives of farmers to make productivity-enhancing investments in land (e.g. irrigation, drainage, terracing and the application of organic fertilizer), and hinders the efficient use of labour (Brandt et al., 2002; Deininger and Feder, 2001), as a result decreasing agricultural productivity.

China's major agricultural policy objectives have been consistent in their aims to increase grain production capacity to largely ensure food self-sufficiency and at the

[1]The statistics are taken from China Statistical Yearbook 2015, National Bureau of Statistics of China.

same time improve farmers' income. Since 2004, the No. 1 Documents[2] of each year have concentrated on issues related to agriculture, farmers and the countryside (the so-called 'three nongs'). In recent years these documents have focused on investments in agricultural technology to boost production and the adjustment of farm structure, emphasizing a transition to larger-scale farms (OECD, 2013, 2015). In this context, the role of adjustment costs and dynamic cost structure are becoming important issues for investigating performance in Chinese agriculture. Whether adjustment costs are significant and whether they can be regarded as a source of the sluggish adjustment processes are of interest to policymakers. Considering the major challenges in Chinese agricultural production, the extent to which Chinese farms could perform better remains an important research question. A measure of cost efficiency and its decomposition provides an indicator that measures the exploitation of resources (technical efficiency) in Chinese agriculture, as well as an indicator that characterises the economic losses due to suboptimal allocation of resources (allocative inefficiency). Furthermore, this study addresses the issue by characterizing the cost structure of Chinese farms under dynamic adjustment, to measure their performance.

The frontier approach has become the state-of-the-art for analysing the performance of firms in the literature. Modern efficiency and productivity methodologies measure firm performance relative to best-practice frontiers. Both parametric and nonparametric techniques have been continuously developed to

[2]No. 1 Documents are the top-priority documents issued jointly at the beginning of each year by the Central Committee of the Communist Party and the State Council. They are the first major policy directives of the year and give policy suggestions for the National People's Congress (OECD, 2009).

identify the best-practice frontier. Recent empirical studies that have conducted the frontier-based model using both parametric and nonparametric techniques to measure firms' efficiency and productivity in various industries include Lee et al. (2017), Johnstone et al. (2017), Fujii and Managi (2017) and Tamaki et al. (2017).

Frontier-based models using a parametric approach to estimate firm efficiency have been an important area of research, which has been continuously developed for more than half a decade. Following the pioneering work of Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), the frontier analysis model has been employed for both primal and dual representations of production technologies. With the availability of input quantity and cost share data, a dual cost frontier approach allows researchers to estimate and decompose the firm's cost efficiency into technical and allocative efficiencies. Analysis of the cost frontier models has further grown with important contributions by many researchers (Schmidt and Lovell; 1979; Kopp and Diewert 1982; Zieschang 1983; Bauer 1990; Greene 1993; Kumbhakar 1997; Maietta 2000; Atkinson and Primont 2002; Assaf and Matawie 2008). However, the cost frontier models presented in these studies were developed in a static context. The shortcomings of the static frontier-based model include ignoring the explicit role of time and how the adjustment of quasi-fixed inputs to the observed long-run level takes place. As a result, efficiency scores measured from the static efficiency model may be inaccurate and misleading. The absence of an explicit analysis of the transition path of quasi-fixed factors toward their desired long-run levels can be remedied by explicitly incorporating the costs of adjustment for the quasi-fixed factors. The framework of the optimal inter-temporal behaviour of the firm using the notion of adjustment costs as a means of solving the firm's optimization problem was first introduced by Eisner and Strotz (1963). The theory of inter-temporal duality was improved upon by McLaren and Cooper (1980a) and Epstein (1981). This theory represents an alternative and powerful method for solving inter-temporal optimization problems by using the optimal value function of the dynamic programming equation (DPE) approach. This field has further grown with important contributions by many researchers (i.e. Vasavada and Chambers 1986; Howard and Shumway 1988; Luh and Stefanou 1991, 1993; Fernandez-Cornejo et al. 1992; Manera 1994; Pietola and Myers 2000; Sckokai and Moro 2009). Though the static efficiency model and the dynamic duality model of inter-temporal decision making have been continuously developed, they have moved in separate directions. Recently, Rungsuriyawiboon and Stefanou (2007) formalized theoretical and econometric models of dynamic efficiency in the presence of inter-temporal cost-minimizing firm behaviour. The dynamic efficiency model is developed by integrating the static production efficiency model and the dynamic duality model of inter-temporal decision making. The dynamic efficiency model defines the relationship between the actual and behavioural value function of the DPE for a firm's inter-temporal cost minimisation behaviour. Therefore, the dynamic efficiency model provides a system of equations that allows the measurement of both the technical and allocative inefficiency of firms.

Other studies of Chinese agricultural performance have relied on conventional approaches and employed static frontier-based models (Brümmer et al., 2006; Wang et al., 2012; Zhang et al., 2011). In addition, given that these studies mostly investigated the performance of Chinese farms based on different data sets and time periods, it goes without saying that a cross-study comparison is precluded by the lack of a common basis. Brümmer et al. (2006) use a distance function approach with farm household data in the Zhejiang Province for the period 1986–2000, and the results show that the level of technical efficiency range from 0.326 to 0.878. Zhang et al. (2011) apply a two-stage model with a panel data set containing households from Zhejiang, Hubei and Yunnan to analyse the impact of land reallocation on farm production, and the estimated level of technical efficiency is relatively high, with average scores of 0.96, 0.91, and 0.87, respectively. Within a meta-frontier framework, Wang et al. (2012) provide evidence that technical efficiency is significantly affected by farm heterogeneity and that farming technology exhibits region-specific characteristics.

To fill these gaps, the main purpose of the study is to understand the state of adjustment process and dynamic structure in Chinese agriculture. To meet this goal, our paper extends the model of Rungsuriyawiboon and Stefanou (2007) into a more general context with a multiple quasi-fixed factor case. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) over the period of 2003-2006. This is the first study to investigate the allocative and technical efficiency of Chinese agriculture using a dynamic shadow cost approach. The production technology of Chinese farms is presented by one output variable, two variable inputs (labour and intermediate inputs) and two quasi-fixed factors (land and capital).

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework and mathematical derivations of the dynamic efficiency model for the multiple quasi-fixed factor case; Section 3 discusses the data set and the definitions of the variables used in this study; The next section elaborates the econometric model of the dynamic efficiency model with the two quasi-fixed factor cases; The results of our empirical analysis are presented and discussed in Section 4; while the final Section 5 concludes and summarizes.

2. Model specification

2.1 Derivation of a dynamic efficiency model of inter-temporal cost minimization

This section develops a dynamic efficiency model in the context of inter-temporal cost minimization. The framework of the optimal inter-temporal behaviour of the firm uses the notion of adjustment costs as a means of solving the firm's optimization problem. The adjustment cost approach attempts to capture all of the unobserved forces that slow down the adjustment of certain factors in production, such as learning costs, search costs, costs arising from market forces, or contractual obligations (Stefanou, 1989). The presence of adjustment costs formalizes the process of characterizing a firm's dynamic production decisions. In the presence of adjustment costs for the quasi-fixed factors, a firm faces additional costs for the adjustment of quasi-fixed factors beyond acquisition costs in the decision-making process.

The dynamic economic problem facing the firm can be addressed by characterizing firm investment behaviour as the firm seeks to minimize the discounted sum of future production costs over an infinite horizon. The firm's decision-making focuses on the optimal determination of its factor inputs use, which has implications for its capacity utilization. For instance, the purchase and installation of quasi-fixed factors involve a cost of adjustment since the firm must devote internal resources to acquire and adapt the newly-purchased quasi-fixed inputs. Production costs arise from purchasing new inputs, including both variable and quasi-fixed inputs. Units of the quasi-fixed inputs are acquired both for enlarging the existing productive capacity and for replacing worn-out units.

Let $\mathbf{x} \in R_{+}^{N}$ and $\mathbf{q} \in R_{+}^{Q}$ denote non-negative vectors of variable and quasi-fixed inputs, respectively. Similarly, $\mathbf{w} \in R_{++}^{N}$ and $\mathbf{p} \in R_{++}^{Q}$ denote strictly non-negative vectors for variable input prices and quasi-fixed factor prices, respectively.

Following Epstein and Denny (1983) and Stefanou (1989), who assume that economic agents are risk-neutral and that their price expectations are static, the dynamic inter-temporal model of a firm's cost minimization problem can be expressed as

(1) $$J(\mathbf{w}',\mathbf{p}',\mathbf{q}',y(t)) = \min_{\mathbf{I}>0} \int_{t}^{\infty} e^{-rs}[\mathbf{w}'\mathbf{x}(s) + \mathbf{p}'\mathbf{q}(s)]ds$$

subject to $\dot{\mathbf{q}}(s) = \mathbf{I}(s) - \delta\mathbf{q}(s)$, $\mathbf{q}(0) = \mathbf{q}_0 > 0$, $\mathbf{q}(s) > 0$, $y(s) = F[\mathbf{x}(s), \mathbf{q}(s), \dot{\mathbf{q}}(s)]$ $\forall s \in [t, \infty)$

where r is the constant discount rate, δ is the constant depreciation rate, y is output, $\dot{\mathbf{q}} \in R_+^Q$ and $\mathbf{I} \in R_+^Q$ are non-negative vectors of net investment and gross investment in quasi-fixed factors, $y(s)$ is a sequence of production targets over the planning horizon starting at time t, and $F[\mathbf{x}'(s), \mathbf{q}'(s), \dot{\mathbf{q}}'(s)]$ is the single output production function. Including net investment $\dot{\mathbf{q}}$ in the production function reflects the internal costs associated with the adjustment of quasi-fixed factors in terms of foregone output. The presence of internal adjustment cost implies output decreases (increases) with the expansion (contraction) of the quasi-fixed factor stocks (i.e. $\dot{\mathbf{q}}\nabla_{\dot{\mathbf{q}}} F < 0$). In addition, the marginal cost of adjustment in physical terms is assumed to increase with the speed of adjustment, implying $\nabla_{\dot{\mathbf{q}}\dot{\mathbf{q}}} F < 0$, where the diseconomies accompanying adjustment takes place. Therefore, sluggish or gradual behaviour in adjusting the levels of quasi-fixed factors is assured. The production function is assumed to be concave in $\dot{\mathbf{q}}$, implying an increasing marginal cost of adjustment.

McLaren and Cooper (1980a) and Epstein (1981) introduced the inter-temporal duality theory, which presents the relationship between the underlying technology and value functions. The dynamic duality between the underlying technology and value functions permits the derivation of a system of variable and dynamic demand equations. Analytically, the dynamic decision problem can be solved using the dynamic duality approach, which allows the use of appropriate static optimization techniques as expressed in the dynamic programming equation (DPE) or Hamilton-Jacobi-Bellman equation. The value function of the DPE for the inter-temporal cost minimization can be expressed as

(2) $$rJ(\mathbf{w}',\mathbf{p}',\mathbf{q}',y,t)=\min_{\mathbf{x},\dot{\mathbf{q}}>0}\left\{\mathbf{w}'\mathbf{x}+\mathbf{p}'\mathbf{q}+\nabla_{\mathbf{q}}J'\dot{\mathbf{q}}+\gamma(y-F[\mathbf{x}',\mathbf{q}',\dot{\mathbf{q}}',t])+\nabla_t J\right\}$$

where t is the time trend variable, γ is the Lagrangian multiplier associated with the production function, and $\nabla_t J$ is the shift of the value function due to technical change.

The result of inter-temporal duality theory provides readily-implemented systems of dynamic factor demands. Differentiating the optimized version of the DPE with respect to $\mathbf{p}$ and $\mathbf{w}$ yields optimal net investment demand and optimal variable input demand, respectively,

(3) $$\dot{\mathbf{q}}^o=(\nabla_{\mathbf{qp}}J)^{-1}(r\nabla_{\mathbf{p}}J-\mathbf{q}-\nabla_{\mathbf{p}t}J)$$

(4) $$\mathbf{x}^o=r\nabla_{\mathbf{w}}J-\nabla_{\mathbf{wq}}J\dot{\mathbf{q}}^o-\nabla_{\mathbf{w}t}J\ .$$

Equation (2) can be interpreted as the dynamic inter-temporal model of a firm's cost minimization problem in the presence of perfect efficiency. When a firm neither minimizes its factor inputs given output levels, nor uses the factors according to respective prices and production technology, it is operating inefficiently, both technically and allocatively. A measure of inefficiency can be obtained by adopting a shadow price approach, as described in Kumbhakar and Lovell (2000).

The dynamic efficiency model is constructed by defining the relationship between actual and shadow (behavioural) value functions of the DPE for the firms' inter-temporal cost minimization behaviour. The actual value function can be viewed as the perfectly efficient condition, whereas the behavioural value function of the DPE is expressed in terms of shadow input prices, quasi-fixed factors and output. The shadow input prices are constructed to generate an optimality relationship. Moreover, as the shadow input prices will differ from market (actual) prices in the presence of inefficiency, a firm’s inefficiency can be estimated and evaluated as the deviation between the actual and behavioural value function.

The behavioural value function of the DPE for the firms’ inter-temporal cost minimization behaviour that corresponds to the shadow prices and quantities can be expressed as

(5) $$rJ^{b}(\mathbf{w}^{b}{}', \mathbf{p}', \mathbf{q}', y, t) = \mathbf{w}^{b}{}'\mathbf{x}^{b} + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^{b}{}'\dot{\mathbf{q}}^{b} + \gamma^{b}(y - F[\mathbf{x}^{b}{}', \mathbf{q}', \dot{\mathbf{q}}^{b}{}', t]) + \nabla_{t} J^{b}$$

where $\mathbf{x}^{b} \in R_{+}^{N}$ and $\dot{\mathbf{q}}^{b} \in R_{+}^{Q}$ are nonnegative vectors of behavioural variable and quasi-fixed inputs, respectively, $\mathbf{w}^{b} \in R_{++}^{N}$ and $\nabla_{\mathbf{q}} J^{b} \in R_{++}^{Q}$ are strictly non-negative vectors of behavioural variable input prices and the marginal valuation of behavioural dynamic factors, γ^{b} is the behavioural Lagrangian multiplier defined as the short-run, instantaneous marginal cost, and $\nabla_{t} J^{b}$ is the shift of the behavioural value function.

Following the shadow price approach, $\mathbf{x}^{b}$ and $\dot{\mathbf{q}}^{b}$ can be expressed in terms of actual variable and dynamic factors as $\mathbf{x}^{b} = \boldsymbol{\tau}_{x}{}^{-1}\mathbf{x}$ and $\dot{\mathbf{q}}^{b} = \boldsymbol{\tau}_{q}{}^{-1}\dot{\mathbf{q}}$, respectively, where $\boldsymbol{\tau}_{x} \geq 1$ and $\boldsymbol{\tau}_{q} \geq 1$ represent inverse producer-specific scalars that provide input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively. Similarly, the behavioural prices can be expressed in terms of actual prices of variable inputs $\mathbf{w}^{b} = \boldsymbol{\Lambda}_{\mathbf{w}}\mathbf{w}$ and dynamic factors $\nabla_{\mathbf{q}} J^{b} = \boldsymbol{\Sigma}_{\mathbf{q}} \nabla_{\mathbf{q}} J^{a}$, where $\boldsymbol{\Lambda}_{\mathrm{w}}$ and $\boldsymbol{\Sigma}_{\mathbf{q}}$ are allocative inefficiencies of the variable and quasi-fixed inputs, respectively.

Differentiating equation (5) with respect to $\mathbf{p}$ and $\mathbf{w}^{b}$ yields the behavioural conditional demand for the dynamic and variable factors, respectively.

In the presence of technical inefficiency of dynamic and variable factors, the corresponding observed demand for the dynamic and variable factors using the input-oriented approach can be written in terms of the optimized demand for the dynamic and variable factors as

(6) $$\dot{\mathbf{q}}^o = \boldsymbol{\tau}_q \dot{\mathbf{q}}^b = \boldsymbol{\tau}_q (\nabla_{\mathbf{qp}} J^b)^{-1}(r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)$$

(7) $$\mathbf{x}^o = \boldsymbol{\tau}_x \mathbf{x}^b = \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(r\nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{wq}} J^b \dot{\mathbf{q}}^b - \nabla_{\mathbf{w}t} J^b)$$

where $\nabla_{\mathbf{w}^b} J^b = \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \nabla_{\mathbf{w}} J^b$.

The value function corresponding to the actual prices and quantities at the optimal level can be defined as

(8) $$rJ^a(\cdot) = \mathbf{w}'\mathbf{x}^o + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^a{}' \dot{\mathbf{q}}^o + \nabla_t J^a .$$

Inserting equations (6) and (7) in equation (8), the optimized actual value function can be rewritten in terms of the behavioural value function as

(9) $$\begin{aligned} rJ^a(\cdot) = {} & \mathbf{w}'\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(r\nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{qw}} J^b{}'[(\nabla_{\mathbf{qp}} J^b)^{-1}(r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] - \nabla_{\mathbf{w}t} J^b) \\ & + \mathbf{p}'\mathbf{q} + \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{q}} J^b{}' \boldsymbol{\tau}_q [(\nabla_{\mathbf{qp}} J^b)^{-1}(r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] + \nabla_t J^a \end{aligned}$$

where $\nabla_t J^a = \nabla_t J^b$ implies that the shift in the behavioural value function is proportional to that in the actual value function.

Differentiating equation (9) with respect to $\mathbf{p}$ (up to second-order derivatives), the optimized actual demand for the dynamic factors in terms of the behavioural value function yields

(10) $$\begin{aligned} & \left[\mathbf{ii}'/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1}(\nabla_{\mathbf{qp}} J^b + \nabla_{\mathbf{qq}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b - \mathbf{ii}'/r) - \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{qp}} J^b\right] \dot{\mathbf{q}}^o = \\ & \quad + [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(\nabla_{\mathbf{wp}} J^b - \nabla_{\mathbf{qw}} J^b{}'(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b)'\mathbf{w} \\ & \quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1}\left[r(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}} J^b - (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}t} J^b\right] \\ & \quad + (\mathbf{i} - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1}) \nabla_{\mathbf{p}t} J^b] \end{aligned}$$

where $\mathbf{i}$ is a unit vector of appropriate dimension.

Similarly, differentiating equation (9) with respect to $\mathbf{w}$ (up to second-order derivatives), the optimized actual demand for the variable inputs in terms of the behavioural value function yields[3]

$$
\begin{aligned}
\mathbf{x}^o = {} & \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \begin{bmatrix} r[\nabla_{\mathbf{ww}} J^b - \nabla_{\mathbf{qw}} J^b{}'(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{wp}} J^b{}']\mathbf{w} + r\nabla_{\mathbf{w}} J^b \\ -\nabla_{\mathbf{w}t} J^b + \nabla_{\mathbf{qw}} J^b{}'(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{p}t} J^b \end{bmatrix} \\
& + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[r\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}} J^b - \nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}t} J^b \right] \\
& + \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \left[\nabla_{\mathbf{qw}} J^b{}' - \nabla_{\mathbf{qw}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} (\nabla_{\mathbf{qp}} J^b - \mathbf{i}/r) + \boldsymbol{\tau}_q \nabla_{\mathbf{qw}} J^b{}' \right] \dot{\mathbf{q}}^o \\
& + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{qq}} J^b \right] \dot{\mathbf{q}}^o
\end{aligned} \tag{11}
$$

Equations (10) and (11) form the system equations of the dynamic efficiency model for inter-temporal cost minimization. When all inefficiency parameters in the model are equal to one, the dynamic efficiency model is reduced to the dynamic inter-temporal model of a firm's cost minimization problem in the presence of perfect efficiency as presented in Epstein and Denny (1983).

By using an econometric approach based on the dynamic optimization behaviour developed by Treadway (1974), the optimal investment demand function can be expressed as

$$\dot{\mathbf{q}}^* = \dot{\mathbf{q}}^b = \mathbf{M}(\mathbf{q} - \mathbf{q}^*) \tag{12}$$

where $\mathbf{M} = (r\mathbf{ii}' - \nabla_{\mathbf{qp}} J^b)^{-1}$ is the partial adjustment coefficient that indicates how quickly the gap between the current level of quasi-fixed factors stock ($\mathbf{q}$) and the optimal capital stock levels ($\mathbf{q}^*$) is closed in a given instant.

---

[3] Hence, the optimized actual demand for the numeraire variable input can be derived as

$$x_n^o = \boldsymbol{\tau}_x \mathbf{x}^b = rJ^b - \mathbf{p}'\mathbf{q} - \nabla_{\mathbf{q}} J^b{}' \dot{\mathbf{q}}^b - \nabla_t J^b$$

The stock of quasi-fixed factors evolves over time at an endogenous rate and the steady state or optimal quasi-fixed factors stock is defined as

(13) $$\mathbf{q}^{*} = \mathbf{q} - \mathbf{M}^{-1}(\nabla_{\mathbf{qp}} J^{b})^{-1} \cdot (r\nabla_{\mathbf{p}} J^{b} - \mathbf{q} - \nabla_{\mathbf{p}t} J^{b}) .$$

2.2 Econometric model

An econometric model of the dynamic efficiency model for inter-temporal cost minimization is presented in this section. This study focuses on a production technology with two quasi-fixed factors (capital and land), i.e. $\mathbf{q} \in (k, l)$. When farmers decide to increase farm land, capital will not be simultaneously affected. Rather, it might take several periods for net investment to adjust. Therefore, the decision to increase farm land is not fully dependent on the decision to increase a farm's capital. When both capital and land are independent, the off-diagonal elements of the $\nabla_{\mathbf{qp}} J^{b}$, $\nabla_{\mathbf{qq}} J^{b}$ and $\nabla_{\mathbf{pp}} J^{b}$ matrices, i.e. $J^{b}_{kp_l}$, $J^{b}_{lp_k}$, J^{b}_{kl} , and $J^{b}_{p_k p_l}$ are each equal to zero.

The optimized actual demand for the dynamic factors in equation (10) can be written as

(14) $$\begin{aligned} &[1/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}(J^{b}_{kp_k} + J^{b}_{kk}(J^{b}_{kp_k})^{-1} J^{b}_{p_k p_k} - 1/r) - \boldsymbol{\Sigma}_k^{-1} J^{b}_{kp_k}]\dot{k} \\ &\quad = [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J^{b}_{\mathbf{w}p_k} - J^{b}_{k\mathbf{w}}{}'(J^{b}_{kp_k})^{-1} J^{b}_{p_k p_k})'\mathbf{w} \\ &\quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}[r(J^{b}_{kp_k})^{-1} J^{b}_{p_k p_k} J^{b}_{k} - (J^{b}_{kp_k})^{-1} J^{b}_{p_k p_k} J^{b}_{tk}] + (1 - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}) J^{b}_{p_k t}] + \varepsilon_1 \end{aligned}$$

(15) $$\begin{aligned} &[1/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}(J^{b}_{lp_l} + J^{b}_{ll}(J^{b}_{lp_l})^{-1} J^{b}_{p_l p_l} - 1/r) - \boldsymbol{\Sigma}_l^{-1} J^{b}_{lp_l}]\dot{l} \\ &\quad = [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J^{b}_{\mathbf{w}p_l} - J^{b}_{l\mathbf{w}}{}'(J^{b}_{lp_l})^{-1} J^{b}_{p_l p_l})'\mathbf{w} \\ &\quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}[r(J^{b}_{lp_l})^{-1} J^{b}_{p_l p_l} J^{b}_{l} - (J^{b}_{lp_l})^{-1} J^{b}_{p_l p_l} J^{b}_{tl}] + (1 - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}) J^{b}_{p_l t}] + \varepsilon_2 \end{aligned}$$

where $\boldsymbol{\tau}_x$ and $\boldsymbol{\tau}_q$ are inverse producer-specific scalars providing input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively, $\mathbf{\Lambda}_{\mathbf{w}}$ represents the allocative inefficiencies of variable inputs, $\mathbf{\Sigma}_k$ and $\mathbf{\Sigma}_l$ are allocative inefficiencies of capital and land inputs, respectively, ε_1 and ε_2 are the two-sided error terms representing random errors that $\varepsilon_1 :$ iid $N(0,\sigma_1^2)$ and $\varepsilon_2 :$ iid $N(0,\sigma_2^2)$. Further, ε_1 and ε_2 are distributed independently of each other, and of the regressors.

In addition, the optimized actual demand for the variable inputs in equation (11) is given by

$$
\begin{aligned}
x^o = {} & \boldsymbol{\tau}_x \mathbf{\Lambda}_{\mathbf{w}}^{-1} \begin{bmatrix} (rJ^b_{\mathbf{ww}}\mathbf{w} - rJ^b_{k\mathbf{w}}{}'(J^b_{kp_k})^{-1} J^b_{\mathbf{w}p_k}{}'\mathbf{w} - rJ^b_{l\mathbf{w}}{}'(J^b_{lp_l})^{-1} J^b_{\mathbf{w}p_l}{}'\mathbf{w} \\ +rJ^b_{\mathbf{w}} - J^b_{\mathbf{w}t} + J^b_{k\mathbf{w}}{}'(J^b_{kp_k})^{-1} J^b_{p_k t} + J^b_{l\mathbf{w}}{}'(J^b_{lp_l})^{-1} J^b_{p_l t} \end{bmatrix} \\
& + \boldsymbol{\tau}_q \mathbf{\Sigma}_k^{-1} [rJ^b_{\mathbf{w}p_k}(J^b_{kp_k})^{-1} J^b_k - J^b_{\mathbf{w}p_k}(J^b_{kp_k})^{-1} J^b_{kt}] \\
& + \boldsymbol{\tau}_q \mathbf{\Sigma}_l^{-1} [rJ^b_{\mathbf{w}p_l}(J^b_{lp_l})^{-1} J^b_l - J^b_{\mathbf{w}p_l}(J^b_{lp_l})^{-1} J^b_{lt}] \\
& - \begin{bmatrix} \boldsymbol{\tau}_x \mathbf{\Lambda}_{\mathbf{w}}^{-1} [J^b_{k\mathbf{w}}{}' - J^b_{k\mathbf{w}}(J^b_{kp_k})^{-1}(J^b_{kp_k} - 1/r) + \boldsymbol{\tau}_q J^b_{k\mathbf{w}}{}'] \\ +\boldsymbol{\tau}_q \mathbf{\Sigma}_k^{-1} [J^b_{\mathbf{w}p_k}(J^b_{kp_k})^{-1} J^b_{kk}] \end{bmatrix} \dot{k} \\
& - \begin{bmatrix} \boldsymbol{\tau}_x \mathbf{\Lambda}_{\mathbf{w}}^{-1} [J^b_{l\mathbf{w}}{}' - J^b_{l\mathbf{w}}(J^b_{lp_l})^{-1}(J^b_{lp_l} - 1/r) + \boldsymbol{\tau}_q J^b_{l\mathbf{w}}{}'] \\ +\boldsymbol{\tau}_q \mathbf{\Sigma}_l^{-1} [J^b_{\mathbf{w}p_l}(J^b_{lp_l})^{-1} J^b_{ll}] \end{bmatrix} \dot{l} + \boldsymbol{\varepsilon}
\end{aligned}
\tag{16}
$$

where $\boldsymbol{\varepsilon}$ is a linear disturbance vector with mean vector $\mathbf{0}$ and variance-covariance matrix Σ.

Equations (14) to (16) present an econometric model of the dynamic efficiency model with a two quasi-fixed factors case. To estimate this model, it is necessary to specify the functional form of the behavioural value function. A quadratic behavioural value function assuming symmetry of the parameters can be expressed as

$$
J^b(\cdot) = \beta_0 + \mathbf{w}'\boldsymbol{\beta} + \frac{1}{2}\mathbf{w}'\mathbf{B}\mathbf{w} \tag{17}
$$

where $\mathbf{w}' = (\mathbf{w}^b \; p_k \; p_l \; k \; l \; y \; t)$, $\boldsymbol{\beta}$ denotes a vector of parameters, and $\mathbf{B}$ is a symmetric matrix of parameters, each of the appropriate dimension.

In addition, all producer- and input-specific estimates of technical and allocative efficiencies must be specified to implement the estimation of all coefficient parameters of the behavioural value function. The system of equations (14) to (16) is recursive, with the endogenous variables of net investment demands in capital and land serving as explanatory variables in the variable input demand equations. The estimation can be accomplished in two stages. In the first stage, the optimized actual investment demands in capital and land are estimated by using the maximum likelihood estimation (MLE). Given that the optimized actual variable input demand equations are over-identified, the system of variable input demand equations is estimated in the second stage by using a generalized method of moments (GMM) estimation with all parameter values as determined in the first stage. All predetermined variables, including exogenous and dummy variables from each equation in the variable input demand equations, are defined as the instrumental variables of the system equation in the second stage. The details of the econometric approach used in the dynamic efficiency model are presented in Rungsuriyawiboon and Stefanou (2007).

2.3 Dynamic structures of production

Dynamic structures of production can be investigated using the parameter estimates of the behavioural value function obtained from the procedure of estimation in section 2.2. This section presents the derivations of two measures of farm scale, e.g. scale and cost elasticities. The scale elasticity is associated with the technology represented by the production, while the cost elasticity involves analysing the movement along the cost curves. With the presence of adjustment costs, the scale elasticity is no longer equivalent to the inverse of the cost elasticity.

2.3.1 Scale elasticity

The scale elasticity is defined as the percentage that change in output responds to a percentage change in all inputs. Following Stefanou (1989), the dynamic theory of cost allows for the selection of dynamic and variable factor demands. The long-run scale elasticity is defined as the ratio of long-run average variable shadow cost (*LRAVC*) to short-run marginal cost (*SRMC*), whereas the short-run scale elasticity is defined as the ratio of short-run average variable shadow cost (*SRAVC*) to short-run marginal cost (*SRMC*). Values of scale elasticity greater than one imply increasing returns to scale, while values less than one imply decreasing returns to scale, and values equal to one imply constant returns to scale.

The optimized actual dynamic programming in equation (9) can be viewed as the long-run cost function associated with the actual quantities. The short-run cost function associated with the actual quantities is defined as the sum of variable costs and fixed costs. The long-run average cost (*LRAC*) at time t is calculated by dividing equation (9) with output, while the short-run average cost (*SRAC*) at time t is calculated by dividing the short-run cost function with output. The long-run marginal cost (*LRMC*) at time t is calculated by differentiating equation (9) with respect to output, while the short-run marginal cost (*SRMC*) at time t is calculated by differentiating the short-run cost function with output.

The short-run scale elasticity associated with the actual quantities yields

(18) $$SE^{SR} = \frac{SRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*}}{\gamma^{a*} y}$$

where $\gamma^{a*} = \nabla_y (\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l)$ is the SRMC at time t.

The long-run scale elasticity associated with the actual quantities yields

(19) $$SE^{LR} = \frac{LRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*} + J_k^a \dot{k}^{*} + J_l^a \dot{l}^{*} + J_t^a}{\gamma^{a*} y}$$

where $J_k^a = \Sigma_k^{-1} J_k^b$, $J_l^a = \Sigma_l^{-1} J_l^b$ and $J_t^a = J_t^b$.

2.3.2 Cost elasticity

The cost elasticity is defined as the percentage change in costs given a percentage change in outputs. The instantaneous or short-run cost elasticity (CE^{SR}) is the ratio of short-run marginal cost (*SRMC*) to the short-run average total cost (*SRAC*), whereas the long-run cost elasticity (CE^{LR}) is defined as the ratio of long-run marginal shadow cost (*LRMC*) to the long-run average total cost (*LRAC*). Values of cost elasticity greater than one imply decreasing returns to scale, while values less than one imply increasing returns to scale and values equal to one imply constant returns to scale.

The short-run cost elasticity associated with the actual quantities in equation (9) yields

(20) $$CE^{SR} = \frac{SRMC}{SRAC} = \frac{\gamma^{a^*} y}{\mathbf{w}'\mathbf{x}^{o^*} + p_k k + p_l l}.$$

The long-run cost elasticity associated with the actual quantities yields

(21) $$CE^{LR} = \frac{LRMC}{LRAC} = \frac{(\gamma^{a^*} + J_{ky}^{a}\dot{k}^{*} + J_{ly}^{a}\dot{l}^{*} + J_{ty}^{a})y}{\mathbf{w}'\mathbf{x}^{o^*} + p_k k + p_l l + J_{k}^{a}\dot{k}^{*} + J_{l}^{a}\dot{l}^{*} + J_{t}^{a}}.$$

In contrast to the static setting that the scale elasticity is the inverse of the cost elasticity, the inverse of the dynamic cost elasticity is no longer equal to the dynamic scale elasticity. The primary differences between the two scale measures are the terms $J_{ky}^{a}\dot{k}^{*}$, $J_{ly}^{a}\dot{l}^{*}$ and J_{ty}^{a}.

3. Data discussion

The data used in this study is drawn from the National Fixed Point (NFP) survey data series, conducted annually by the Research Center for Rural Economy (RCRE) of the Ministry of Agriculture, China. The NFP survey is based on a multistage, random-cluster process to attain rich information on rural reform of agricultural production and rural development.[4] We use individual household data in the Zhejiang, Hubei, and Yunnan provinces covering the period from 2003 to 2006. The three provinces were chosen to reflect the different regional economic development and the diversity of China's agricultural production. The Zhejiang Province is one of the richest provinces in East China; the Hubei Province is a central middle-income region and is the traditional heartland of China's agricultural production; located in West China, the Yunnan Province is one of the poorest regions in the country.

[4]Benjamin et al. (2005) provide a detailed description of the data and history of the NFP survey.

The agricultural production technology in this study is represented by one output (y), two variable inputs (x_1 = labor, x_2 = intermediate inputs), and two quasi-fixed factors (q_1 = l = land, q_2 = k = capital). Output is the total value of crop production measured at constant 2003 prices. Labour input is expressed as the total number of annual working days of the whole household in crop production. Our dataset contains information on employment in crop production. The wage of labour is hence obtained as the quotient of total expenses paid to employees and their total working days. Intermediate inputs include expenses on seeds, chemical fertilizers, pesticides, and diesel oil for agricultural machinery. The volume of intermediate inputs is calculated as the quotient of the total expenses on intermediate inputs and agricultural productive materials price indices. The Divisia price indices are computed for intermediate inputs with value shares of each component as weights.

Capital input is defined as the fixed-capital assets of the household at the end of each year, including draught animals, production tools, production buildings, and machinery for agriculture. The volume of capital input is calculated as the quotient of the capital input value and the price index of productive agricultural fixed assets (p_{ki}). According to Jorgenson (1963), the rental price for capital is expressed as $p_{ki} * (r + \delta)$, where r is the nominal interest rate and δ is the depreciation rate.[5] Land input is the total utilized arable land area in mu.[6] The rental price for land is calculated as the quotient of expenses for leasing land and leased land area from other

[5]The nominal interest rate is approximated using the interest rate of rural credit cooperatives production loan. The depreciation rate is calculated as the quotient of depreciation and fixed assets.
[6] 1 mu = 1/15 hectare.

households. The descriptive statistics of the variables are listed in Table 1. Households in Zhejiang have a relatively lower output of crop production compared to Hubei and Yunnan. This is not surprising, if we look further into the various inputs of households in the three provinces. The volume of labour input in Zhejiang is 63.59 working days on average, which is roughly 40% of that in Hubei and Yunnan. Actually, rural labourers in Zhejiang are more likely to engage in off-farm employment, and non-agricultural income has accounted for a major share of the household total income. At the same time, labour productivity (y/x_1) in Zhejiang is the highest among the three provinces. In comparison to the relatively lower crop output, the capital input in Zhejiang is impressive and much higher than that in Hubei and Yunnan. Regarding land input, the statistics of our sample sufficiently reflect the land endowment of the three provinces. Arable land is scarce in Zhejiang, with an average of 2.42 mu per household; the next is 4.79 mu in Hubei; Yunnan has the highest arable land area per household, which is 7.35 mu. Compared to Hubei and Yunnan, households in Zhejiang have lower capital productivity (y/k) but higher land productivity (y/l). When further comparing input prices across the provinces, it can be seen that the differences in prices have perfectly reflected varying factor endowments of the three in crop production.

Table 1. Descriptive statistics of the variables, 2003-2006

Variable description		Zhejiang		Hubei		Yunnan	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Output of crop production (Yuan)	y	2,262.38	2,020.37	3,716.76	2,741.78	4,356.72	3,151.30
Volume of labour input (working days)	x_1	63.59	64.58	164.88	125.09	151.50	126.86
Wage of labour (Yuan/working day)	w_1	34.29	19.63	22.24	12.33	14.82	10.96
Volume of intermediate input (Yuan)	x_2	611.44	528.93	626.11	522.88	805.03	855.58
Divisia price indices of intermediate input	w_2	1.14	0.10	1.19	0.14	1.10	0.06
Volume of capital input (Yuan)	k	8,864.49	1,2913.47	2,116.49	2,757.61	4,647.75	5,170.73
Rental price indices for capital	p_k	5.29	4.20	12.62	7.12	12.23	4.07
Volume of land input (mu)	l	2.42	1.59	4.79	2.47	7.35	5.75
Rental price for land (Yuan/mu)	p_l	163.83	51.83	70.35	43.35	97.39	87.14
No. of observations		**428**		**2,421**		**1,352**	

4. Results and discussion

The dynamic efficiency model defined in Section 2 can be viewed as the perfectly inefficient model. Following Cornwell, Schmidt and Sickles (1990), all allocative and technical efficiencies of the dynamic and variable factors are specified to vary across provinces and through time. Table 2 reports the estimated coefficients for the structural parameters of the dynamic coefficients model using ML and GMM estimations, assuming a constant real interest rate of 5%. The full set of estimated coefficients, including the dummy variables used to calculate the allocative inefficiency parameters of variable inputs and net investment demands and the technical inefficiency parameter of variable input demand, are available from the authors on request. Most estimated parameters from the ML estimation are significant at the .05 level using a two-tailed test except for the estimated parameters β_{w1k} and β_{pkt} in the net investment demand for capital equation. The R^2 values of net investment demand for capital and land are 0.345 and 0.532, respectively. A lag of two periods of autocorrelation terms is used to compute the covariance matrix of the orthogonality conditions for the GMM estimation. Most coefficient estimates from the GMM estimation, particularly the first-order coefficients, are significant at the 95% confidence interval using a two-tailed test, except for the estimated parameters β_l. The R^2 value of variable inputs demand is 0.847. The test of overidentifying restrictions from the GMM estimation using the Hansen (1982) J test is significant. The null hypothesis fails to be rejected, implying that the additional instrumental variables are valid, given that a subset of the instrumental variables is valid and exactly identifies the coefficient.[7]

Table 2. Estimated parameters of dynamic efficiency model

Parameter[a] Estimates	Capital Equation	Land Equation	Variable Input Equation
β_0	0.214**	0.831**	0.559***
β_{pk}	0.352***	-	-
β_{pl}	-	0.047**	-
β_k	-	-	0.331***
β_l	-	-	-0.058
β_y	-	-	0.073***
β_t	-	-	0.053***
β_{w1w1}	-	-	0.113***
β_{pkpk}	-0.876***	-	-
β_{plpl}	-	1.038***	-
β_{kk}	-	-	-2.068***
β_{ll}	-	-	-1.088**
β_{yy}	-	-	-0.033
β_{tt}	-	-	0.018
β_{w1pk}	3.083***	-	-
β_{w1pl}		0.478***	-
β_{w1k}	-0.124	-	-
β_{w1l}	-	-0.220***	-
β_{w1y}	-	-	0.056***
β_{w1t}	-	-	0.609***
β_{pkk}	21.739***	-	-
β_{pky}		-	0.403***
β_{pkt}	-0.291	-	-

[7]Further, a hypothesis test regarding the presence of perfect efficiency in production is conducted using the likelihood ratio (LR) test. The LR test is approximately chi-square distributed with the degrees of freedom being equal to the number of restrictions. The LR test of the null hypothesis that farms are perfectly efficient in dynamic and variable factor demands is rejected at the 95% confidence level, implying that the farms in this study operated inefficiently in the production.

β_{pll}	-	76.207***	-
β_{ply}	-		0.033
β_{plt}	-	2.370***	-
β_{ky}	-	-	2.821***
β_{kt}	-2.790**	-	-
β_{ly}	-	-	0.468***
β_{lt}	-	0.072***	-
β_{yt}	-	-	0.516***
Equation	**R^2**		
- Capital	0.345		
- Land		0.532	
- Labour			0.847
Test of overidentifying restrictions			214.168

[a] Price of intermediate input (w_2) was normalized.
Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. The regressions also include dummy variables used to calculate all efficiency parameters of dynamic and variable inputs, and the estimates are not reported here.

Table 3 presents the average farm technical and allocative efficiencies of dynamic and variable factors by province from 2003-2006. An estimate of the technical efficiency of dynamic and variable factors is bounded between zero and unity. The value of technical efficiency scores equal to one implies that a farm can minimize both dynamic and variable factors to produce a given level of output. The estimated technical efficiencies of variable inputs range from 0.325 to 0.910 with an average of 0.694, whereas those of net investment in quasi-fixed factors range from 0.382 to 0.837 with an average of 0.594. These findings imply that the Chinese farms in this study, on average, could reduce the variable and dynamic factors by 30.6% and 40.6%, respectively, and still produce the same level of output. The average value of the technical efficiency of variable and dynamic factors is 71.0% and 64.2% (for Zhejiang), 69.5% and 60.6% (for Hubei) and 66.5% and 59.2% (for Yunnan). Farms in Zhejiang achieved higher technical efficiencies of dynamic and variable factors than those in Hubei and Yunnan. Farms in Yunnan have the lowest technical efficiency scores in terms of both dynamic and variable factors.

When further checking the differences of scores across the three provinces, it can be seen that farms in Yunnan are less efficient at using variable inputs of labour and intermediate input, while farms in Zhejiang are much more efficient at using quasi-fixed inputs of land and capital. China's current land tenure system is actually a two-tier land tenure system in which the village collective and the individual household share the land rights, and the balance point can be anywhere from complete collective ownership to complete individual ownership (Dong 1996; Yao 2010). This characteristic also explains the considerable variations in land rights or land tenure security across regions in rural China. In Zhejiang, two mechanisms are applied to protect arable land and the right of rural households. One is the adoption of a 3-category provincial land classification scheme to influence the conversion of agricultural land for non-agricultural purposes, and the other is the implementation of a land compensation system which regulates the supply of agricultural land by requiring that agricultural land taken out of cultivation is replaced with reclaimed land of equal quantity and quality (Skinner et al. 2001). All these measures, which help mitigate or even eliminate the threat of insecurity, clearly motivate farm households to use labour forces more efficiently and to invest in the land.

Considering the allocative efficiency scores, the value of the allocative efficiency of dynamic factors is bound between zero and unity. The value of one implies that farms can use the dynamic factors in optimal proportions given their respective prices and the production technology. Average farm allocative efficiencies of net investments in capital and land are 0.758 and 0.628, respectively. These results suggest that Chinese farms could potentially reduce net investment in capital and land demands by 24.2% and 37.2%, respectively, to a cost-minimizing level. The average value of the allocative efficiency of capital and land inputs is 85.4% and 70.4% (for Zhejiang), 79.7% and 62.9% (for Hubei) and 61.8% and 57.0% (for Yunnan). The results indicate that farms in Zhejiang achieved higher allocative efficiencies of capital and land than those in Hubei and Yunnan. This finding is consistent with previous observations that factor markets function relatively better in Zhejiang – for example, the development of the land rental market. Statistics in Zhang et al. (2011) show that land rental activities are much more important in Zhejiang than in the other two provinces; the share of arable land rented out is, on average, 8.2% in Zhejiang, but only 1.3% in Hubei and 2.3% in Yunnan.

Following the shadow price approach, the price of intermediate input is arbitrarily specified as the numeraire. The value of the allocative efficiency of variable input demands represents price distortions of labour relative to the intermediate input. An estimate of allocative efficiency of labour input demands less (greater) than one means that the ratio of the shadow price of labour relative to the intermediate input is considerably less (greater) than the corresponding ratio of actual prices. This implies that farms are overusing (underusing) labour relative to the intermediate input. Table 3 also reports that average farm allocative efficiencies of labour input demands is 0.395. These results imply that farms in the three provinces are over-utilizing labour relative to the intermediate input in the crop production. The average value of the allocative efficiency of labour input demands is 40.5% (for Zhejiang), 36.6% (for Hubei) and 37.7% (for Yunnan). This relatively severe price distortion is not particularly surprising since obstacles[8] still hinder the free migration of rural labour, although controls on rural labour mobility were greatly relaxed after the Reform.

Table 3. Average farm technical and allocative efficiency scores of dynamic and variable factor demands, 2003-2006

Efficiency scores*	Zhejiang	Hubei	Yunnan	All provinces
TE(x)	0.710	0.695	0.665	0.694
TE(q)	0.642	0.606	0.592	0.594
AE(k)	0.854	0.794	0.618	0.758
AE(l)	0.704	0.629	0.570	0.628
AE(w_1)	0.405	0.366	0.377	0.395

Note: *TE(x) = technical efficiency of variable inputs; TE(q) = technical efficiency of dynamic factors; AE(k) = allocative efficiency of net investment in capital; AE(l) = allocative efficiency of net investment in land; AE(w_1) = allocative efficiency of labour input.

Table 4 presents average annual technical and allocative efficiency scores of the dynamic and variable factor demands for each province over the period 2003-2006. The findings in Table 4 allow us to examine the performance of crop production on farms after three decades of reform. Farms in Zhejiang and Hubei have an average annual technical efficiency of dynamic and variable factors higher than those in Yunnan. During the period 2003-2006, technical efficiency scores of variable inputs in all provinces increase over time. In contrast, technical efficiency scores of dynamic factors

[8]For instance, the implementation of Household Registration System (hukou) divided people into those holding a rural hukou and those with an urban hukou. Under the constraints of the hukou system, rural migrants face residence discrimination and lack access to public services like education, health care and public welfare in cities (OECD, 2009).

in all provinces decrease over time. Average annual allocative efficiencies of dynamic factors for both capital and land in Zhejiang and Hubei are higher than in Yunnan in every year over the study period. This result suggests that farms in Zhejiang and Hubei were able to adjust their dynamic factors to a cost-minimizing level, more easily than those in Yunnan. During the period 2003-2006, allocative efficiency scores of the net investment in capital by farms in Zhejiang increase over time. In contrast, allocative efficiency scores of the net investment in capital by farms in Yunnan decrease over time, while the allocative efficiency score of the net investment in capital in Hubei varies considerably over the period. Allocative efficiency scores of the net investment in land by farms in Zhejiang and Hubei also increase over time, while the allocative efficiency score of the net investment in capital by farms in Yunnan varies with a decreasing trend over the period. The allocative efficiency estimates of the variable inputs during the 2003-2006 period indicates that farms in Hubei and Yunnan tend to increase over-utilization in labour relative to intermediate input, whereas farms in Zhejiang tend to decrease over-utilization in labour relative to intermediate input.

Table 4. Average annual technical and allocative efficiency scores of dynamic and variable factor demands for each province, 2003-2006

Efficiency scores	Zhejiang				Hubei			
	2003	**2004**	**2005**	**2006**	**2003**	**2004**	**2005**	**2006**
TE(x)	0.642	0.658	0.754	0.787	0.646	0.670	0.720	0.742
TE(q)	0.683	0.667	0.616	0.603	0.666	0.635	0.570	0.551
AE(k)	0.819	0.839	0.864	0.892	0.769	0.808	0.788	0.817
AE(l)	0.675	0.696	0.717	0.727	0.575	0.620	0.655	0.665
AE(w_1)	0.373	0.395	0.412	0.440	0.440	0.350	0.319	0.358
Efficiency scores	**Yunnan**				**All provinces**			
	2003	**2004**	**2005**	**2006**	**2003**	**2004**	**2005**	**2006**
TE(x)	0.627	0.655	0.679	0.698	0.638	0.661	0.718	0.742
TE(q)	0.606	0.644	0.569	0.548	0.652	0.649	0.585	0.567
AE(k)	0.652	0.657	0.596	0.567	0.747	0.759	0.756	0.759
AE(l)	0.626	0.547	0.564	0.534	0.625	0.628	0.637	0.645
AE(w_1)	0.431	0.343	0.398	0.338	0.415	0.362	0.376	0.378

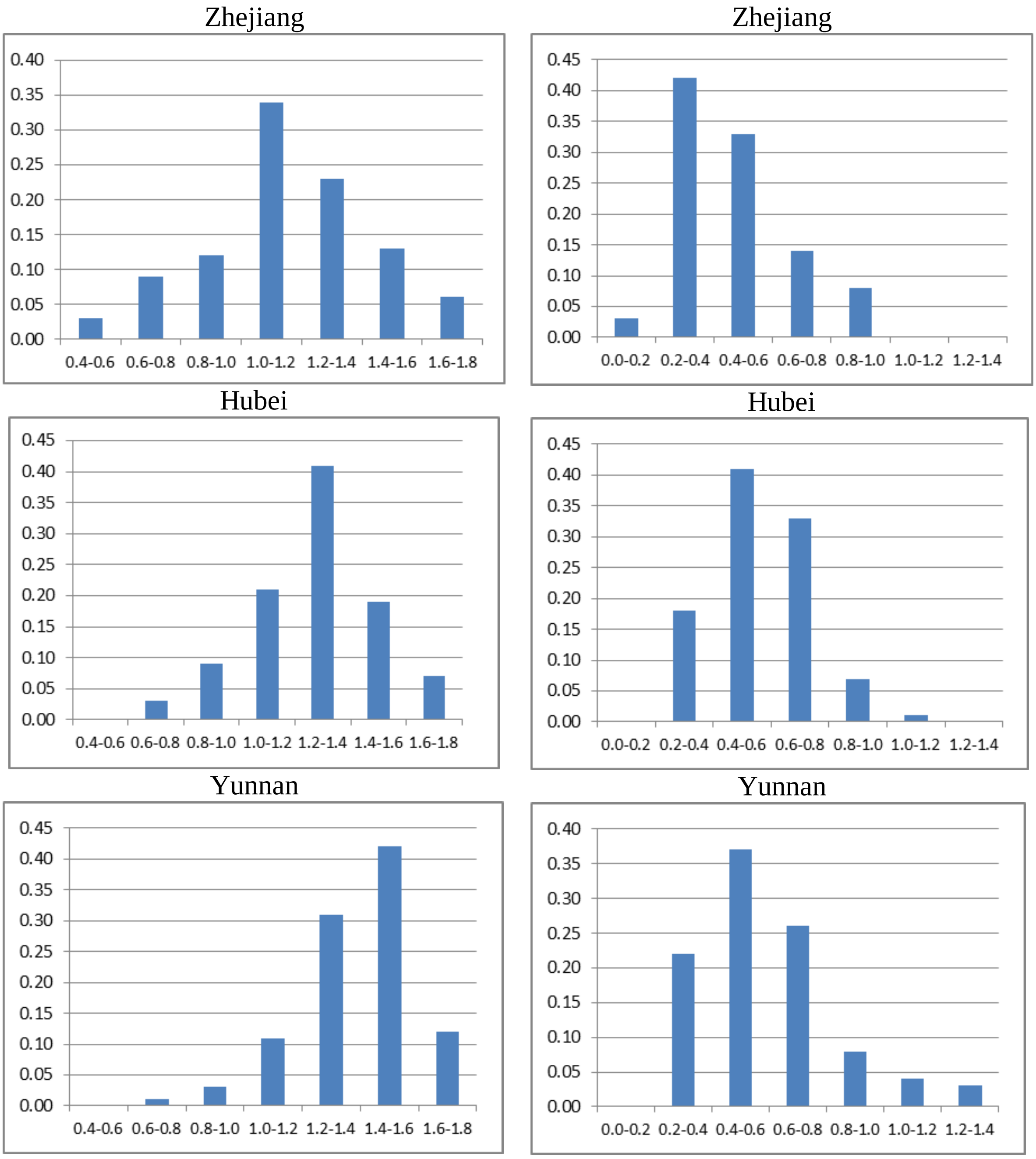
Turning to the role of adjustment costs in Chinese farm crop production, the partial adjustment coefficient of quasi-fixed factors is defined in equation (12) in section 2.1. Given the discount rate of 5%, the findings (Table 2) show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low. The estimated adjustment rate is 4.54% per annum for capital and 3.84% per annum for land, or it may take capital approximately 22 years and land approximately 26 years to adjust fully to its long-run equilibrium level.

Further, the optimal stocks defined in equation (13) in section 2.1 are calculated and compared to the actual stocks. The ratio of optimal quasi-fixed factors to actual quasi-fixed factors accounts for capacity utilization, which provides some insights into the efficiency of quasi-fixed factor uses by a farm. Values of the ratio of optimal quasi-fixed factors to actual quasi-fixed factor stocks greater than one imply that a farm is under-utilizing quasi-fixed factors, while values less than one imply that a farm is over-utilizing quasi-fixed factors.

Figure 1 and Appendix Table A1 present the distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors by farm in each province. The findings in Figure 1(a) show that the estimates of the ratio of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745 with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, which is a sign of under-utilization in capital prevailing in crop production. Looking into the statistics of each province, the differences are evident, with 42% of the farms in Zhejiang, 67% in Hubei, and 85% in Yunnan being under-capitalized. The performance of Zhejiang is relatively good, with 34% of the farms nearly optimizing their capital use in the range of 1.0-1.2. On the contrary, most of the farms in Hubei and Yunnan still have the potential to reach the optimal level by increasing their capital stocks.

Turning to land utilization, Figure 1(b) provides some insights into the efficiency of land use by a farm in each province. The estimates of the ratio of optimal land (L^*) to actual land (L) range from 0.124 to 1.354, with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels, which is explained as an over-utilization of land input. This finding is consistent with the common inverse relationship between farm size and productivity in developing country agriculture (Berry and Cline, 1979) where smaller farms tend to more intensively use their labour in the absence of perfect factor markets. As is shown in our results, the area of actual land utilization is higher than that of the optimal level for most of the farms.

Figure 1. Distribution of the ratio of optimal capital to actual capital



(a) K^*/K **(b) L^*/L**

Table 5 presents weighted-average estimates of the short- and long-run dynamic scale and cost elasticities by province and all farms from 2003-2006. The estimates of the short-run scale elasticities range from 0.624 to 0.945 with an average of 0.828, while the long-run scale elasticities range from 0.678 to 0.985 with an average of 0.857. All farms indicate the presence of decreasing returns to scale in both the short and long run. In addition, the weighted-average estimated results of scale elasticities indicate modestly decreasing returns to scale in the long run and considerably higher ones in the short run. The weighted-average estimate of scale elasticities of farms in Zhejiang is higher than those in Hubei and Yunnan in both the short and long run, respectively. The estimates of the short-run cost elasticities range from 1.064 to 1.628, with an average of 1.269, while the long-run cost elasticities range from 1.078 to 1.715, with an average of 1.222. All farms present decreasing returns to scale in both the short and long run. Consistent with the measure of scale elasticity, the results of cost elasticities are hence robust. The estimated results of the short- and long-run dynamic cost elasticities suggests that farms in Yunnan have a higher degree of decreasing returns to scale compared to farms in Zhejiang and Hubei.

Table 5. Short- and long-run scale and cost elasticity (2003-2006)

	Zhejiang	Hubei	Yunnan	All provinces
Scale Elasticity				
- Short-run	0.893	0.865	0.742	0.828
- Long-run	0.945	0.915	0.725	0.857
Cost Elasticity				
- Short-run	1.194	1.215	1.389	1.269
- Long-run	1.025	1.142	1.427	1.222

5. Conclusions

This study contributes to the ongoing debate on the structural transformation of farm production in China. We analysed this phenomenon by examining the economic performance of Chinese farms. By developing a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making, the dynamic cost efficiency model allows us to consider the impact of allocative and technical efficiency in Chinese agriculture, as well as the adjustment costs resulting from the change of quasi-fixed input use. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006. This is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. With the parameter estimates from the model, we further calculate the partial adjustment coefficients of quasi-fixed factors, the optimal stocks of quasi-fixed factors, and the short- and long-run dynamic scale and cost elasticities.

Our results show that, in terms of technical efficiency, the farms in this study, on average, could have reduced their variable and dynamic factors by 30.6% and 40.6%, respectively, and still have produced the same level of output. Regional differences are evident, indicating that farms in Zhejiang perform the best while farms in Yunnan have the lowest scores. Considering the allocative efficiency scores of net investments in dynamic factors, our results show that farms could potentially reduce their net investments in capital and land demands by 24.2% and 37.2% to reach a cost-minimizing level. Farms in Zhejiang still achieve the highest level compared to those in the other two provinces. The average allocative efficiency of net investment in labour demands is relatively low at 0.395, indicating a severe price distortion of labour relative to the intermediate input, which implies the over-utilization of labour relative to the intermediate input in crop production.

Turning to the role of adjustment costs in Chinese farm crop production, the findings show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low, which implies a rather sluggish adjustment process and considerably high adjustment costs. The ratios of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745, with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, a sign that the under-utilization of capital prevails in crop production. On the contrary, the ratios of optimal land (L*) to actual land (L) range from 0.124 to 1.354 with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels. According to these findings, there also exist high degrees of over-utilization in land, prevailing in crop production. The estimates of the short- and long-run dynamic scale and cost elasticities are robustly consistent, which indicates the presence of decreasing returns to scale in both the short and long run.

Based on the findings of this study, important policy implications can be derived for the future development of agricultural production in China. The relatively low levels of technical and allocative efficiencies indicate that most farms are unable to catch up with the production frontier under the existing production technology, or to use various inputs in appropriate proportions given their respective prices. Since the inefficiencies are normally associated with motivation, information, and institutional environment problems, policy makers should pay more attention to various factor market reforms as a whole. This statement is reinforced by the relatively low estimated adjustment rates of the quasi-fixed factors, implying high adjustment costs. We introduced adjustment costs in the model to capture those forces or economic situations that impose some penalty on the farm beyond the acquisition cost, and hence slow down the adjustment process of production factors.

Farmers' rights to land should be strengthened and extended so that land tenure is more secure. Possible policy measures could include complete land titling to grant full property rights to farmers and hence establish a foundation for the development of rural rental and credit markets where land could be used as collateral; extending the duration of land-use contracts to perpetuation; this duration is currently 30 years. At the same time, policy measures are needed to encourage rural labour mobility, for instance, the Household Registration System (hukou) needs to be reformed to provide migrant workers with equal access to public services in cities. The migration process will be smoother when farmers' rights to land are protected and secure.

The presence of decreasing returns to scale in both the short and long run also has important policy implications with respect to the government's recent policy focus on supporting the creation of large-scale farms. The simple action of integrating farms will neither increase productivity nor farmers' income. Adjusting the structure of farm production is needed in order to reach the optimal proportion of various input use. The progress of this adjustment will also rely on the successful reform of land and labour markets.

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Appendix

Table A1. The distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors

	Frequency		
K^*/K	**Zhejiang**	**Hubei**	**Yunnan**
0.4-0.6	0.03	0.00	0.00
0.6-0.8	0.09	0.03	0.01
0.8-1.0	0.12	0.09	0.03
1.0-1.2	0.34	0.21	0.11
1.2-1.4	0.23	0.41	0.31
1.4-1.6	0.13	0.19	0.42
1.6-1.8	0.06	0.07	0.12
	1.00	1.00	1.00
	Frequency		
L^*/L	**Zhejiang**	**Hubei**	**Yunnan**
0.0-0.2	0.03	0.00	0.00
0.2-0.4	0.42	0.18	0.22
0.4-0.6	0.33	0.41	0.37
0.6-0.8	0.14	0.33	0.26
0.8-1.0	0.08	0.07	0.08
1.0-1.2	0.00	0.01	0.04
1.2-1.4	0.00	0.00	0.03
	1.00	1.00	1.00

Output จากโครงการวิจัยที่ได้รับทุนจาก สกว.

1. ผลงานตีพิมพ์ในฐานข้อมูลวารสารวิชาการนานาชาติ

บทความ Rungsuriyawiboon, S. and Zhang, Y. “Examining the Economic Performance of Chinese Farms: A Dynamic Efficiency and Adjustment Cost Approach” Economic Analysis and Policy. (accepted) (Thomson Reuters ISI 2016 Impact Factor: 0.289)

2. การนำผลงานวิจัยไปใช้ประโยชน์

ได้รับเชิญให้ไปบรรยายให้นักศึกษาปริญญาเอกในหัวข้อเรื่อง”Efficiency and Productivity Analysis: Deterministic Approaches” ร่วมกับ Professor Uwe Latacz-Lohmann จาก Department of Agricultural Economics, Kiel University ณ Institute of Agricultural Development in Central and Eastern Europe ประเทศสหพันธสาธารณรัฐเยอรมันนี ระหว่างวันที่ 13-16 พฤษภาคม 2560 โดยในระหว่างการอบรมได้นำเอาแบบจำลองที่พัฒนาขึ้นและผลการศึกษาที่ได้จากงานวิจัยเป็นตัวอย่างที่ใช้ในการบรรยาย

3. การเสนอผลงานในที่ประชุมวิชาการนานาชาติ

ผลงานเรื่อง “Examining the Economic Performance of Chinese Farms: A Dynamic Efficiency and Adjustment Cost Approach” ในการประชุมวิชาการนานาชาติ 15th European Workshop on Efficiency and Productivity Analysis (EWEPA) ที่จัดขึ้น ณ กรุงลอนดอน ประเทศสหราชอาณาจักรระหว่างวันที่ 12-15 มิถุนายน 2560

ภาคผนวก

เอกสารในส่วนของภาคผนวกประกอบไปด้วย

1. เอกสารการตอบรับตีพิมพ์บทความจากบรรณาธิการวารสาร Economic Analysis and Policy
2. เอกสารการตอบรับการนำเสนอบทความในการประชุมวิชาการนานาชาติ 15th European Workshop on Efficiency and Productivity Analysis (EWEPA) ณ กรุงลอนดอน ประเทศสหราชอาณาจักรระหว่างวันที่ 12-15 มิถุนายน 2560
3. บทความสำหรับการเผยแพร่

---------- Forwarded message ----------
From: **Economic Analysis and Policy** <EviseSupport@elsevier.com>
Date: Wed, Nov 29, 2017 at 2:48 PM
Subject: Received revision EAP_2017_141_R3
To: supawat@econ.tu.ac.th, yanjiezhang2007@gmail.com

Ref: EAP_2017_141_R3
Title: Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach
Journal: Economic Analysis and Policy

Dear Prof. Supawat and Dr. Zhang,

I am pleased to inform you that your paper has been accepted for publication. Now that your manuscript has been accepted for publication it will proceed to copy-editing and production.

Thank you for submitting your work to Economic Analysis and Policy. We hope you consider us again for future submissions.

Kind regards,

Clevo Wilson
Editor-in-Chief
Economic Analysis and Policy

Have questions or need assistance?
For further assistance, please visit our Customer Support site. Here you can search for solutions on a range of topics, find answers to frequently asked questions, and learn more about EVISE® via interactive tutorials. You can also talk 24/5 to our customer support team by phone and 24/7 by live chat and email.

Dear corresponding author,

We are very pleased to inform you that your paper "Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach" has been accepted for presentation at the forthcoming 15th EWEPA Conference to be held at Senate House, Malet Street, London, WC1E 7HU, UK, on June 12 - 15, 2017.

The 15th EWEPA Conference will be hosted by the School of Business and Economics, Loughborough University, UK, and its Centre for Productivity and Performance.

Please note that you have to register to be included in the program as paper submission is not regarded as registration. The deadline for early registration at the discounted rate is 1 March, 2017. After this date the late registration rate will apply. All details about registration are on the conference website:

http://ewepa.org/conferences/london2017/index.php/submit

Participants registering as students must provide evidence from their university that they are full-time students at the point of registration. Students can either send via email a scanned official letter on headed paper to Claire Walker (C.Walker@lboro.ac.uk) to confirm their status. Alternatively, students can bring a hard copy of an official letter confirming their status to the registration desk at the conference.

Finally, for those who need an official letter of acceptance from the 15th EWEPA conference to facilitate travel, please contact Claire Walker (C.Walker@lboro.ac.uk) to request this letter.

We look forward to your company in London in June.

Kind Regards,

The Local Organising Committee:
David Saal (Loughborough University)
Victor Podinovski (Loughborough University)
Robin Sickles (Rice University and Loughborough University)
Karligash Glass (Loughborough University)
Anthony Glass (Loughborough University)

EUROPEAN WORKSHOP ON EFFICIENCY AND PRODUCTIVITY (EWEPA) 2017 CONFERENCE PROGRAMME

(Version 2.0, 17 May 2017)

Registration

We will be open for registration every day of the conference from 8:00-17:00 in the foyer on the ground floor of the conference venue, Senate House, Malet Street, London, WC1E 7HU.

Student participants that have not already confirmed their student status in correspondence with Claire Walker, please remember to bring the required confirmation (official letter from your university) to the conference.

The registration desk will also be available to provide assistance each day throughout the conference.

Conference Mechanics

- All sessions, breaks, lunches and the reception will take place at Senate House.
- Internet access is available within Senate House and the Wi-Fi code required will be provided daily.
- For most parallel sessions, each paper has been allocated 30 minutes (either 3 papers in a 1.5 hour session, or 4 papers in a 2 hour session). In some rare cases it is necessary to schedule 4 papers in a 1.5 hour session. In the latter case, there are 22.5 minutes for each paper. Please time your presentations accordingly.
- The Chair of each parallel session is the last presenting author.
- In the case of a presenter not being present in a parallel session the session will continue and finish early. In this situation more time can be given to each presentation at the discretion of the Session Chair.
- Sessions in this Programme are identified using three parameters: (i) day (TU for Tuesday, WE for Wednesday and TH for Thursday); (ii) time slot (A-D), and (iii) parallel session number (1-7).

Catering

The following catering items are included in the registration fee for all participants.

- A light breakfast (tea, coffee and Danish pastries) will be served between 8:00 - 9:00 am.
- Lunches on all four days.
- Tea and coffee will be served during the breaks between the sessions.
- Drinks Reception on Monday 12th June.
- Welcome Reception on Tuesday 13th June. This includes a light buffet and drinks.

The Conference Dinner on Wednesday 14 June is an additional registration item and is NOT included in the standard registration fee and must be pre-booked. The Conference Dinner will be held at the Grand Connaught Rooms, 61-65 Great Queen Street, London, WC2B 5DA. The pre-booked tickets for the dinner will be available for collection at the EWEPA 2017 registration desk at Senate House. The conference dinner will commence at 19:30 with pre-dinner drinks served from 18:30.

CONFERENCE AT A GLANCE

Monday 12 June - Early Career Research Day (ECRD)

9:00-10:30	Session
10:30-11:00	Break
11:00-12:00	Plenary Session for ECRD
12:00-13:00	Lunch
13:00-14:30	Session
14:30-15:00	Break
15:00-16:30	Session
16:30-17:00	Break
17:00-18:00	Session
18:00-19:00	Drinks Reception

Tuesday 13 June

9:00-9:45	Opening Session and recognition of the contribution of Peter Schmidt
9:45-10:45	Plenary Session 1
10:45-11:15	Break
11:15-12:45	Parallel Sessions (B)
12:45-14:00	Lunch
14:00-15:30	Parallel Sessions (C), includes feature session “Can we ‘learn’ to be efficient?”
15:30-16:00	Break
16:00-18:00	Parallel Sessions (D)
18:00-19:30	Welcome Reception

Wednesday 14 June

9:00-10:30	Parallel Sessions (A)
10:30-11:00	Break
11:00-12:30	Plenary Session 2
12:30-14:00	Lunch
14:00-15:30	Parallel Sessions (C), includes feature session “UK Productivity Puzzle”
15:30-16:00	Break
16:00-17:30	Parallel Sessions (D)
18:30 -	Conference Dinner (additional registration item)

Thursday 15 June

9:00-10:30	Parallel Sessions (A)
10:30-11:00	Break
11:00-12:30	Plenary Session 3
12:30-14:00	Lunch
14:00-15:30	Parallel Sessions (C)
15:30-16:00	Break
16:00-17:30	Parallel Sessions (D)
17:30-18:00	Closing Session

SESSIONS ON 13-15 JUNE 2017

	1	2	3	4	5	6	7
Room	Beveridge Hall	Woburn Room Room 22	Montague Room Room 26	Brunswick Room Room G07	Bloomsbury Room Room G35	Gordon Room Room G34	Room G21A

Tuesday 13 June

TU-A 9:00-10:45	Opening Session, Special Award to Professor Peter Schmidt Plenary Session 1						
TU-B 11:15-12:45	Agriculture 1	SFA 1	Energy 1	DEA 1	Health 1	Justice	Public sector 1
TU-C 14:00-15:30	Feature Session 1	SFA 2	Energy 2	DEA 2	Health 2	Aggregation 1	Public sector 2
TU-D 16:00-18:00	Non-Parametric	Models 1	Energy 3	Applications 1	Health 3	Aggregation 2	Public sector 3
18:00-19:30	Welcome Reception						

Wednesday 14 June

WE-A 9:00-10:30	Agriculture 2	SFA 3	Profits & Performance	DEA 3	Banking 1	Environment	DEA 4
WE-B 11:00-12:30	Plenary Session 2						
WE-C 14:00-15:30	Feature Session 2	Agriculture 3	Applications 2	DEA 5	Fisheries	Wellbeing 1	Manufacturing 1
WE-D 16:00-17:30	Software	Agriculture 4	Energy 4	DEA 6	Education 1	Productivity change 1	Models 2

Thursday 15 June

TH-A 9:00-10:30	Bad outputs 1	Agriculture 5	Agriculture 6	Banking 2	Education 2	Productivity change 2	Manufacturing 2
TH-B 11:00-12:30	Plenary Session 3						
TH-C 14:00-15:30	Bad outputs 2	Agriculture 7	Agriculture 8	DEA 7	Education 3	Productivity change 3	Models 3
TH-D 16:00-17:30	Bad outputs 3	Agriculture 9	Food	DEA 8	Transportation	Manufacturing 3	Wellbeing 2
17:30-18:00	Closing Session						

MONDAY 12 JUNE
Early Career Research Day

8:00-9:00 Arrival and light breakfast

8:00-17:00 Registration

All sessions on this day are held in Chancellor's Hall

The presenting author is identified by *

9:00-10:30: ESTIMATION
Session Chair: Christopher O'Donnell

Iterative nonparametric S-shape estimation
Daisuke Yagi*, Andrew L. Johnson and Hiroshi Morita
Discussant: Ole Bent Olesen

Robustness to outliers in stochastic frontier analysis: The Student's t-half normal model vs. the normal-half normal model
Alexander Stead*, Phill Wheat and William Greene
Discussant: William Horrace

The impact of labour subsidy on total factor productivity
Pontus Mattsson*
Discussant: Christopher O'Donnell

10:30-11:00 Break

11:00-12:00: PLENARY SESSION

Heterogeneity in efficiency analyses: The good, the bad and the ugly
Jaap Bos*

12:00-13:00 Lunch

13:00-14:30: SECTORAL APPLICATIONS
Session Chair: Vania Sena

The impact of banking reforms on efficiency and competition in Ghana's banking sector
John Dadzie* and Alessandra Ferrari
Discussant: David Tripe

Are Mexican water utilities efficient? A nonparametric answer
Ulises Genis*, Nicolas Gravel and Nicholas P. Sisto
Discussant: David Saal

Stock vs. mutual insurers: Long-term convergence or dominance?
Philipp Schaper*
Discussant: Vania Sena

14:30-15:00 Break

15:00-16:30: REGIONAL APPLICATIONS
Session Chair: Cinzia Daraio

Heterogeneous spillovers among Spanish provinces: A generalized spatial stochastic frontier model
Alberto Gude*, Inmaculada Alvarez and Luis Orea
Discussant: Anthony Glass

The inefficiency of the missing middle
Hien Pham* and Antonio Peyrache
Discussant: Niels Christian Petersen

Size and productivity: A conditional efficiency approach for the Italian pharmaceutical sector
Pierluigi Toma* and Camilla Mastromarco
Discussant: Cinzia Daraio

16:30-17:00 Break

17:00-18:00: ESTIMATION
Session Chair: Valentin Zelenyuk

Adaptive LASSO for stochastic frontier models with many efficient firms
Hyunseok Jung*
Discussant: Christopher Parmeter

Direction selection in stochastic directional distance functions
Kevin Layer*, Andrew Johnson and Robin Sickles
Discussant: Valentin Zelenyuk

DRINKS RECEPTION
18:00-19:00, Senate House

TUESDAY 13 JUNE

8:00-9:00 Arrival and light breakfast

8:00-17:00 Registration

OPENING SESSION
9:00-9:45, Beveridge Hall

Special Award in recognition of the contribution of Professor Peter Schmidt

TU-A: PLENARY SESSION 1
9:45-10:45, Beveridge Hall
Session Chair: Shawna Grosskopf

Twenty years of frontier analysis in the service of regulatory economics: Perspectives and open questions
Per Agrell*
Discussant: Emili Grifell-Tatjé

10:45-11:15 Break

TU-B-1: AGRICULTURE 1
11:15-12:45, Beveridge Hall
Session Chair: Bob Chambers

Spatial regimes in farms' technologies
Cristina Salvioni*, Anna Gloria Billé and Roberto Benedetti

Do productivity convergence approaches converge? A meta-frontier Luenberger-Färe-Primont indicator decomposition in the French agriculture
K. Hervé Dakpo*, Yann Desjeux, Philippe Jeanneaux and Laure Latruffe*

Parsing US agricultural productivity growth: Weather, technology change, efficiency change, and inputs
Bob Chambers* and Simone Pieralli

TU-B-2: SFA 1
11:15-12:45, Woburn Room
Session Chair: Inmaculada Alvarez

Discrete approximation of the stochastic frontier model
Aljar Meesters and Christopher Parmeter*

Measuring spatial competition using efficiency spillovers
Anthony Glass*, Karligash Kenjegalieva and Thomas Weyman-Jones

A new stochastic frontier model with spatial effects in both noise and inefficiency terms
Luis Orea* and Inmaculada Alvarez*

TU-B-3: ENERGY 1
11:15-12:45, Montague Room
Session Chair: Endre Bjørndal

An application of stochastic frontier analysis to measure the influence of weather on electricity distribution businesses: Evidence from developing economies
Karim Anaya Stucchi* and Michael G. Pollitt

Efficiency analysis of electricity distribution by electric cooperative companies in the Philippines
Trishit Bandyopadhyay* and Fernando Roxas

Learning and adaptation under incentive regulation: A survey of Norwegian electricity distribution companies
Edda Nermoen Burheim, Elise Ivara Dahl, Endre Bjørndal* and Mette Bjørndal

TU-B-4: DEA 1
11:15-12:45, Brunswick Room
Session Chair: Joseph Atwood

Efficiency analysis with ratio measures
Ole Ben Olesen*, Niels Christian Petersen and Victor V. Podinovski

DEA models with ratio measures & potential ratio inefficiency
Ole Bent Olesen, Niels Christian Petersen* and Victor V. Podinovski

Radial efficiency metrics using worst-case reference points
Joseph Atwood*, Saleem Shaik and John Walden

TU-B-5: HEALTH 1
11:15-12:45, Bloomsbury Room
Session Chair: Nina Boogen

Spanish hospitals ranking with regard to performance and quality
Sophie Gorgemans*, Enrique Bernal-Delgado, Manuel Ridao-López and Micaela Comendeiro-Maalooe

The contribution of resident physicians to hospital productivity
Maria J. Perez-Villadoniga*, Ana M. Rodriguez-Alvarez and David Roibas

Cost efficiency of the Swiss nursing home sector
Nina Boogen*, Massimo Filippini and William Greene

TU-B-6: JUSTICE
11:15-12:45, Gordon Room
Session Chair: Maria Silva

De lege ferenda, de lege lata: Efficient management structures in legal systems
Samantha Bielen and Jaap Bos*

Network DEA, industry structure, and backlog congestion in the Italian justice sector
Antonio Peyrache and Angelo Zago*

Output-specific inputs in DEA: An application to courts of justice in Portugal
Maria Silva*

TU-B-7: PUBLIC SECTOR 1
11:15-12:45, Room G21A
Session Chair: Finn Førsund

Quality of life shift in Spanish municipalities (2001-2011)
Eduardo Gonzalez*, Ana Carcaba and Juan Ventura

Municipal efficiency, management forms for the waste collection service and the impact of environmental variables
Gemma Perez-Lopez*, Diego Prior and José Luis Zafra-Gómez

Measuring effectiveness of production in the public sector
Finn Førsund*

12:45-14:00 Lunch

TU-C-1: FEATURE SESSION 1
CAN WE "LEARN" TO BE EFFICIENT?
14:00-15:30, Beveridge Hall
Session Chair: Konstantinos Triantis

The space-time continuum (or, at least, movements in space over time)
Mette Asmild* and Dorte Kronborg

Cherry picking in the fall: How banks select takeover candidates
Jaap Bos*

Informing enterprise operational assessment through a complex adaptive systems efficiency measurement approach
Konstantinos Triantis*, Glen Lyddane and Oscar Herrera-Restrepo

TU-C-2: SFA 2
14:00-15:30, Woburn Room
Session Chair: Ian Wright

Endogeneity in panel data stochastic frontier model with determinants of persistent and transient inefficiency
Hung-Pin Lai* and Subal C. Kumbhakar

A flexible estimator for dynamic panel stochastic frontier models
Hung-Jen Wang*, Yu-Fan Huang and Sui Luo

Stationary points for parametric stochastic frontier models
Ian Wright* and William Horrace

TU-C-3: ENERGY 2
14:00-15:30, Montague Room
Session Chair: Gerald Granderson

Objectives and incentives: Evidence from the privatisation of Great Britain's power plants
Thomas Triebs* and Michael Pollitt

Estimation of cost efficiency in restoring biodiversity loss at hydropower plants in Sweden
Wondmagegn Tafesse Tirkaso*

Impact of the 1990 Clean Air Act, RECLAIM program, and ISO membership, on production cost and efficiency in the electric utility industry
Gerald Granderson* and Finn Førsund

TU-C-4: DEA 2
14:00-15:30, Brunswick Room
Session Chair: Paul Rouse

Determination of efficiency scores in a partially negative DEA problem using directional distance model
Subhadip Sarkar*

A DEA-based methodology to determine customer value
Laurens Cherchye, Bram De Rock, Bart Dierynck, Pieter Jan Kerstens* and Filip Roodhooft

A new metric for scale elasticity in data envelopment analysis
Maryam Hasannasab, Dimitris Margaritis, Israfil Roshdi and Paul Rouse*

TU-C-5: HEALTH 2
14:00-15:30: Bloomsbury Room
Session Chair: Sverre A.C. Kittelsen

Technical efficiency in the nursing home sector in Ireland – A stochastic frontier input distance function approach
Marta Zieba, Declan Dineen and Shiovan Ni Luasa*

Evaluating the cost of waiting lists: A primal approach
Ana Rodriguez-Alvarez, David Roibas* and Ana Gonzalez-Vidales

Scale and quality in Nordic hospitals
Sverre A.C. Kittelsen*

TU-C-6: AGGREGATION 1
14:00-15:30, Gordon Room
Session Chair: Valentin Zelenyuk

A family of superlative indexes under Hicks neutral technical change
Hideyuki Mizobuchi* and Valentin Zelenyuk*

Olley-Pakes decomposition with revenue and physical productivity measures
Giannis Karagiannis* and Suzanna-Maria Paleologou

Central limit theorems for aggregate efficiency
Leopold Simar and Valentin Zelenyuk*

TU-C-7: PUBLIC SECTOR 2
14:00-15:30, Room G21A
Session Chair: Pablo Arocena

A conditional directional distance function approach for measuring tax collection efficiency: Evidence from Spanish regional offices
Jose Manuel Cordero, Carlos Díaz*, Francisco Pedraja and Nickolaos Tzeremes

Efficiency measurement of Spanish municipalities: An application of conditional nonparametric frontiers
Jose Manuel Cordero, Carlos Diaz-Caro and Cristina Polo*

Explaining differences in efficiency: the case of local government literature
Francesco Aiello*, Graziella Bonnano and Luigi Capristro Bonanno

Allocating regional funds to local governments using a DEA-based resource allocation model
Pablo Arocena*, Fermín Cabasés and Pedro Pascual

15:30-16:00 Break

TU-D-1: NON-PARAMETRIC METHODS
16:00-18:00, Beveridge Hall
Session Chair: Camilla Mastromarco

Dimension reduction in nonparametric models of production
Paul W. Wilson*

Confidence intervals for efficiency scores in non-convex technologies
Luiza Badin*, Valentin Patilea and Leopold Simar

Nonparametric frontier estimation in the presence of noise: Recent developments
Jean-Pierre Florens, Leopold Simar* and Ingrid Van Keilegom

Predicting recessions in Italy: A nonparametric discrete choice models for time series
Camilla Mastromarco*, Leopold Simar and Valentin Zelenyuk

TU-D-2: MODELS 1
16:00-18:00, Woburn Room
Session Chair: Antonio Peyrache

Measuring capital value: A distance function approach
John Walden*, Rolf Färe and Shawna Grosskopf

Estimating and decomposing optimal shifts of the world technology frontier
Benjamin Hampf* and Jens Krüger

It takes two to tango: The impact of ICT and R&D on efficiency
Fabio Pieri, Ana Rincon Aznar, Francesco Venturini and Michela Vecchi*

A decentralized resource allocation industry model
Antonio Peyrache* and Prasada Rao

TU-D-3: ENERGY 3
16:00-18:00, Montague Room
Session Chair: Tooraj Jamasb

Electricity market reform performance in Sub-Saharan Africa: A parametric distance function approach
Adwoa Asantewaa*, Tooraj Jamasb and Manuel Llorca

Cost efficiency analysis of electric energy distribution sector under model uncertainty
Kamil Makieła and Jacek Osiewalski*

Regional comparisons of energy use efficiency in Indian manufacturing: An index number approach
Kankana Mukherjee*

The effect of institutions on sectoral performance: The case of electricity distribution in Indian states
Tooraj Jamasb*, Pavan Khetrapal, Manuel Llorca and Tripta Thakur

TU-D-4: APPLICATIONS 1
16:00-18:00, Brunswick Room
Session Chair: Daniel Wikström

Estimating efficiency of Italian water utilities by accounting for quality issues
Giovanna D'Inverno*, Laura Carosi, Andrea Guerrini and Giulia Romano

Temporal perception as a source of productivity measure distortion
Fabian von Schéele* and Darek Haftor

Identifying most productive networks derived using unstructured longitudinal data
Arun Bhattacharyya*

Procurement auctions for road resurfacing projects – The efficiency of regional procurement engineers
Jan-Eric Nilsson, Ivan Ridderstedt and Daniel Wikström*

TU-D-5: HEALTH 3
16:00-18:00, Bloomsbury Room
Session Chair: Gary Ferrier

Economies of scale: A meta-analysis on the scale of hospitals
Bart van Hulst* and Jos Blank

Economies of scope in health sector: The case of Portuguese hospitals
Diogo Ferreira*, Rui Marques and Alexandre Morais Nunes

Fuel poverty, health and subjective assessment: A latent class approach and application to the case of Spain
Manuel Llorca*, Tooraj Jamasb and Ana Rodríguez-Álvarez

An expanded decomposition of the Luenberger productivity Indicator with an application to the Chinese healthcare sector
Gary Ferrier*, Hervé Leleu and Zhiyang Shen

TU-D-6: AGGREGATION 2
16:00-18:00, Gordon Room
Session Chair: Kevin Fox

The fourth decomposition of aggregate total factor productivity change
Bert M. Balk*

Parametric decomposition of the input-oriented Malmquist productivity index: With Ethiopian agriculture
Anbes Tenaye Kidane*

Composite Indicators as generalized benefit-of-the-doubt weighted averages
Nicky Rogge*

Decomposing value added growth into explanatory factors
Erwin Diewert and Kevin Fox*

TU-D-7: PUBLIC SECTOR 3
16:00-18:00, Room G21A
Session Chair: Kristof De Witte

Which estimator to measure local governments’ cost efficiency? Evidence from Spanish municipalities
Isabel Narbón Perpiñá*, María Teresa Balaguer Coll, Emili Tortosa Ausina and Marko Petrovic

The impact of public funds on firms’ technical efficiency of the Italian performing arts sector
Concetta Castiglione, Davide Infante and Marta Zieba*

Overall, allocative and technical efficiency for Swedish district courts 2012–2015
Christian Andersson*, Fredrik Bonander and Jonas Månsson

Direct democracy and local government efficiency
Kristof De Witte* and Zareh Asatryan

WELCOME RECEPTION
18:00-19:30, Senate House

WEDNESDAY 14 JUNE

8:00-9:00 Arrival and light breakfast

8:00-17:00 Registration

WE-A-1: AGRICULTURE 2
9:00-10:30, Beveridge Hall
Session Chair: Jesus T. Pastor

Sustainability and efficiency of dairy sheep production systems in Castilla-La Mancha, Spain
Martiña Morantes, Rafaela Dios-Palomares, David Alcaide-Lopez-De-Pablo*, José Rivas and Antón García

The effect of cow comfort on productive efficiency: An application to Spanish dairy farms
José Antonio Pérez, David Roibás and Alan Wall*

A bounded weighted additive model to assess technical inefficiency: The case of milk production in Canada
Jesus T. Pastor*, Juan Aparicio, Magdalena Kapelko, Lidia Ortiz and Juan F. Monge

WE-A-2: SFA 3
9:00-10:30, Woburn Room
Session Chair: Thomas Weyman-Jones

Allowing for outliers in stochastic frontier models: A mixture noise distribution approach
Phill Wheat*, Alexander D. Stead and William Greene

Heteroscedastic generalized true random effects model (GTRE Het)
Oleg Badunenko, Astrid Cullmann, Subal Kumbhakar and Maria Nieswand*

Energy efficiency and stochastic frontier analysis using the Box-Cox transformation functional form
Thomas Weyman-Jones*, Júlia Mendonça Boucinha and Catarina Feteira Inácio

WE-A-3: PROFITS, PRODUCTIVITY AND BUSINESS PERFORMANCE
9:00-10:30, Montague Room
Session Chair: Jos Blank

Business models interaction: Walmart vs Kmart
Humberto Brea-Solís, Ramon Casadesus-Masanell and Emili Grifell-Tatjé*

An integrated analysis of cash flow, economic costs and economic profitability
David Saal* and Pablo Arocena

The profitability function as an alternative theoretical framework for productivity measurement: An application to the Dutch drinking water sector
Jos Blank*

WE-A-4: DEA 3
9:00-10:30, Brunswick Room
Session Chair: Victor Podinovski

A DEA-based incentive mechanism under central management
Mohsen Afsharian*, Heinz Ahn and Emmanuel Thanassoulis

A DEA-based incentives system under varying degrees of decentralisation
Mohsen Afsharian, Heinz Ahn and Emmanuel Thanassoulis*

DEA models with weight restrictions: What is the meaning of optimal weights?
Victor Podinovski*

WE-A-5: BANKING 1
9:00-10:30, Bloomsbury Room
Session Chair: Joseph Paradi

Risk preference and efficiency in Chinese banking
Ning Zhu*, Yanrui Wu, Bing Wang and Zhiqian Yu*

Achieving a sustainable cost efficient business model in banking: The case of European banks
Oleg Badunenko*, Subal Kumbakhar and Ana Lozano-Vivas*

Improving pension funds' performance by considering an expert's opinions and mutual funds' information using DEA
Joseph Paradi* and Maryam Badrizadeh*

WE-A-6: ENVIRONMENT
9:00-10:30, Gordon Room
Session Chair: Jose L. Zofio

The efficiency and distributional effects of China's carbon mitigation policies: A distance function analysis
Atakelty Hailu* and Chunbo Ma

Operational and environmental performance in wine sector: A unified efficiency DEA-based assessment
Samah Jradi*, Tatiana Bouzdine-Chameeva, Bernard Delhomme and Anicia Jeagler

Environmental productivity change in world air emissions: A new Malmquist-Luenberger index approach
Jose L. Zofio*, Juan Aparicio, Javier Barbero, Magdalena Kapelko and Jesus Pastor

WE-A-7: DEA 4
9:00-10:30, Room G21A
Session Chair: Theodoros Skevas

Evaluating mergers a-priori: The case of European air navigation service providers
Nicole Adler, Ole B. Olesen and Nicola Volta*

Measuring corporate sustainability performance
Tadesse Engida*, Xudong Rao and Alfons G.J.M. Oude Lansink

Derivation of netput shadow prices under different levels of pest pressure
Theodoros Skevas* and Teresa Serra

10:30-11:00 Break

WE-B: PLENARY SESSION 2
11:00-12:30, Beveridge Hall
Session Chair: David Saal

Efficiency analysis in competition and regulation policy
Marc Ivaldi*
Discussant: Robin Sickles

12:30-14:00 Lunch

WE-C-1: FEATURE SESSSION 2
THE UK PRODUTIVITY PUZZLE
14:00-15:30, Beveridge Hall
Session Chair: Jonathan Haskel

The speakers are:

Jonathan Haskel (Imperial College London)

Diane Coyle, OBE (University of Manchester)

Rebecca Riley (National Institute of Economic and Social Research, UK)

WE-C-2: AGRICULTURE 3
14:00-15:30, Woburn Room
Session Chair: Fabian Frick

Productivity change analysis of Polish dairy farms after Poland's accession to the EU – An output growth decomposition approach
Kamil Makieła*, Jerzy Marzec and Andrzej Pisulewski

Efficiency in U.S. farm production and the role of distribution (structure and conduct) of farm programs: Evidence from a national survey
Saleem Shaik* and Hisham El-Osta

Deregulation and productivity: Empirical evidence on dairy production
Fabian Frick* and Johannes Sauer

WE-C-3: APPLICATIONS 2
14:00-15:30, Montague Room
Session Chair: Ørjan Mydland

The efficiency analysis of the shale revolution in the global oilfield market
Binlei Gong*

The opportunity costs of financial fair play regulations in professional football – An efficiency analysis
Ronan Gallagher and Barry Quinn*

Lost economies of scope and merger gains in the Norwegian electricity industry
Ørjan Mydland*

WE-C-4: DEA 5
14:00-15:30, Brunswick Room
Session Chair: Wen-Chih Chen

Sorting items with DEASort in ABC classes
Alessio Ishizaka*, Rita Cavallieri and Francesco Lolli

A stepwise benchmarking method for finding projection points involving returns to scale properties
Akram Dehnokhalaji* and Narges Soltani

Recent updates in DEA computation
Wen-Chih Chen*

WE-C-5: FISHERIES
14:00-15:30, Bloomsbury Room
Session Chair: Antonio Alvarez

Hooked on quotas: Analysis of the performance of the Icelandic small vessel fleet before and after the introduction of ITQs
Arnar Mar Buason and Sveinn Agnarsson*

An evaluation of the Norwegian fisheries management system for the conventional coastal vessels
Ruth Pincinato*, Frank Asche, Andreea Cojocaru and Kristin Roll

Decomposing revenue efficiency into price and technical efficiency. An application to fisheries
Antonio Alvarez*, Lorena Couce and Lourdes Trujillo

WE-C-6: WELLBEING 1
14:00-15:30, Gordon Room
Session Chair: Mikulas Luptacik

The relationship between democracy index and corruption perception index and a nation's innovation efficacy and productivity
Yung-Hsiang Lu and Yi-Chen Lee*

The impact of human capital on technical efficiency: Evidence from Eastern European and Central Asia countries
Salem Gheit*

Measuring income inequalities beyond Gini coefficient
Mikulas Luptacik* and Eduard Nezinsky*

WE-C-7: MANUFACTURING 1
14:00-15:30, Room G21A
Session Chair: Ana Camanho

A green bargain? The impact of an energy saving program on productivity growth in China's iron and steel industry
Thomas Geissmann*, Massimo Filippini, Valerie Karplus and Da Zhang

Export intensity-firm performance nexus: New evidence from basic metals industry in India
Anup Kumar Bhandari* and Vipin Valiyattoor

Manufacturing strategies and operations performance: A frontier approach
Ana Camanho*, Behrouz Arabi, Maria Silva and Rui Sousa

15:30-16:00 Break

WE-D-1: SOFTWARE
16:00-17:30, Beveridge Hall
Session Chair: Ali Emrouznejad

Productivity and efficiency analysis software: A survey of the options
Cinzia Daraio*, Kristiaan Kerstens, Thyago C. Nepomuceno* and Robin C. Sickles

Frontier visualization algorithms for FDH models
Vladimir Krivonozhko* and Andrey Lychev

Measuring efficiency of decision making units: Software update for advanced users
Ali Emrouznejad* and Emmanuel Thanassoulis

WE-D-2: AGRICULTURE 4
16:00-17:30, Woburn Room
Session Chair: Ioannis Skevas

Large and small farms excel in Brazil
Steven Helfand, Nicholas Rada* and Marcelo Magalhaes

Agricultural productivity and farm size in Malawi, Tanzania, and Uganda: A total factor productivity approach
Jacques Julien* and Boris E. Bravo-Ureta

Productivity growth in German dairy farming using a dynamic inefficiency specification: A Bayesian approach
Ioannis Skevas*, Grigorios Emvalomatis and Bernhard Bruemmer

WE-D-3: ENERGY 4
16:00-17:30, Montague Room
Session Chair: Nilkanth Kumar

Efficiency-based system configuration assessment: The case of micro-grids
Taylan Topcu, Konstantinos Triantis* and Matthew Robinson

Equilibrium specification of technology: Implications for energy demand and capacity utilization analysis
Sourour Baccar*

The role of energy and investment literacy for residential electricity demand and end-use efficiency
Julia E. Blasch, Nina Boogen, Massimo Filippini and Nilkanth Kumar*

WE-D-4: DEA 6
16:00-17:30, Brunswick Room
Session Chair: Mette Asmild

The good, the bad and the socially responsible: A production analysis approach to firm's performance ranking
Daniela Puggioni* and Spiro E. Stefanou

Nonparametric production analysis with unobserved heterogeneity
Laurens Cherchye, Thomas Demuynck, Bram De Rock and Marijn Verschelde*

Examining production conditions
Mette Asmild*, Tomas Balezentis and Jens Leth Hougaard

WE-D-5: EDUCATION 1
16:00-17:30, Bloomsbury Room
Session Chair: Jill Johnes

Predicting financial sustainability in a competitive higher education marketplace
Andrew McConnell* and Jill Johnes

Does the governance of the HE system affect the efficiency of universities? A comparison of German and Italian public institutions
Tommaso Agasisti and Sabine Gralka*

Efficiency and VC pay: Exploring the value conundrum
Deborah Allcock, Jill Johnes* and Swati Virmani

WE-D-6: PRODUCTIVITY CHANGE 1
16:00-17:30, Gordon Room
Session Chair: Bernhard Mahlberg

Source of industrial output growth and productivity decomposition analysis for selected Asia countries using DEA Malmquist and KLEMS data bases
Tsu-Tan Fu* and Yih-Ming Lin

Reconsidering non-neutral technical change
Jaap Bos and Ming Li*

Total factor productivity change based on partial productivities
Juan Aparicio, Bernhard Mahlberg* and Jesus T. Pastor

WE-D-7: MODELS 2
16:00-17:30, Room G21A
Session Chair: Kristiaan Kerstens

Computational complexity of shape constrained estimation
Andrew Johnson*

Parsimonious functional forms for multiple-output cost functions: Output-output relationships
Arne Henningsen*

Short- and long-run plant capacity notions: Definitions and comparison
Giovanni Cesaroni, Kristiaan Kerstens* and Ignace Van de Woestyn

THURSDAY 15 JUNE

8:00-9:00 Arrival and light breakfast

8:00-17:00 Registration

TH-A-1: BAD OUTPUTS 1
9:00-10:30, Beveridge Hall
Session Chair: Rolf Färe

Bad outputs
Sushama Murty and R. Robert Russell*

Weak disposability in nonparametric production analysis: Which reference technology is appropriate?
Manh D. Pham* and Valentin Zelenyuk

Employment and pollution abatement: A nonparametric cost function approach
Shawna Grosskopf*, Rolf Färe*, Carl Pasurka and Ron Shadbegian

TH-A-2: AGRICULTURE 5
9:00-10:30, Woburn Room
Session Chair: Supawat Rungsuriyawiboon

How to minimize the production cost of marine cage lobster aquaculture in Vietnam
Au Ton Nu Hai*, The Bui Dung and Stijn Speelman

Short-run and long-run efficiency and their determinants: A study of crop production in Norway
Gudbrand Lien*, Subal C Kumbhakar and Habtamu Alem

Examining the economic performance of Chinese farms: A dynamic efficiency and adjustment cost approach
Supawat Rungsuriyawiboon* and Yanjie Zhang

TH-A-3: AGRICULTURE 6
9:00-10:30, Montague Room
Session Chair: Boris E. Bravo-Ureta

Cross-country comparison of agricultural productivity between the United States, Canada and Australia: The superlative versus the quantity-only based index
Yu Sheng*, Xinpeng Xu and Eldon Ball

Measuring scale efficiency of farms across regions - A Bayesian stochastic metafrontier approach
Stefan Wimmer* and Johannes Sauer

Technology and management gaps using stochastic frontiers with 2-round panel data: Preliminary evidence from an agricultural development project
Boris E. Bravo-Ureta*, William Greene, Mario González-Flores, Lina Salazar and Daniel Solís

TH-A-4: BANKING 2
9:00-10:30, Brunswick Room
Session Chair: David Tripe

Persistent effects in loan loss provisioning concerning Italian banks
Aristeidis Dadoukis*, Giulia Fusi and Richard Simper

The effects of regional differentials in macroeconomic conditions on cost structures of banks
Yuzhu Li* and Richard Simper

Translog cost function estimation: Banking efficiency
Toby Daglish, Oliver Robertson, David Tripe* and Laurent Weill

TH-A-5: EDUCATION 2
9:00-10:30, Bloomsbury Room
Session Chair: Jose M. Cordero

Impact evaluation through frontier methods
Daniel Santín and Gabriela Sicilia*

What is the quality of European universities? Model uncertainty, endogeneity and testing of unobserved heterogeneity
Cinzia Daraio*, Leopold Simar and Paul W. Wilson

Using fuzzy DEA to assess efficiency in education: An application to American schools
Juan Aparicio, Jose M. Cordero* and Lidia Ortiz

TH-A-6: PRODUCTIVITY CHANGE 2
9:00-10:30, Gordon Room
Session Chair: Amparo Sanchis

The productivity puzzle and credit constraints: Is there a cohort effect?
Mustapha Douch*

Misallocation and intersectoral linkages
Latchezar Popov* and Sophie Osotimehin

The effect of the cycle on within-industry productivity convergence: Evidence from the EU
M. Dolores Añón-Higón, Juan A. Máñez, Maria E. Rochina-Barrachina, Amparo Sanchis* and Juan A. Sanchis

TH-A-7: MANUFACTURING 2
9:00-10:30, Room G21A
Session Chair: Tommy Lundgren

Three-step returns to scale analysis using SFA: Russian manufacturing industry
Irina Ipatova*

Internal devaluation versus productivity: Competitiveness of manufacturing across Europe
Charles-Henri Di Maria* and Chiara Peroni

The rebound effect in Swedish heavy industry
Tommy Lundgren*, Golnaz Amjadi and Lars Persson

10:30-11:00 Break

TH-B: PLENARY SESSION 3
11:00-12:30, Beveridge Hall
Session Chair: tbc

Productivity analysis in the presence of uncertainty
Christopher O'Donnell*
Discussant: tbc

12:30-14:00 Lunch

TH-C-1: BAD OUTPUTS 2
14:00-15:30, Beveridge Hall
Session Chair: Shawna Grosskopf

How to integrate material balance issues in productive efficiency analysis: Review of models and practical use
Ludwig Lauwers* and Jef Van Meensel

Do we use fertilizer efficiently? Performance of fertilizer overuse in China's arable agricultural production
Wei Huang* and Li Jiang

Recent developments in modeling technology with unintended outputs
Shawna Grosskopf*, Rolf Färe, Tommy Lundgren and Moriah Bostian

TH-C-2: AGRICULTURE 7
14:00-15:30, Woburn Room
Session Chair: Tomasz Czekaj

Does market information improve technical efficiency? A stochastic frontier analysis for Peruvian farmers
Joanna Kamiche-Zegarra* and Boris Bravo-Ureta

Technical efficiency and household human capital: A data envelopment analysis (DEA)
Emanuele Zucchini*

Multi-output technologies and changing market conditions: Animals' health and dairy farms' efficiency in Denmark
Tomasz Czekaj*, Christine Windfeld Hansen, Jakob Vesterlund Olsen and Anna Plum

TH-C-3: AGRICULTURE 8
14:00-15:30, Montague Room
Session Chair: Timo Sipiläinen

Who is harvesting our grapes? Estimating the impact of the European migrant crisis on vineyard productivity in Southern Italy
Stefan Seifert* and Marica Valente

Input-specific managerial and program inefficiency in the Malaysian dairy industry: A multi-directional efficiency analysis
Nurul Aisyah Mohd Suhaimi*, Yann de Mey and Alfons Oude Lansink

Is there a fair comparison of technical efficiency for conventional and organic dairy farms?
Timo Sipiläinen*

TH-C-4: DEA 7
14:00-15:30, Brunswick Room
Session Chair: Romain Petiot

Size efficiency reconsidered
Kenneth Løvold Rødseth*, Paal Brevik Wangsness, Finn R. Førsund and Halvor Schøyen

The assessment of corporate social responsibility of mining firms
Renata Oliveira*, Andreia Zanella and Ana Camanho

Emphasizing price effects in the US economy sectors 1987-2014
Raluca Parvulescu, Jean-Philippe Boussemart, Hervé Leleu and Karina Shitikova*

Analysis of French logistics services providers performance using data envelopment analysis
Romain Petiot* and Laurent Cavaignac*

TH-C-5: EDUCATION 3
14:00-15:30, Bloomsbury Room
Session Chair: Vania Sena

Measuring performance and productivity growth in education with PISA: The case of Latin-American countries
Sergio Perelman* and Daniel Santin

A multi-level cost model with sub-DMU specific economies of scale: An application to Dutch school boards and schools
Thomas Niaounakis* and Jos Blank

Is less really more? Academic performance of first-year students in Italy in the wake of two institutional reforms
Vania Sena*, Sergio Destefanis, Roberto Zotti and Cristian Barra

TH-C-6: PRODUCTIVITY CHANGE 3
14:00-15:30, Gordon Room
Session Chair: Bill Weber

Biased technological change in the Japanese non-life insurance industry
Takayoshi Nakaoka*, Takuya Urakami and Hiroyuki Inaba

Accounting for Intangible assets in Russia's growth in 1995 – 2014, comparative perspective
Ksenia Bobyleva*

Technical change and von Neumann's coefficient of uniform expansion
Rolf Färe, Daniel Primont and Bill Weber*

TH-C-7: MODELS 3
14:00-15:30, Room G21A
Session Chair: Darek Haftor

Trade friction analysis: Ranking trade barriers in a network model
Flavius Badau*

Socioemotional wealth and productivity differences between family and non-family firms: A distributional analysis
Sarah Creemers, Mark Vancauteren*, Wim Voordeckers and Ludo Peeters

IT complementarities and software programmers' productivity: Results and insights from an online experiment
Natallia Pashkevich and Darek Haftor*

15:30-16:00 Break

TH-D-1: BAD OUTPUTS 3
16:00-17:30, Beveridge Hall
Session Chair: Moriah Bostian

The proof of the pudding is in the eating: Empirical analyses of five environmentally-adjusted efficiency models
K Hervé Dakpo*, Finn Førsund, Ludwig Lauwers* and Jef Van Meensel*

Assessing substitutability among undesirable outputs using parametric directional output distance function: A Monte Carlo analysis
Viktor Khanzhyn*

Prevention or cure? Evaluating the tradeoffs between emissions abatement measures
Moriah Bostian*, Rolf Färe, Shawna Grosskopf and Tommy Lundgren

TH-D-2: AGRICULTURE 9
16:00-17:30, Woburn Room
Session Chair: Suthathip Yaisawarng

Yield gaps and technical efficiency: The case of wheat farmers in Afghanistan
Aziz Karimov* and Rajiv Kumar Sharma

The effects of model specification and assumptions about the nature of inefficiency on cost efficiency scores: A case study of Norwegian cropping farms
Habtamu Alem*, Gudbrand Lien and J. Brian Hardaker

Nerlovian profit efficiency of small-sized, owner-operated sugarcane farms in the Northeastern region of Thailand
Suthathip Yaisawarng* and Thanaporn Athipanyakul

TH-D-3: FOOD
16:00-17:30, Montague Room
Session Chair: Magdalena Kapelko

Measuring price efficiency in infant milk market
Roxani Karagiannis* and Giannis Karagiannis

Industrial concentration and technical inefficiency: A dynamic approach
Maman Setiawan*, Grigorios Emvalomatis and Alfons Oude Lansink

Measuring productivity change accounting for adjustment costs: Evidence from the food industry in the European Union
Magdalena Kapelko*

TH-D-4: DEA 8
16:00-17:30, Brunswick Room
Session Chair: Rafael Leme

A formula for efficiency based on DEA scores
Chris Tofallis*

Facilitating supplier development in construction supply chain: Data envelopment analysis approach
Abdollah Noorizadeh* and Antti Peltokorpi

Efficiency analysis for project portfolio adjustment
Guilherme Marcondes and Rafael Leme*

TH-D-5: TRANSPORTATION
16:00-17:30, Bloomsbury Room
Session Chair: Andrew Smith

Measuring the efficiency of Italian airports: How to counter unexpected shocks
Graziella Bonanno*, Tiziana D'Alfonso and Alberto Nastasi

20 Years of DEA of airports efficiency: A meta-analysis
Laurent Cavaignac* and Romain Petiot*

The relationship between costs and travel time reliability of train operating companies
Andrew Smith* and Manuel Ojeda-Cabral

TH-D-6: MANUFACTURING 3
16:00-17:30, Gordon Room
Session Chair: J.A. Sanchis-Llopis

Credit constraints and technical efficiency: Evidence from Vietnamese manufacturing firms
Chau M. Chu*, Kausik Chaudhuri and Sandra Lancheros

The role of services in enhancing the technical efficiency of Indian manufacturing firms: An analysis using the stochastic production frontier method
Sonia Mukherjee*

Markups, exports and R&D: Evidence for Spanish manufacturing
J.A. Máñez, M.E. Rochina-Barrachina and J.A. Sanchis-Llopis*

TH-D-7: WELLBEING 2
16:00-17:30, Room G21A
Session Chair: Ana Rodríguez-Álvarez

Welfare growth accounting revisited
Tarek Harchaoui* and Paul Willemsen

Regional wage frontiers in pre & post-crisis Spain
Joanna Maria Bashford Fernández*

Fuel poverty and well-being: A consumer theory and stochastic frontier approach
Ana Rodríguez-Álvarez*, Luis Orea and Tooraj Jamasb

CLOSING SESSION
17:30-18:00, Beveridge Hall

Examining the Economic Performance of Chinese Farms: A Dynamic Efficiency and Adjustment Cost Approach

Supawat Rungsuriyawiboon[1] and Yanjie Zhang[2]

(This manuscript has been accepted for the Economic Analysis and Policy Journal)

Abstract

To understand the state of adjustment processes and the dynamic structure in Chinese agriculture, this paper proposes a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making. Using a panel data set of 4,201 Chinese farms from three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006, this is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. The findings show that the adjustment of quasi-fixed inputs is rather sluggish, implying that adjustment costs are considerably high on Chinese farms. The relatively low levels of allocative and technical efficiencies indicate that most farms are unable to catch up with the production frontier under the existing production technology and that they are unable to use various inputs in the appropriate proportion given their respective prices.

Keywords: Chinese agriculture, dynamic efficiency, adjustment cost, shadow cost approach

JEL codes: D21, D61, Q12

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Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach

1. Introduction

China's agricultural development has been remarkable over the past four decades. The rural reform that began in the late 1970s improved farmers' incentives and had a huge impact on China's agricultural productivity, growth, and output. The value of agricultural output increased enormously, from 139.7 billion Chinese yuan in 1978, to 10,222.6 billion yuan in 2014.[3] Agricultural total factor productivity (TFP) has also grown extremely fast—by 4% per annum on average from 1979 to 2008 (Zhang and Brümmer, 2011). The great achievement of China's agricultural production has so far come almost entirely from smallholder farming, represented by about 200 million small-scale farms.

Despite great successes, many challenges remain or have even increased over the last decade. For instance, the continued rising opportunity costs of agricultural labour will lead to the gradual loss of China's competitive labour advantage. Further, household rights to land are still incomplete after several waves of land tenure reforms (Ma et al., 2015). This induced land insecurity reduces the incentives of farmers to make productivity-enhancing investments in land (e.g. irrigation, drainage, terracing and the application of organic fertilizer), and hinders the efficient use of labour (Brandt et al., 2002; Deininger and Feder, 2001), as a result decreasing agricultural productivity.

China's major agricultural policy objectives have been consistent in their aims to increase grain production capacity to largely ensure food self-sufficiency and at the same time improve farmers' income. Since 2004, the No. 1 Documents[4] of each year have concentrated on issues related to agriculture, farmers and the countryside (the so-called 'three nongs'). In recent years these documents have focused on investments in agricultural technology to boost production and the adjustment of farm structure, emphasizing a transition to larger-scale farms (OECD, 2013, 2015). In this context, the role of adjustment costs and dynamic cost structure are becoming important issues for investigating performance in Chinese agriculture. Whether adjustment costs are significant and whether they can be regarded as a source of the sluggish adjustment processes are of interest to policymakers. Considering the major challenges in Chinese agricultural production, the extent to which

[3]The statistics are taken from China Statistical Yearbook 2015, National Bureau of Statistics of China.

[4]No. 1 Documents are the top-priority documents issued jointly at the beginning of each year by the Central Committee of the Communist Party and the State Council. They are the first major policy directives of the year and give policy suggestions for the National People's Congress (OECD, 2009).

Chinese farms could perform better remains an important research question. A measure of cost efficiency and its decomposition provides an indicator that measures the exploitation of resources (technical efficiency) in Chinese agriculture, as well as an indicator that characterises the economic losses due to suboptimal allocation of resources (allocative inefficiency). Furthermore, this study addresses the issue by characterizing the cost structure of Chinese farms under dynamic adjustment, to measure their performance.

The frontier approach has become the state-of-the-art for analysing the performance of firms in the literature. Modern efficiency and productivity methodologies measure firm performance relative to best-practice frontiers. Both parametric and nonparametric techniques have been continuously developed to identify the best-practice frontier. Recent empirical studies that have conducted the frontier-based model using both parametric and nonparametric techniques to measure firms' efficiency and productivity in various industries include Lee et al. (2017), Johnstone et al. (2017), Fujii and Managi (2017) and Tamaki et al. (2017).

Frontier-based models using a parametric approach to estimate firm efficiency have been an important area of research, which has been continuously developed for more than half a decade. Following the pioneering work of Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), the frontier analysis model has been employed for both primal and dual representations of production technologies. With the availability of input quantity and cost share data, a dual cost frontier approach allows researchers to estimate and decompose the firm's cost efficiency into technical and allocative efficiencies. Analysis of the cost frontier models has further grown with important contributions by many researchers (Schmidt and Lovell; 1979; Kopp and Diewert 1982; Zieschang 1983; Bauer 1990; Greene 1993; Kumbhakar 1997; Maietta 2000; Atkinson and Primont 2002; Assaf and Matawie 2008). However, the cost frontier models presented in these studies were developed in a static context. The shortcomings of the static frontier-based model include ignoring the explicit role of time and how the adjustment of quasi-fixed inputs to the observed long-run level takes place. As a result, efficiency scores measured from the static efficiency model may be inaccurate and misleading. The absence of an explicit analysis of the transition path of quasi-fixed factors toward their desired long-run levels can be remedied by explicitly incorporating the costs of adjustment for the quasi-fixed factors. The framework of the optimal inter-temporal behaviour of the firm using the notion of adjustment costs as a means of solving the firm's optimization problem was first introduced by Eisner and Strotz (1963). The theory of inter-temporal duality was improved upon by McLaren and Cooper (1980a) and Epstein (1981). This theory represents an alternative and powerful method for solving inter-temporal optimization problems by using the optimal value function of the dynamic programming equation (DPE) approach. This field has further grown with important contributions by many researchers (i.e. Vasavada and Chambers 1986; Howard and Shumway 1988; Luh and Stefanou 1991, 1993; Fernandez-Cornejo et al. 1992; Manera 1994; Pietola and Myers 2000; Sckokai and Moro 2009). Though the static efficiency model and the dynamic duality model of inter-temporal decision making have been continuously developed, they have moved in separate directions. Recently, Rungsuriyawiboon and Stefanou (2007) formalized theoretical and econometric models of dynamic efficiency in the presence of inter-temporal cost-minimizing firm behaviour. The dynamic efficiency model is developed by integrating the static production efficiency model and the dynamic duality model of inter-temporal decision making. The dynamic efficiency model defines the relationship between the actual and behavioural value function of the DPE for a firm's inter-temporal cost minimisation behaviour. Therefore, the dynamic efficiency model provides a system of equations that allows the measurement of both the technical and allocative inefficiency of firms.

Other studies of Chinese agricultural performance have relied on conventional approaches and employed static frontier-based models (Brümmer et al., 2006; Wang et al., 2012; Zhang et al., 2011). In addition, given that these studies mostly investigated the performance of Chinese farms based on different data sets and time periods, it goes without saying that a cross-study comparison is precluded by the lack of a common basis. Brümmer et al. (2006) use a distance function approach with farm household data in the Zhejiang Province for the period 1986–2000, and the results show that the level of technical efficiency range from 0.326 to 0.878. Zhang et al. (2011) apply a two-stage model with a panel data set containing households from Zhejiang, Hubei and Yunnan to analyse the impact of land reallocation on farm production, and the estimated level of technical efficiency is relatively high, with average scores of 0.96, 0.91, and 0.87, respectively. Within a meta-frontier framework, Wang et al. (2012) provide evidence that technical efficiency is significantly affected by farm heterogeneity and that farming technology exhibits region-specific characteristics.

To fill these gaps, the main purpose of the study is to understand the state of adjustment process and dynamic structure in Chinese agriculture. To meet this goal, our paper extends the model of Rungsuriyawiboon and Stefanou (2007) into a more general context with a multiple quasi-fixed factor case. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) over the period of 2003-2006. This is the first study to investigate the allocative and technical efficiency of Chinese agriculture using a dynamic shadow cost approach. The production technology of Chinese farms is presented by one output variable, two variable inputs (labour and intermediate inputs) and two quasi-fixed factors (land and capital).

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework and mathematical derivations of the dynamic efficiency model for the multiple quasi-fixed factor case; Section 3 discusses the data set and the definitions of the variables used in this study; The next section elaborates the econometric model of the dynamic efficiency model with the two quasi-fixed factor cases; The results of our empirical analysis are presented and discussed in Section 4; while the final Section 5 concludes and summarizes.

2. Model specification

2.1 Derivation of a dynamic efficiency model of inter-temporal cost minimization

This section develops a dynamic efficiency model in the context of inter-temporal cost minimization. The framework of the optimal inter-temporal behaviour of the firm uses the notion of adjustment costs as a means of solving the firm's optimization problem. The adjustment cost approach attempts to capture all of the unobserved forces that slow down the adjustment of certain factors in production, such as learning costs, search costs, costs arising from market forces, or contractual obligations (Stefanou, 1989). The presence of adjustment costs formalizes the process of characterizing a firm's dynamic production decisions. In the presence of adjustment costs for the quasi-fixed factors, a firm faces additional costs for the adjustment of quasi-fixed factors beyond acquisition costs in the decision-making process.

The dynamic economic problem facing the firm can be addressed by characterizing firm investment behaviour as the firm seeks to minimize the discounted sum of future production costs over an infinite horizon. The firm's decision-making focuses on the optimal determination of its factor inputs use, which has implications for its capacity utilization. For instance, the purchase and installation of quasi-fixed factors involve a cost of adjustment since the firm must devote internal resources to acquire and adapt the newly-purchased quasi-fixed inputs. Production costs arise from purchasing new inputs, including both variable and quasi-fixed inputs. Units of the quasi-fixed inputs are acquired both for enlarging the existing productive capacity and for replacing worn-out units.

Let $\mathbf{x} \in R_{+}^{N}$ and $\mathbf{q} \in R_{+}^{Q}$ denote non-negative vectors of variable and quasi-fixed inputs, respectively. Similarly, $\mathbf{w} \in R_{++}^{N}$ and $\mathbf{p} \in R_{++}^{Q}$ denote strictly non-negative vectors for variable input prices and quasi-fixed factor prices, respectively.

Following Epstein and Denny (1983) and Stefanou (1989), who assume that economic agents are risk-neutral and that their price expectations are static, the dynamic inter-temporal model of a firm’s cost minimization problem can be expressed as

$$(1) \qquad J(\mathbf{w}',\mathbf{p}',\mathbf{q}',y(t)) = \min_{\mathbf{I}>0} \int_t^{\infty} e^{-rs}[\mathbf{w}'\mathbf{x}(s)+\mathbf{p}'\mathbf{q}(s)]ds$$

subject to $\dot{\mathbf{q}}(s) = \mathbf{I}(s) - \delta\mathbf{q}(s)$, $\mathbf{q}(0) = \mathbf{q}_0 > 0$, $\mathbf{q}(s) > 0$, $y(s) = F[\mathbf{x}(s),\mathbf{q}(s),\dot{\mathbf{q}}(s)]\ \forall s \in [t,\infty)$ where r is the constant discount rate, δ is the constant depreciation rate, y is output, $\dot{\mathbf{q}} \in R_+^Q$ and $\mathbf{I} \in R_+^Q$ are non-negative vectors of net investment and gross investment in quasi-fixed factors, $y(s)$ is a sequence of production targets over the planning horizon starting at time t, and $F[\mathbf{x}'(s),\mathbf{q}'(s),\dot{\mathbf{q}}'(s)]$ is the single output production function. Including net investment $\dot{\mathbf{q}}$ in the production function reflects the internal costs associated with the adjustment of quasi-fixed factors in terms of foregone output. The presence of internal adjustment cost implies output decreases (increases) with the expansion (contraction) of the quasi-fixed factor stocks (i.e. $\dot{\mathbf{q}}\nabla_{\dot{\mathbf{q}}}F < 0$). In addition, the marginal cost of adjustment in physical terms is assumed to increase with the speed of adjustment, implying $\nabla_{\dot{\mathbf{q}}\dot{\mathbf{q}}}F < 0$, where the diseconomies accompanying adjustment takes place. Therefore, sluggish or gradual behaviour in adjusting the levels of quasi-fixed factors is assured. The production function is assumed to be concave in $\dot{\mathbf{q}}$, implying an increasing marginal cost of adjustment.

McLaren and Cooper (1980a) and Epstein (1981) introduced the inter-temporal duality theory, which presents the relationship between the underlying technology and value functions. The dynamic duality between the underlying technology and value functions permits the derivation of a system of variable and dynamic demand equations. Analytically, the dynamic decision problem can be solved using the dynamic duality approach, which allows the use of appropriate static optimization techniques as expressed in the dynamic programming equation (DPE) or Hamilton-Jacobi-Bellman equation. The value function of the DPE for the inter-temporal cost minimization can be expressed as

$$(2) \qquad rJ(\mathbf{w}',\mathbf{p}',\mathbf{q}',y,t) = \min_{\mathbf{x},\dot{\mathbf{q}}>0} \left\{ \mathbf{w}'\mathbf{x} + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}}J'\dot{\mathbf{q}} + \gamma(y - F[\mathbf{x}',\mathbf{q}',\dot{\mathbf{q}}',t]) + \nabla_t J \right\}$$

where t is the time trend variable, γ is the Lagrangian multiplier associated with the production function, and $\nabla_t J$ is the shift of the value function due to technical change.

The result of inter-temporal duality theory provides readily-implemented systems of dynamic factor demands. Differentiating the optimized version of the DPE with respect to $\mathbf{p}$

and $\mathbf{w}$ yields optimal net investment demand and optimal variable input demand, respectively,

(3) $$\dot{\mathbf{q}}^o = (\nabla_{\mathbf{qp}} J)^{-1}(r\nabla_{\mathbf{p}} J - \mathbf{q} - \nabla_{\mathbf{p}t} J)$$

(4) $$\mathbf{x}^o = r\nabla_{\mathbf{w}} J - \nabla_{\mathbf{wq}} J \dot{\mathbf{q}}^o - \nabla_{\mathbf{w}t} J \ .$$

Equation (2) can be interpreted as the dynamic inter-temporal model of a firm's cost minimization problem in the presence of perfect efficiency. When a firm neither minimizes its factor inputs given output levels, nor uses the factors according to respective prices and production technology, it is operating inefficiently, both technically and allocatively. A measure of inefficiency can be obtained by adopting a shadow price approach, as described in Kumbhakar and Lovell (2000).

The dynamic efficiency model is constructed by defining the relationship between actual and shadow (behavioural) value functions of the DPE for the firms' inter-temporal cost minimization behaviour. The actual value function can be viewed as the perfectly efficient condition, whereas the behavioural value function of the DPE is expressed in terms of shadow input prices, quasi-fixed factors and output. The shadow input prices are constructed to generate an optimality relationship. Moreover, as the shadow input prices will differ from market (actual) prices in the presence of inefficiency, a firm's inefficiency can be estimated and evaluated as the deviation between the actual and behavioural value function.

The behavioural value function of the DPE for the firms' inter-temporal cost minimization behaviour that corresponds to the shadow prices and quantities can be expressed as

(5) $$rJ^b(\mathbf{w}^{b\prime}, \mathbf{p}', \mathbf{q}', y, t) = \mathbf{w}^{b\prime}\mathbf{x}^b + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^{b\prime}\dot{\mathbf{q}}^b + \gamma^b(y - F[\mathbf{x}^{b\prime}, \mathbf{q}', \dot{\mathbf{q}}^{b\prime}, t]) + \nabla_t J^b$$

where $\mathbf{x}^b \in R_+^N$ and $\dot{\mathbf{q}}^b \in R_+^Q$ are nonnegative vectors of behavioural variable and quasi-fixed inputs, respectively, $\mathbf{w}^b \in R_{++}^N$ and $\nabla_{\mathbf{q}} J^b \in R_{++}^Q$ are strictly non-negative vectors of behavioural variable input prices and the marginal valuation of behavioural dynamic factors, γ^b is the behavioural Lagrangian multiplier defined as the short-run, instantaneous marginal cost, and $\nabla_t J^b$ is the shift of the behavioural value function.

Following the shadow price approach, $\mathbf{x}^b$ and $\dot{\mathbf{q}}^b$ can be expressed in terms of actual variable and dynamic factors as $\mathbf{x}^b = \boldsymbol{\tau}_x^{-1}\mathbf{x}$ and $\dot{\mathbf{q}}^b = \boldsymbol{\tau}_q^{-1}\dot{\mathbf{q}}$, respectively, where $\boldsymbol{\tau}_x \geq 1$ and $\boldsymbol{\tau}_q \geq 1$ represent inverse producer-specific scalars that provide input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively. Similarly, the behavioural prices can be expressed in terms of actual prices of variable inputs $\mathbf{w}^b = \boldsymbol{\Lambda}_{\mathbf{w}}\mathbf{w}$

and dynamic factors $\nabla_{\mathbf{q}} J^b = \boldsymbol{\Sigma}_{\mathbf{q}} \nabla_{\mathbf{q}} J^a$, where $\boldsymbol{\Lambda}_{\mathbf{w}}$ and $\boldsymbol{\Sigma}_{\mathbf{q}}$ are allocative inefficiencies of the variable and quasi-fixed inputs, respectively.

Differentiating equation (5) with respect to $\mathbf{p}$ and $\mathbf{w}^b$ yields the behavioural conditional demand for the dynamic and variable factors, respectively.

In the presence of technical inefficiency of dynamic and variable factors, the corresponding observed demand for the dynamic and variable factors using the input-oriented approach can be written in terms of the optimized demand for the dynamic and variable factors as

(6) $$\dot{\mathbf{q}}^o = \boldsymbol{\tau}_q \dot{\mathbf{q}}^b = \boldsymbol{\tau}_q (\nabla_{\mathbf{qp}} J^b)^{-1} (r \nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)$$

(7) $$\mathbf{x}^o = \boldsymbol{\tau}_x \mathbf{x}^b = \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (r \nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{wq}} J^b \dot{\mathbf{q}}^b - \nabla_{\mathbf{w}t} J^b)$$

where $\nabla_{\mathbf{w}^b} J^b = \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \nabla_{\mathbf{w}} J^b$.

The value function corresponding to the actual prices and quantities at the optimal level can be defined as

(8) $$r J^a(\cdot) = \mathbf{w}'\mathbf{x}^{\mathrm{o}} + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^a{}' \dot{\mathbf{q}}^o + \nabla_t J^a .$$

Inserting equations (6) and (7) in equation (8), the optimized actual value function can be rewritten in terms of the behavioural value function as

(9) $$\begin{aligned} r J^a(\cdot) = {} & \mathbf{w}' \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (r \nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{qw}} J^b{}' [(\nabla_{\mathbf{qp}} J^b)^{-1} (r \nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] - \nabla_{\mathbf{w}t} J^b) \\ & + \mathbf{p}'\mathbf{q} + \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{q}} J^b{}' \boldsymbol{\tau}_q [(\nabla_{\mathbf{qp}} J^b)^{-1} (r \nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] + \nabla_t J^a \end{aligned}$$

where $\nabla_t J^a = \nabla_t J^b$ implies that the shift in the behavioural value function is proportional to that in the actual value function.

Differentiating equation (9) with respect to $\mathbf{p}$ (up to second-order derivatives), the optimized actual demand for the dynamic factors in terms of the behavioural value function yields

(10) $$\begin{aligned} & \left[\mathbf{ii}'/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} (\nabla_{\mathbf{qp}} J^b + \nabla_{\mathbf{qq}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b - \mathbf{ii}'/r) - \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{qp}} J^b \right] \dot{\mathbf{q}}^o = \\ & \quad + [r \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (\nabla_{\mathbf{wp}} J^b - \nabla_{\mathbf{qw}} J^b{}' (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b)' \mathbf{w} \\ & \quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[r (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}} J^b - (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}t} J^b \right] \\ & \quad + (\mathbf{i} - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1}) \nabla_{\mathbf{p}t} J^b] \end{aligned}$$

where $\mathbf{i}$ is a unit vector of appropriate dimension.

Similarly, differentiating equation (9) with respect to $\mathbf{w}$ (up to second-order derivatives), the optimized actual demand for the variable inputs in terms of the behavioural value function yields[5]

[5] Hence, the optimized actual demand for the numeraire variable input can be derived as

$$
\begin{aligned}
\mathbf{x}^o &= \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \begin{bmatrix} r[\nabla_{\mathbf{ww}} J^b - \nabla_{\mathbf{qw}} J^b{}'(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{wp}} J^b{}']\mathbf{w} + r\nabla_{\mathbf{w}} J^b \\ -\nabla_{\mathbf{w}t} J^b + \nabla_{\mathbf{qw}} J^b{}'(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{p}t} J^b \end{bmatrix} \\
&+ \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[r\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}} J^b - \nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}t} J^b \right] \\
&+ \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \left[\nabla_{\mathbf{qw}} J^b{}' - \nabla_{\mathbf{qw}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} (\nabla_{\mathbf{qp}} J^b - \mathbf{i}/r) + \boldsymbol{\tau}_q \nabla_{\mathbf{qw}} J^b{}' \right] \dot{\mathbf{q}}^o \\
&+ \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{qq}} J^b \right] \dot{\mathbf{q}}^o
\end{aligned} \qquad (11)
$$

Equations (10) and (11) form the system equations of the dynamic efficiency model for inter-temporal cost minimization. When all inefficiency parameters in the model are equal to one, the dynamic efficiency model is reduced to the dynamic inter-temporal model of a firm's cost minimization problem in the presence of perfect efficiency as presented in Epstein and Denny (1983).

By using an econometric approach based on the dynamic optimization behaviour developed by Treadway (1974), the optimal investment demand function can be expressed as

$$\dot{\mathbf{q}}^* = \dot{\mathbf{q}}^b = \mathbf{M}(\mathbf{q} - \mathbf{q}^*) \qquad (12)$$

where $\mathbf{M} = (r\mathbf{ii}' - \nabla_{\mathbf{qp}} J^b)^{-1}$ is the partial adjustment coefficient that indicates how quickly the gap between the current level of quasi-fixed factors stock ($\mathbf{q}$) and the optimal capital stock levels ($\mathbf{q}^*$) is closed in a given instant.

The stock of quasi-fixed factors evolves over time at an endogenous rate and the steady state or optimal quasi-fixed factors stock is defined as

$$\mathbf{q}^* = \mathbf{q} - \mathbf{M}^{-1} (\nabla_{\mathbf{qp}} J^b)^{-1} \cdot (r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b) . \qquad (13)$$

2.2 Econometric model

An econometric model of the dynamic efficiency model for inter-temporal cost minimization is presented in this section. This study focuses on a production technology with two quasi-fixed factors (capital and land), i.e. $\mathbf{q} \in (k, l)$. When farmers decide to increase farm land, capital will not be simultaneously affected. Rather, it might take several periods for net investment to adjust. Therefore, the decision to increase farm land is not fully dependent on the decision to increase a farm's capital. When both capital and land are independent, the off-diagonal elements of the $\nabla_{\mathbf{qp}} J^b$, $\nabla_{\mathbf{qq}} J^b$ and $\nabla_{\mathbf{pp}} J^b$ matrices, i.e. $J^b_{kp_l}$, $J^b_{lp_k}$, J^b_{kl}, and $J^b_{p_k p_l}$ are each equal to zero.

The optimized actual demand for the dynamic factors in equation (10) can be written as

---

$$x_n^o = \boldsymbol{\tau}_x \mathbf{x}^b = rJ^b - \mathbf{p}'\mathbf{q} - \nabla_{\mathbf{q}} J^b{}' \dot{\mathbf{q}}^b - \nabla_t J^b$$

$$
\begin{aligned}
&[1/r+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_k^{-1}(J_{kp_k}^b+J_{kk}^b(J_{kp_k}^b)^{-1}J_{p_kp_k}^b-1/r)-\boldsymbol{\Sigma}_k^{-1}J_{kp_k}^b]\dot{k}\\
(14)\qquad &=[r\boldsymbol{\tau}_x\boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J_{\mathbf{w}p_k}^b-J_{k\mathbf{w}}^b{}'(J_{kp_k}^b)^{-1}J_{p_kp_k}^b)'\mathbf{w}\\
&+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_k^{-1}[r(J_{kp_k}^b)^{-1}J_{p_kp_k}^bJ_k^b-(J_{kp_k}^b)^{-1}J_{p_kp_k}^bJ_{tk}^b]+(1-\boldsymbol{\tau}_q\boldsymbol{\Sigma}_k^{-1})J_{p_kt}^b]+\varepsilon_1
\end{aligned}
$$

$$
\begin{aligned}
&[1/r+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_l^{-1}(J_{lp_l}^b+J_{ll}^b(J_{lp_l}^b)^{-1}J_{p_lp_l}^b-1/r)-\boldsymbol{\Sigma}_l^{-1}J_{lp_l}^b]\dot{l}\\
(15)\qquad &=[r\boldsymbol{\tau}_x\boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J_{\mathbf{w}p_l}^b-J_{l\mathbf{w}}^b{}'(J_{lp_l}^b)^{-1}J_{p_lp_l}^b)'\mathbf{w}\\
&+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_l^{-1}[r(J_{lp_l}^b)^{-1}J_{p_lp_l}^bJ_l^b-(J_{lp_l}^b)^{-1}J_{p_lp_l}^bJ_{tl}^b]+(1-\boldsymbol{\tau}_q\boldsymbol{\Sigma}_l^{-1})J_{p_lt}^b]+\varepsilon_2
\end{aligned}
$$

where $\boldsymbol{\tau}_x$ and $\boldsymbol{\tau}_q$ are inverse producer-specific scalars providing input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively, $\boldsymbol{\Lambda}_{\mathbf{w}}$ represents the allocative inefficiencies of variable inputs, $\boldsymbol{\Sigma}_k$ and $\boldsymbol{\Sigma}_l$ are allocative inefficiencies of capital and land inputs, respectively, ε_1 and ε_2 are the two-sided error terms representing random errors that $\varepsilon_1 : \text{iid}\,N(0,\sigma_1^2)$ and $\varepsilon_2 : \text{iid}\,N(0,\sigma_2^2)$. Further, $\varepsilon_1 \text{ and } \varepsilon_2$ are distributed independently of each other, and of the regressors.

In addition, the optimized actual demand for the variable inputs in equation (11) is given by

$$
\begin{aligned}
&x^o=\boldsymbol{\tau}_x\boldsymbol{\Lambda}_{\mathbf{w}}^{-1}\begin{bmatrix}(rJ_{\mathbf{ww}}^b\mathbf{w}-rJ_{k\mathbf{w}}^b{}'(J_{kp_k}^b)^{-1}J_{\mathbf{w}p_k}^b{}'\mathbf{w}-rJ_{l\mathbf{w}}^b{}'(J_{lp_l}^b)^{-1}J_{\mathbf{w}p_l}^b{}'\mathbf{w}\\ +rJ_{\mathbf{w}}^b-J_{\mathbf{w}t}^b+J_{k\mathbf{w}}^b{}'(J_{kp_k}^b)^{-1}J_{p_kt}^b+J_{l\mathbf{w}}^b{}'(J_{lp_l}^b)^{-1}J_{p_lt}^b\end{bmatrix}\\
&\quad+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_k^{-1}[rJ_{\mathbf{w}p_k}^b(J_{kp_k}^b)^{-1}J_k^b-J_{\mathbf{w}p_k}^b(J_{kp_k}^b)^{-1}J_{kt}^b]\\
(16)\qquad&\quad+\boldsymbol{\tau}_q\boldsymbol{\Sigma}_l^{-1}[rJ_{\mathbf{w}p_l}^b(J_{lp_l}^b)^{-1}J_l^b-J_{\mathbf{w}p_l}^b(J_{lp_l}^b)^{-1}J_{lt}^b]\\
&\quad-\begin{bmatrix}\boldsymbol{\tau}_x\boldsymbol{\Lambda}_{\mathbf{w}}^{-1}[J_{k\mathbf{w}}^b{}'-J_{k\mathbf{w}}^b(J_{kp_k}^b)^{-1}(J_{kp_k}^b-1/r)+\boldsymbol{\tau}_qJ_{k\mathbf{w}}^b{}']\\ +\boldsymbol{\tau}_q\boldsymbol{\Sigma}_k^{-1}[J_{\mathbf{w}p_k}^b(J_{kp_k}^b)^{-1}J_{kk}^b]\end{bmatrix}\dot{k}\\
&\quad-\begin{bmatrix}\boldsymbol{\tau}_x\boldsymbol{\Lambda}_{\mathbf{w}}^{-1}[J_{l\mathbf{w}}^b{}'-J_{l\mathbf{w}}^b(J_{lp_l}^b)^{-1}(J_{lp_l}^b-1/r)+\boldsymbol{\tau}_qJ_{l\mathbf{w}}^b{}']\\ +\boldsymbol{\tau}_q\boldsymbol{\Sigma}_l^{-1}[J_{\mathbf{w}p_l}^b(J_{lp_l}^b)^{-1}J_{ll}^b]\end{bmatrix}\dot{l}+\boldsymbol{\varepsilon}
\end{aligned}
$$

where $\boldsymbol{\varepsilon}$ is a linear disturbance vector with mean vector $\mathbf{0}$ and variance-covariance matrix Σ.

Equations (14) to (16) present an econometric model of the dynamic efficiency model with a two quasi-fixed factors case. To estimate this model, it is necessary to specify the functional form of the behavioural value function. A quadratic behavioural value function assuming symmetry of the parameters can be expressed as

$$(17)\qquad J^b(\cdot)=\beta_0+\mathbf{w}'\boldsymbol{\beta}+\frac{1}{2}\mathbf{w}'\mathbf{B}\mathbf{w}$$

where $\mathbf{w}'=(\mathbf{w}^b\ p_k\ p_l\ k\ l\ y\ t)$, $\boldsymbol{\beta}$ denotes a vector of parameters, and $\mathbf{B}$ is a symmetric matrix of parameters, each of the appropriate dimension.

In addition, all producer- and input-specific estimates of technical and allocative efficiencies must be specified to implement the estimation of all coefficient parameters of the behavioural value function. The system of equations (14) to (16) is recursive, with the endogenous variables of net investment demands in capital and land serving as explanatory variables in the variable input demand equations. The estimation can be accomplished in two stages. In the first stage, the optimized actual investment demands in capital and land are estimated by using the maximum likelihood estimation (MLE). Given that the optimized actual variable input demand equations are over-identified, the system of variable input demand equations is estimated in the second stage by using a generalized method of moments (GMM) estimation with all parameter values as determined in the first stage. All predetermined variables, including exogenous and dummy variables from each equation in the variable input demand equations, are defined as the instrumental variables of the system equation in the second stage. The details of the econometric approach used in the dynamic efficiency model are presented in Rungsuriyawiboon and Stefanou (2007).

2.3 Dynamic structures of production

Dynamic structures of production can be investigated using the parameter estimates of the behavioural value function obtained from the procedure of estimation in section 2.2. This section presents the derivations of two measures of farm scale, e.g. scale and cost elasticities. The scale elasticity is associated with the technology represented by the production, while the cost elasticity involves analysing the movement along the cost curves. With the presence of adjustment costs, the scale elasticity is no longer equivalent to the inverse of the cost elasticity.

2.3.1 Scale elasticity

The scale elasticity is defined as the percentage that change in output responds to a percentage change in all inputs. Following Stefanou (1989), the dynamic theory of cost allows for the selection of dynamic and variable factor demands. The long-run scale elasticity is defined as the ratio of long-run average variable shadow cost (*LRAVC*) to short-run marginal cost (*SRMC*), whereas the short-run scale elasticity is defined as the ratio of short-run average variable shadow cost (*SRAVC*) to short-run marginal cost (*SRMC*). Values of scale elasticity greater than one imply increasing returns to scale, while values less than one imply decreasing returns to scale, and values equal to one imply constant returns to scale.

The optimized actual dynamic programming in equation (9) can be viewed as the long-run cost function associated with the actual quantities. The short-run cost function associated with the actual quantities is defined as the sum of variable costs and fixed costs.

The long-run average cost (*LRAC*) at time t is calculated by dividing equation (9) with output, while the short-run average cost (*SRAC*) at time t is calculated by dividing the short-run cost function with output. The long-run marginal cost (*LRMC*) at time t is calculated by differentiating equation (9) with respect to output, while the short-run marginal cost (*SRMC*) at time t is calculated by differentiating the short-run cost function with output.

The short-run scale elasticity associated with the actual quantities yields

$$(18) \qquad SE^{SR} = \frac{SRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*}}{\gamma^{a*} y}$$

where $\gamma^{a*} = \nabla_y (\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l)$ is the SRMC at time t.

The long-run scale elasticity associated with the actual quantities yields

$$(19) \qquad SE^{LR} = \frac{LRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*} + J_k^a \dot{k}^{*} + J_l^a \dot{l}^{*} + J_t^a}{\gamma^{a*} y}$$

where $J_k^a = \Sigma_k^{-1} J_k^b$, $J_l^a = \Sigma_l^{-1} J_l^b$ and $J_t^a = J_t^b$.

2.3.2 Cost elasticity

The cost elasticity is defined as the percentage change in costs given a percentage change in outputs. The instantaneous or short-run cost elasticity (CE^{SR}) is the ratio of short-run marginal cost (*SRMC*) to the short-run average total cost (*SRAC*), whereas the long-run cost elasticity (CE^{LR}) is defined as the ratio of long-run marginal shadow cost (*LRMC*) to the long-run average total cost (*LRAC*). Values of cost elasticity greater than one imply decreasing returns to scale, while values less than one imply increasing returns to scale and values equal to one imply constant returns to scale.

The short-run cost elasticity associated with the actual quantities in equation (9) yields

$$(20) \qquad CE^{SR} = \frac{SRMC}{SRAC} = \frac{\gamma^{a*} y}{\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l}.$$

The long-run cost elasticity associated with the actual quantities yields

$$(21) \qquad CE^{LR} = \frac{LRMC}{LRAC} = \frac{(\gamma^{a*} + J_{ky}^a \dot{k}^{*} + J_{ly}^a \dot{l}^{*} + J_{ty}^a) y}{\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l + J_k^a \dot{k}^{*} + J_l^a \dot{l}^{*} + J_t^a}.$$

In contrast to the static setting that the scale elasticity is the inverse of the cost elasticity, the inverse of the dynamic cost elasticity is no longer equal to the dynamic scale elasticity. The primary differences between the two scale measures are the terms $J_{ky}^a \dot{k}^{*}$, $J_{ly}^a \dot{l}^{*}$ and J_{ty}^a.

3. Data discussion

The data used in this study is drawn from the National Fixed Point (NFP) survey data series, conducted annually by the Research Center for Rural Economy (RCRE) of the Ministry of Agriculture, China. The NFP survey is based on a multistage, random-cluster process to attain rich information on rural reform of agricultural production and rural development.[6] We use individual household data in the Zhejiang, Hubei, and Yunnan provinces covering the period from 2003 to 2006. The three provinces were chosen to reflect the different regional economic development and the diversity of China's agricultural production. The Zhejiang Province is one of the richest provinces in East China; the Hubei Province is a central middle-income region and is the traditional heartland of China's agricultural production; located in West China, the Yunnan Province is one of the poorest regions in the country.

The agricultural production technology in this study is represented by one output (y), two variable inputs (x_1 = labor, x_2 = intermediate inputs), and two quasi-fixed factors (q_1 = l = land, q_2 = k = capital). Output is the total value of crop production measured at constant 2003 prices. Labour input is expressed as the total number of annual working days of the whole household in crop production. Our dataset contains information on employment in crop production. The wage of labour is hence obtained as the quotient of total expenses paid to employees and their total working days. Intermediate inputs include expenses on seeds, chemical fertilizers, pesticides, and diesel oil for agricultural machinery. The volume of intermediate inputs is calculated as the quotient of the total expenses on intermediate inputs and agricultural productive materials price indices. The Divisia price indices are computed for intermediate inputs with value shares of each component as weights.

Capital input is defined as the fixed-capital assets of the household at the end of each year, including draught animals, production tools, production buildings, and machinery for agriculture. The volume of capital input is calculated as the quotient of the capital input value and the price index of productive agricultural fixed assets (p_{ki}). According to Jorgenson (1963), the rental price for capital is expressed as $p_{ki} * (r + \delta)$, where r is the nominal interest rate and δ is the depreciation rate.[7] Land input is the total utilized arable land area in mu.[8] The rental price for land is calculated as the quotient of expenses for leasing land and leased land area from other households. The descriptive statistics of the variables are listed in Table 1. Households in Zhejiang have a relatively lower output of crop production compared

[6] Benjamin et al. (2005) provide a detailed description of the data and history of the NFP survey.

[7] The nominal interest rate is approximated using the interest rate of rural credit cooperatives production loan. The depreciation rate is calculated as the quotient of depreciation and fixed assets.

[8] 1 mu = 1/15 hectare.

to Hubei and Yunnan. This is not surprising, if we look further into the various inputs of households in the three provinces. The volume of labour input in Zhejiang is 63.59 working days on average, which is roughly 40% of that in Hubei and Yunnan. Actually, rural labourers in Zhejiang are more likely to engage in off-farm employment, and non-agricultural income has accounted for a major share of the household total income. At the same time, labour productivity (y/x_1) in Zhejiang is the highest among the three provinces. In comparison to the relatively lower crop output, the capital input in Zhejiang is impressive and much higher than that in Hubei and Yunnan. Regarding land input, the statistics of our sample sufficiently reflect the land endowment of the three provinces. Arable land is scarce in Zhejiang, with an average of 2.42 mu per household; the next is 4.79 mu in Hubei; Yunnan has the highest arable land area per household, which is 7.35 mu. Compared to Hubei and Yunnan, households in Zhejiang have lower capital productivity (y/k) but higher land productivity (y/l). When further comparing input prices across the provinces, it can be seen that the differences in prices have perfectly reflected varying factor endowments of the three in crop production.

Table 1. Descriptive statistics of the variables, 2003-2006

Variable description	***Symbol***	**Zhejiang**		**Hubei**		**Yunnan**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Output of crop production (Yuan)	y	2,262.38	2,020.37	3,716.76	2,741.78	4,356.72	3,151.30
Volume of labour input (working days)	x_1	63.59	64.58	164.88	125.09	151.50	126.86
Wage of labour (Yuan/working day)	w_1	34.29	19.63	22.24	12.33	14.82	10.96
Volume of intermediate input (Yuan)	x_2	611.44	528.93	626.11	522.88	805.03	855.58
Divisia price indices of intermediate input	w_2	1.14	0.10	1.19	0.14	1.10	0.06
Volume of capital input (Yuan)	k	8,864.49	1,2913.47	2,116.49	2,757.61	4,647.75	5,170.73
Rental price indices for capital	p_k	5.29	4.20	12.62	7.12	12.23	4.07
Volume of land input (mu)	l	2.42	1.59	4.79	2.47	7.35	5.75
Rental price for land (Yuan/mu)	p_l	163.83	51.83	70.35	43.35	97.39	87.14
No. of observations		**428**		**2,421**		**1,352**	

4. Results and discussion

The dynamic efficiency model defined in Section 2 can be viewed as the perfectly inefficient model. Following Cornwell, Schmidt and Sickles (1990), all allocative and technical efficiencies of the dynamic and variable factors are specified to vary across provinces and through time. Table 2 reports the estimated coefficients for the structural parameters of the dynamic efficiency model using ML and GMM estimations, assuming a constant real interest rate of 5%. The full set of estimated coefficients, including the dummy variables used to calculate the allocative inefficiency parameters of variable inputs and net investment demands and the technical inefficiency parameter of variable input demand, are available from the authors on request. Most estimated parameters from the ML estimation are significant at the .05 level using a two-tailed test except for the estimated parameters β_{w1k} and β_{pkt} in the net investment demand for capital equation. The R^2 values of net investment demand for capital and land are 0.345 and 0.532, respectively. A lag of two periods of autocorrelation terms is used to compute the covariance matrix of the orthogonality conditions for the GMM estimation. Most coefficient estimates from the GMM estimation, particularly the first-order coefficients, are significant at the 95% confidence interval using a two-tailed test, except for the estimated parameters β_l. The R^2 value of variable inputs demand is 0.847. The test of overidentifying restrictions from the GMM estimation using the Hansen (1982) J test is significant. The null hypothesis fails to be rejected, implying that the additional instrumental variables are valid, given that a subset of the instrumental variables is valid and exactly identifies the coefficient.[9]

Table 2. Estimated parameters of dynamic efficiency model

Parameter[a] Estimates	Capital Equation	Land Equation	Variable Input Equation
β_0	0.214**	0.831**	0.559***
β_{pk}	0.352***	-	-
β_{pl}	-	0.047**	-
β_k	-	-	0.331***
β_l	-	-	-0.058
β_y	-	-	0.073***
β_t	-	-	0.053***
β_{w1w1}	-	-	0.113***
β_{pkpk}	-0.876***	-	-
β_{plpl}	-	1.038***	-
β_{kk}	-	-	-2.068***
β_{ll}	-	-	-1.088**
β_{yy}	-	-	-0.033
β_{tt}	-	-	0.018
β_{w1pk}	3.083***	-	-
β_{w1pl}		0.478***	-
β_{w1k}	-0.124	-	-
β_{w1l}	-	-0.220***	-
β_{w1y}	-	-	0.056***
β_{w1t}	-	-	0.609***
β_{pkk}	21.739***	-	-
β_{pky}		-	0.403***

[9]Further, a hypothesis test regarding the presence of perfect efficiency in production is conducted using the likelihood ratio (LR) test. The LR test is approximately chi-square distributed with the degrees of freedom being equal to the number of restrictions. The LR test of the null hypothesis that farms are perfectly efficient in dynamic and variable factor demands is rejected at the 95% confidence level, implying that the farms in this study operated inefficiently in the production.

β_{pkt}	-0.291	-	-
β_{pll}	-	76.207***	-
β_{ply}	-	-	0.033
β_{plt}	-	2.370***	-
β_{ky}	-	-	2.821***
β_{kt}	-2.790**	-	-
β_{ly}	-	-	0.468***
β_{lt}	-	0.072***	-
β_{yt}	-	-	0.516***
Equation	**R^2**		
- Capital	0.345		
- Land		0.532	
- Labour			0.847
Test of overidentifying restrictions			214.168

[a] Price of intermediate input (w_2) was normalized.
Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. The regressions also include dummy variables used to calculate all efficiency parameters of dynamic and variable inputs, and the estimates are not reported here.

Table 3 presents the average farm technical and allocative efficiencies of dynamic and variable factors by province from 2003-2006. An estimate of the technical efficiency of dynamic and variable factors is bounded between zero and unity. The value of technical efficiency scores equal to one implies that a farm can minimize both dynamic and variable factors to produce a given level of output. The estimated technical efficiencies of variable inputs range from 0.325 to 0.910 with an average of 0.694, whereas those of net investment in quasi-fixed factors range from 0.382 to 0.837 with an average of 0.594. These findings imply that the Chinese farms in this study, on average, could reduce the variable and dynamic factors by 30.6% and 40.6%, respectively, and still produce the same level of output. The average value of the technical efficiency of variable and dynamic factors is 71.0% and 64.2% (for Zhejiang), 69.5% and 60.6% (for Hubei) and 66.5% and 59.2% (for Yunnan). Farms in Zhejiang achieved higher technical efficiencies of dynamic and variable factors than those in Hubei and Yunnan. Farms in Yunnan have the lowest technical efficiency scores in terms of both dynamic and variable factors.

When further checking the differences of scores across the three provinces, it can be seen that farms in Yunnan are less efficient at using variable inputs of labour and intermediate input, while farms in Zhejiang are much more efficient at using quasi-fixed inputs of land and capital. China's current land tenure system is actually a two-tier land tenure system in which the village collective and the individual household share the land rights, and the balance point can be anywhere from complete collective ownership to complete individual ownership (Dong 1996; Yao 2010). This characteristic also explains the considerable variations in land rights or land tenure security across regions in rural China. In Zhejiang, two mechanisms are applied to protect arable land and the right of rural households. One is the adoption of a 3-category provincial land classification scheme to influence the conversion of agricultural land for non-agricultural purposes, and the other is the implementation of a land compensation system which regulates the supply of agricultural land by requiring that agricultural land taken out of cultivation is replaced with reclaimed land of equal quantity and quality (Skinner et al. 2001). All these measures, which help mitigate or even eliminate the threat of insecurity, clearly motivate farm households to use labour forces more efficiently and to invest in the land.

Considering the allocative efficiency scores, the value of the allocative efficiency of dynamic factors is bound between zero and unity. The value of one implies that farms can use the dynamic factors in optimal proportions given their respective prices and the production technology. Average farm allocative efficiencies of net investments in capital and land are 0.758 and 0.628, respectively. These results suggest that Chinese farms could potentially reduce net investment in capital and land demands by 24.2% and 37.2%, respectively, to a cost-minimizing level. The average value of the allocative efficiency of capital and land inputs is 85.4% and 70.4% (for Zhejiang), 79.7% and 62.9% (for Hubei) and 61.8% and 57.0% (for Yunnan). The results indicate that farms in Zhejiang achieved higher allocative efficiencies of capital and land than those in Hubei and Yunnan. This finding is consistent with previous observations that factor markets function relatively better in Zhejiang – for example, the development of the land rental market. Statistics in Zhang et al. (2011) show that land rental activities are much more important in Zhejiang than in the other two provinces; the share of arable land rented out is, on average, 8.2% in Zhejiang, but only 1.3% in Hubei and 2.3% in Yunnan.

Following the shadow price approach, the price of intermediate input is arbitrarily specified as the numeraire. The value of the allocative efficiency of variable input demands represents price distortions of labour relative to the intermediate input. An estimate of allocative efficiency of labour input demands less (greater) than one means that the ratio of the shadow price of labour relative to the intermediate input is considerably less (greater) than the corresponding ratio of actual prices. This implies that farms are overusing (underusing) labour relative to the intermediate input. Table 3 also reports that average farm allocative efficiencies of labour input demands is 0.395. These results imply that farms in the three provinces are over-utilizing labour relative to the intermediate input in the crop production. The average value of the allocative efficiency of labour input demands is 40.5% (for Zhejiang), 36.6% (for Hubei) and 37.7% (for Yunnan). This relatively severe price distortion is not particularly surprising since obstacles[10] still hinder the free migration of rural labour, although controls on rural labour mobility were greatly relaxed after the Reform.

Table 3. Average farm technical and allocative efficiency scores of dynamic and variable factor demands, 2003-2006

Efficiency scores*	Zhejiang	Hubei	Yunnan	All provinces
TE(x)	0.710	0.695	0.665	0.694
TE(q)	0.642	0.606	0.592	0.594
AE(k)	0.854	0.794	0.618	0.758
AE(l)	0.704	0.629	0.570	0.628
AE(w_1)	0.405	0.366	0.377	0.395

Note: *TE(x) = technical efficiency of variable inputs; TE(q) = technical efficiency of dynamic factors; AE(k) = allocative efficiency of net investment in capital; AE(l) = allocative efficiency of net investment in land; AE(w_1) = allocative efficiency of labour input.

Table 4 presents average annual technical and allocative efficiency scores of the dynamic and variable factor demands for each province over the period 2003-2006. The findings in Table 4 allow us to examine the performance of crop production on farms after three decades of reform. Farms in Zhejiang and Hubei have an average annual technical efficiency of dynamic and variable factors higher than those in Yunnan. During the period 2003-2006, technical efficiency scores of variable inputs in all provinces increase over time. In contrast, technical efficiency scores of dynamic factors in all provinces decrease over time. Average annual allocative efficiencies of dynamic factors for both capital and land in Zhejiang and Hubei are higher than in Yunnan in every year over the study period. This result suggests that farms in Zhejiang and Hubei were able to adjust their dynamic factors to a cost-minimizing level, more easily than those in Yunnan. During the period 2003-2006, allocative efficiency scores of the net investment in capital by farms in Zhejiang increase over time. In contrast, allocative efficiency scores of the net investment in capital by farms in Yunnan decrease over time, while the allocative efficiency score of the net investment in capital in Hubei varies considerably over the period. Allocative efficiency scores of the net investment in land by farms in Zhejiang and Hubei also increase over time, while the allocative efficiency score of the net investment in capital by farms in Yunnan varies with a decreasing

[10]For instance, the implementation of Household Registration System (hukou) divided people into those holding a rural hukou and those with an urban hukou. Under the constraints of the hukou system, rural migrants face residence discrimination and lack access to public services like education, health care and public welfare in cities (OECD, 2009).

trend over the period. The allocative efficiency estimates of the variable inputs during the 2003-2006 period indicates that farms in Hubei and Yunnan tend to increase over-utilization in labour relative to intermediate input, whereas farms in Zhejiang tend to decrease over-utilization in labour relative to intermediate input.

Table 4. Average annual technical and allocative efficiency scores of dynamic and variable factor demands for each province, 2003-2006

Efficiency scores	Zhejiang				Hubei			
	2003	2004	2005	2006	2003	2004	2005	2006
TE(x)	0.642	0.658	0.754	0.787	0.646	0.670	0.720	0.742
TE(q)	0.683	0.667	0.616	0.603	0.666	0.635	0.570	0.551
AE(k)	0.819	0.839	0.864	0.892	0.769	0.808	0.788	0.817
AE(l)	0.675	0.696	0.717	0.727	0.575	0.620	0.655	0.665
AE(w_1)	0.373	0.395	0.412	0.440	0.440	0.350	0.319	0.358
Efficiency scores	**Yunnan**				**All provinces**			
	2003	**2004**	**2005**	**2006**	**2003**	**2004**	**2005**	**2006**
TE(x)	0.627	0.655	0.679	0.698	0.638	0.661	0.718	0.742
TE(q)	0.606	0.644	0.569	0.548	0.652	0.649	0.585	0.567
AE(k)	0.652	0.657	0.596	0.567	0.747	0.759	0.756	0.759
AE(l)	0.626	0.547	0.564	0.534	0.625	0.628	0.637	0.645
AE(w_1)	0.431	0.343	0.398	0.338	0.415	0.362	0.376	0.378

Turning to the role of adjustment costs in Chinese farm crop production, the partial adjustment coefficient of quasi-fixed factors is defined in equation (12) in section 2.1. Given the discount rate of 5%, the findings (Table 2) show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low. The estimated adjustment rate is 4.54% per annum for capital and 3.84% per annum for land, or it may take capital approximately 22 years and land approximately 26 years to adjust fully to its long-run equilibrium level.

Further, the optimal stocks defined in equation (13) in section 2.1 are calculated and compared to the actual stocks. The ratio of optimal quasi-fixed factors to actual quasi-fixed factors accounts for capacity utilization, which provides some insights into the efficiency of quasi-fixed factor uses by a farm. Values of the ratio of optimal quasi-fixed factors to actual quasi-fixed factor stocks greater than one imply that a farm is under-utilizing quasi-fixed factors, while values less than one imply that a farm is over-utilizing quasi-fixed factors.

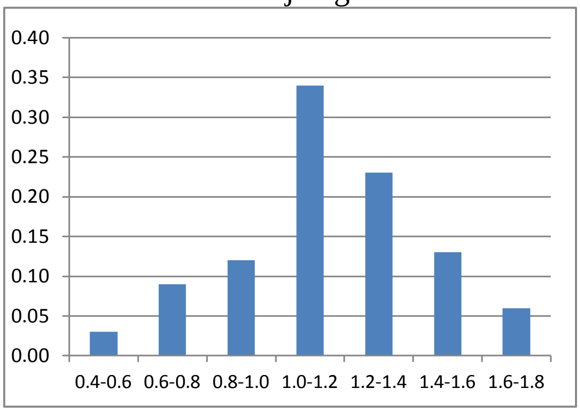
Figure 1 and Appendix Table A1 present the distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors by farm in each province. The findings in Figure

1(a) show that the estimates of the ratio of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745 with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, which is a sign of under-utilization in capital prevailing in crop production. Looking into the statistics of each province, the differences are evident, with 42% of the farms in Zhejiang, 67% in Hubei, and 85% in Yunnan being under-capitalized. The performance of Zhejiang is relatively good, with 34% of the farms nearly optimizing their capital use in the range of 1.0-1.2. On the contrary, most of the farms in Hubei and Yunnan still have the potential to reach the optimal level by increasing their capital stocks.

Turning to land utilization, Figure 1(b) provides some insights into the efficiency of land use by a farm in each province. The estimates of the ratio of optimal land (L^*) to actual land (L) range from 0.124 to 1.354, with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels, which is explained as an over-utilization of land input. This finding is consistent with the common inverse relationship between farm size and productivity in developing country agriculture (Berry and Cline, 1979) where smaller farms tend to more intensively use their labour in the absence of perfect factor markets. As is shown in our results, the area of actual land utilization is higher than that of the optimal level for most of the farms.

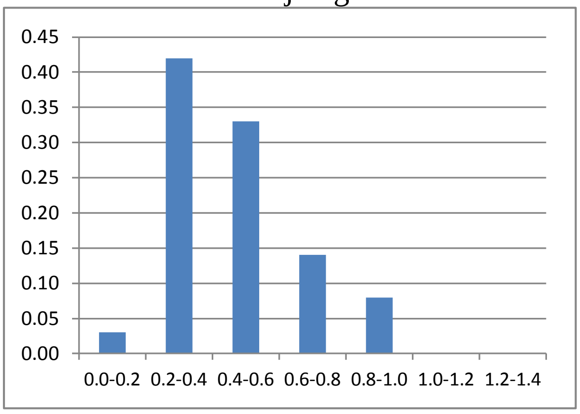
Figure 1. Distribution of the ratio of optimal capital to actual capital

Zhejiang

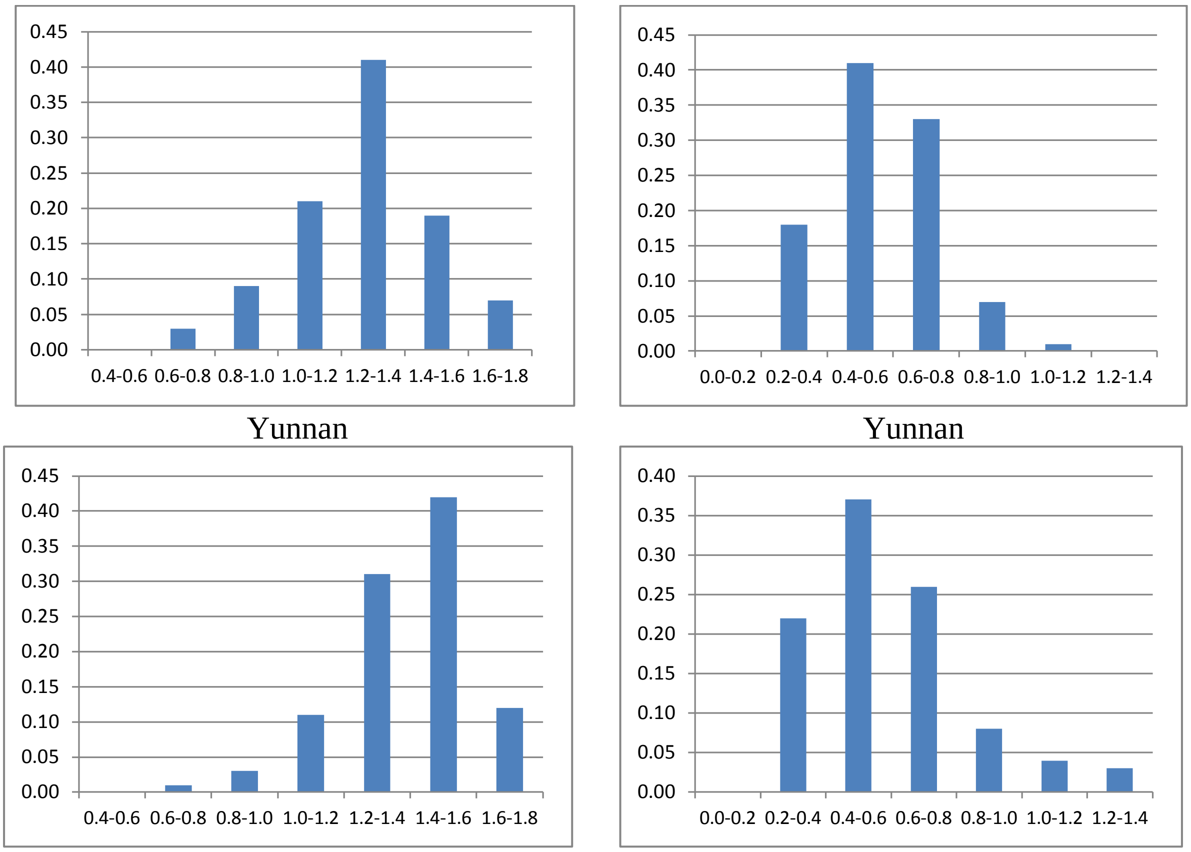


Hubei

Zhejiang



Hubei



(a) K^*/K **(b) L^*/L**

Table 5 presents weighted-average estimates of the short- and long-run dynamic scale and cost elasticities by province and all farms from 2003-2006. The estimates of the short-run scale elasticities range from 0.624 to 0.945 with an average of 0.828, while the long-run scale elasticities range from 0.678 to 0.985 with an average of 0.857. All farms indicate the presence of decreasing returns to scale in both the short and long run. In addition, the weighted-average estimated results of scale elasticities indicate modestly decreasing returns to scale in the long run and considerably higher ones in the short run. The weighted-average estimate of scale elasticities of farms in Zhejiang is higher than those in Hubei and Yunnan in both the short and long run, respectively. The estimates of the short-run cost elasticities range from 1.064 to 1.628, with an average of 1.269, while the long-run cost elasticities range from 1.078 to 1.715, with an average of 1.222. All farms present decreasing returns to scale in both the short and long run. Consistent with the measure of scale elasticity, the results of cost elasticities are hence robust. The estimated results of the short- and long-run dynamic cost elasticities suggests that farms in Yunnan have a higher degree of decreasing returns to scale compared to farms in Zhejiang and Hubei.

Table 5. Short- and long-run scale and cost elasticity (2003-2006)

	Zhejiang	Hubei	Yunnan	All provinces
Scale Elasticity				
- Short-run	0.893	0.865	0.742	0.828
- Long-run	0.945	0.915	0.725	0.857
Cost Elasticity				
- Short-run	1.194	1.215	1.389	1.269
- Long-run	1.025	1.142	1.427	1.222

5. Conclusions

This study contributes to the ongoing debate on the structural transformation of farm production in China. We analysed this phenomenon by examining the economic performance of Chinese farms. By developing a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making, the dynamic cost efficiency model allows us to consider the impact of allocative and technical efficiency in Chinese agriculture, as well as the adjustment costs resulting from the change of quasi-fixed input use. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006. This is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. With the parameter estimates from the model, we further calculate the partial adjustment coefficients of quasi-fixed factors, the optimal stocks of quasi-fixed factors, and the short- and long-run dynamic scale and cost elasticities.

Our results show that, in terms of technical efficiency, the farms in this study, on average, could have reduced their variable and dynamic factors by 30.6% and 40.6%, respectively, and still have produced the same level of output. Regional differences are evident, indicating that farms in Zhejiang perform the best while farms in Yunnan have the lowest scores. Considering the allocative efficiency scores of net investments in dynamic factors, our results show that farms could potentially reduce their net investments in capital and land demands by 24.2% and 37.2% to reach a cost-minimizing level. Farms in Zhejiang still achieve the highest level compared to those in the other two provinces. The average allocative efficiency of net investment in labour demands is relatively low at 0.395, indicating a severe price distortion of labour relative to the intermediate input, which implies the over-utilization of labour relative to the intermediate input in crop production.

Turning to the role of adjustment costs in Chinese farm crop production, the findings show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low, which implies a rather sluggish adjustment process and considerably high adjustment costs. The ratios of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745, with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, a sign that the under-utilization of capital prevails in crop production. On the contrary, the ratios of optimal land (L^*) to actual land (L) range from 0.124 to 1.354 with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels. According to these findings, there also exist high degrees of over-utilization in land, prevailing in crop production. The estimates of the short- and long-run dynamic scale and cost elasticities are robustly consistent, which indicates the presence of decreasing returns to scale in both the short and long run.

Based on the findings of this study, important policy implications can be derived for the future development of agricultural production in China. The relatively low levels of technical and allocative efficiencies indicate that most farms are unable to catch up with the production frontier under the existing production technology, or to use various inputs in appropriate proportions given their respective prices. Since the inefficiencies are normally associated with motivation, information, and institutional environment problems, policy makers should pay more attention to various factor market reforms as a whole. This statement is reinforced by the relatively low estimated adjustment rates of the quasi-fixed factors, implying high adjustment costs. We introduced adjustment costs in the model to capture those forces or economic situations that impose some penalty on the farm beyond the acquisition cost, and hence slow down the adjustment process of production factors.

Farmers' rights to land should be strengthened and extended so that land tenure is more secure. Possible policy measures could include complete land titling to grant full property rights to farmers and hence establish a foundation for the development of rural rental and credit markets where land could be used as collateral; extending the duration of land-use contracts to perpetuation; this duration is currently 30 years. At the same time, policy measures are needed to encourage rural labour mobility, for instance, the Household Registration System (hukou) needs to be reformed to provide migrant workers with equal access to public services in cities. The migration process will be smoother when farmers' rights to land are protected and secure.

The presence of decreasing returns to scale in both the short and long run also has important policy implications with respect to the government's recent policy focus on supporting the creation of large-scale farms. The simple action of integrating farms will neither increase productivity nor farmers' income. Adjusting the structure of farm production is needed in order to reach the optimal proportion of various input use. The progress of this adjustment will also rely on the successful reform of land and labour markets.

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Appendix

Table A1. The distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors

	Frequency		
K^*/K	**Zhejiang**	**Hubei**	**Yunnan**
0.4-0.6	0.03	0.00	0.00
0.6-0.8	0.09	0.03	0.01
0.8-1.0	0.12	0.09	0.03
1.0-1.2	0.34	0.21	0.11
1.2-1.4	0.23	0.41	0.31
1.4-1.6	0.13	0.19	0.42
1.6-1.8	0.06	0.07	0.12
	1.00	1.00	1.00
	Frequency		
L^*/L	**Zhejiang**	**Hubei**	**Yunnan**
0.0-0.2	0.03	0.00	0.00
0.2-0.4	0.42	0.18	0.22
0.4-0.6	0.33	0.41	0.37
0.6-0.8	0.14	0.33	0.26
0.8-1.0	0.08	0.07	0.08
1.0-1.2	0.00	0.01	0.04
1.2-1.4	0.00	0.00	0.03
	1.00	1.00	1.00

Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach

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Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach

Abstract

To understand the state of adjustment processes and dynamic structure in Chinese agriculture, this paper proposes a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making. Using a panel data set of 4,201 Chinese farms from three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006, this is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. The findings show that the adjustment of quasi-fixed inputs is rather sluggish, implying that adjustment costs are considerably high on Chinese farms. The relatively low levels of allocative and technical efficiencies indicate that most of farms are unable to catch up with the production frontier under the existing production technology and that they are unable to use various inputs in the appropriate proportion given their respective prices.

Keywords: Chinese agriculture, dynamic efficiency, adjustment cost, shadow cost approach

JEL codes: D21, D61, Q12

Examining the Economic Performance of Chinese Farms: a Dynamic Efficiency and Adjustment Cost Approach

1. Introduction

China's agriculture development has been remarkable over the past four decades. The rural reform that began in the late 1970s improved farmers' incentives and had a huge impact on China's agricultural productivity growth and output. The value of agricultural output increased enormously, from 139.7 billion Chinese yuan in 1978 to 10,222.6 billion yuan in 2014.[1] Agricultural total factor productivity (TFP) has also grown extremely fast—by 4% per annum on average from 1979 to 2008 (Zhang and Brümmer, 2011). The great achievement of China's agricultural production has so far come almost entirely from smallholder farming, represented by about 200 million small-scale farms.

Despite great successes, many challenges remain or even increased during the last decade. For instance, the continued rising opportunity costs of agricultural labor will lead to the gradual loss of China's competitive labor advantage. Further, household rights to land are still incomplete after several waves of land tenure reforms (Ma et al., 2015). This induced land insecurity reduces the incentives of farmers to perform productivity-enhancing investments in land (e.g. irrigation, drainage, terracing and the application of organic fertilizer), and hinders the efficient use of labor (Brandt et al., 2002; Deininger and Feder, 2001), and as a result decreases agricultural productivity.

China's major agricultural policy objectives have been consistent in their aims to increase grain production capacity to largely ensure food self-sufficiency and at the same time improve farmers' income. Since 2004 the No. 1 Documents[2] of each year have concentrated on issues related to agriculture, farmers and the countryside (the so-called 'three nongs'). In recent years these documents have focused on investments in agricultural technology to boost production and the adjustment of farm structure, emphasizing a transition to larger-scale farms (OECD, 2013, 2015). In this context, the role of adjustment costs and dynamic cost structure are becoming important issues for investigating performance in Chinese agriculture. Whether adjustment costs are significant and whether they can be regarded as a source of the sluggish adjustment processes are of interest to policymakers. Considering the major challenges in Chinese agricultural production, the extent to which

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[1]The statistics are taken from China Statistical Yearbook 2015, National Bureau of Statistics of China.

[2]No. 1 Documents are the top-priority documents issued jointly at the beginning of each year by the Central Committee of the Communist Party and the State Council. They are the first major policy directives of the year and give policy suggestions for the National People's Congress (OECD, 2009).

Chinese farms could perform better remains an important research question. A measure of cost efficiency and its decomposition provides an indicator that measures the exploitation of resources (technical efficiency) in Chinese agriculture, as well as an indicator that characterises the economic losses due to a suboptimal allocation of the resources (allocative inefficiency). Furthermore, this study addresses the issue by characterizing the cost structure of Chinese farms under dynamic adjustment to measure their performance.

A frontier-based model using a parametric approach to estimate firm efficiency has been an important area of research that has been continuously developed for more than half a decade. Following the pioneering work of Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), the frontier analysis model has been employed for both primal and dual representations of production technologies. With the availability of input quantity and cost share data, a dual cost frontier approach allows researchers to estimate and decompose the firm's cost efficiency into technical and allocative efficiencies. Analysis of the cost frontier models has further grown with important contributions by many researchers (Schmidt and Lovell; 1979; Kopp and Diewert 1982; Zieschang 1983; Bauer 1990; Greene 1993; Kumbhakar 1997; Maietta 2000; Atkinson and Primont 2002; Assaf and Matawie 2008). However, the cost frontier models presented in these studies were developed under the static context. The shortcomings of the static frontier-based model include ignoring the explicit role of time and how the adjustment of quasi-fixed inputs to the observed long-run level takes place. As a result, efficiency scores measured from the static efficiency model may be inaccurate and misleading. The absence of an explicit analysis of the transition path of quasi-fixed factors toward their desired long-run levels can be remedied by explicitly incorporating the costs of adjustment for the quasi-fixed factors. The framework of the optimal inter-temporal behavior of the firm using the notion of adjustment costs as a means of solving the firm's optimization problem was first introduced by Eisner and Strotz (1963). The theory of inter-temporal duality was improved upon by McLaren and Cooper (1980a) and Epstein (1981). This theory represents an alternative and powerful method for solving inter-temporal optimization problems by using the optimal value function of the dynamic programming equation (DPE) approach. This field has further grown with important contributions by many researchers (i.e. Vasavada and Chambers 1986; Howard and Shumway 1988; Luh and Stefanou 1991, 1993; Fernandez-Cornejo et al. 1992; Manera 1994; Pietola and Myers 2000; Sckokai and Moro 2009). Though the static efficiency model and the dynamic duality model of inter-temporal decision making have been continuously developed, they have moved in separate directions. Recently, Rungsuriyawiboon and Stefanou (2007) formalized theoretical and econometric models of dynamic efficiency in the presence of inter-temporal cost-minimizing firm behavior. The dynamic efficiency model is developed by integrating the static production efficiency model and the dynamic duality model of inter-temporal decision making. The dynamic efficiency model defines the relationship between the actual and behavioral value function of the DPE for a firm's inter-temporal cost minimisation behavior. Therefore, the dynamic efficiency model provides the system of equations that allows the measurement of both the technical and allocative inefficiency of firms.

Other studies of Chinese agricultural performance have relied on conventional approaches and employed static frontier-based models (Brümmer et al., 2006; Wang et al., 2012; Zhang et al., 2011). In addition, given that these studies mostly investigated the performance of Chinese farms based upon different data sets and time periods, it goes without saying that a cross-study comparison is precluded by the lack of a common basis. Brümmer et al. (2006) use a distance function approach with farm household data in Zhejiang Province for the period 1986–2000, and the results show that the level of technical efficiency range from 0.326 to 0.878. Zhang et al. (2011) apply a two-stage model with a panel data set containing households from Zhejiang, Hubei and Yunnan to analyze the impact of land reallocation on farm production, and the estimated level of technical efficiency is relatively high with the average scores being 0.96, 0.91, and 0.87, respectively. Within a meta-frontier framework, Wang et al. (2012) provide evidence that technical efficiency is significantly affected by farm heterogeneity and that farming technology exhibits region-specific characteristics.

To fill these gaps, the main purpose of the study is to understand the state of adjustment process and dynamic structure in Chinese agriculture. To meet this goal, our paper extents the model of Rungsuriyawiboon and Stefanou (2007) into a more general context with a multiple quasi-fixed factor case. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) over the period 2003-2006. This is the first study to investigate the allocative and technical efficiency of Chinese agriculture using a dynamic shadow cost approach. The production technology of Chinese farms is presented by one output variable, two variable inputs (labor and intermediate inputs) and two quasi-fixed factors (land and capital).

The remainder of the paper is organized as follows. The next section presents the theoretical framework and mathematical derivations of the dynamic efficiency model for the multiple quasi-fixed factor case. The subsequent section discusses the data set and the definitions of the variables used in this study. The next section elaborates the econometric model of the dynamic efficiency model with the two quasi-fixed factor case. The results of our empirical analysis are presented and discussed in the next section, while the final section concludes and summarizes.

2. Model specification

2.1 Derivation of a dynamic efficiency model of inter-temporal cost minimization

This section develops a dynamic efficiency model in the context of inter-temporal cost minimization. The framework of the optimal inter-temporal behavior of the firm uses the notion of adjustment costs as a means of solving the firm's optimization problem. The adjustment cost approach attempts to capture all of the unobserved forces that slow down the adjustment of some factors in production such as learning cost, search costs, costs arising from market forces, or contractual obligations (Stefanou, 1989). The presence of adjustment costs formalizes the process of characterizing a firm's dynamic production decisions. In the presence of adjustment costs for the quasi-fixed factors, a firm faces additional costs for the adjustment of quasi-fixed factors beyond acquisition costs in the decision making process.

The dynamic economic problem facing the firm can be addressed by characterizing firm investment behavior as the firm seeks to minimize the discounted sum of future production costs over an infinite horizon. The firm's decision making focuses on the optimal determination of its factor inputs use, which has implications for its capacity utilization. For instance, the purchase and installation of quasi-fixed factors involve a cost of adjustment since the firm must devote internal resources to acquire and adapt the newly-purchased quasi-fixed inputs. Production costs arise from purchasing new inputs, including both variable and quasi-fixed inputs. Units of the quasi-fixed inputs are acquired both for enlarging the existing productive capacity and for replacing worn-out units.

Let $\mathbf{x} \in R_{+}^{N}$ and $\mathbf{q} \in R_{+}^{Q}$ denote non-negative vectors of variable and quasi-fixed inputs, respectively. Similarly, $\mathbf{w} \in R_{++}^{N}$ and $\mathbf{p} \in R_{++}^{Q}$ denote strictly non-negative vectors for variable input prices and quasi-fixed factor prices, respectively.

Following Epstein and Denny (1983) and Stefanou (1989), who assume that economic agents are risk-neutral and that their price expectations are static, the dynamic inter-temporal model of a firm's cost minimization problem can be expressed as

$$(1) \qquad J(\mathbf{w}',\mathbf{p}',\mathbf{q}',y(t)) = \min_{\mathbf{I}>0} \int_{t}^{\infty} e^{-rs}[\mathbf{w}'\mathbf{x}(s) + \mathbf{p}'\mathbf{q}(s)]ds$$

subject to $\dot{\mathbf{q}}(s) = \mathbf{I}(s) - \delta\mathbf{q}(s)$, $\mathbf{q}(0) = \mathbf{q}_0 > 0$, $\mathbf{q}(s) > 0$, $y(s) = F[\mathbf{x}(s), \mathbf{q}(s), \dot{\mathbf{q}}(s)]$ $\forall s \in [t, \infty)$

where r is the constant discount rate, δ is the constant depreciation rate, y is output, $\dot{\mathbf{q}} \in R_{+}^{Q}$ and $\mathbf{I} \in R_{+}^{Q}$ are non-negative vectors of net investment and gross investment in quasi-fixed factors, $y(s)$ is a sequence of production targets over the planning horizon starting at time t, and $F[\mathbf{x}'(s), \mathbf{q}'(s), \dot{\mathbf{q}}'(s)]$ is the single output production function. Including net investment $\dot{\mathbf{q}}$ in the production function reflects the internal costs associated with the adjustment of quasi-fixed factors in terms of foregone output. The presence of internal adjustment cost implies output decreases (increases) with the expansion (contraction) of the quasi-fixed factor stocks (i.e. $\dot{\mathbf{q}}\nabla_{\dot{\mathbf{q}}}F < 0$). In addition, the marginal cost of adjustment in physical terms is assumed to increase with the speed of adjustment, implying $\nabla_{\dot{\mathbf{q}}\dot{\mathbf{q}}}F < 0$, where the diseconomies accompanying adjustment takes place. Therefore, the sluggish or gradual behavior in adjusting the levels of quasi-fixed factors is assured. The production function is assumed to be concave in $\dot{\mathbf{q}}$, implying an increasing marginal cost of adjustment.

McLaren and Cooper (1980a) and Epstein (1981) introduced the inter-temporal duality theory, which presents the relationship between the underlying technology and value functions. The dynamic duality between the underlying technology and value functions permits the derivation of a system of variable and dynamic demand equations. Analytically, the dynamic decision problem can be solved using the dynamic duality approach, which allows the use of appropriate static optimization techniques as expressed in the dynamic programming equation (DPE) or Hamilton-Jacobi-Bellman equation. The value function of the DPE for the inter-temporal cost minimization can be expressed as

(2) $$rJ(\mathbf{w}', \mathbf{p}', \mathbf{q}', y, t) = \min_{\mathbf{x}, \dot{\mathbf{q}} > 0} \left\{ \mathbf{w}'\mathbf{x} + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J' \dot{\mathbf{q}} + \gamma(y - F[\mathbf{x}', \mathbf{q}', \dot{\mathbf{q}}', t]) + \nabla_t J \right\}$$

where t is the time trend variable, γ is the Lagrangian multiplier associated with the production function, and $\nabla_t J$ is the shift of the value function due to technical change.

The result of inter-temporal duality theory provides readily-implemented systems of dynamic factor demands. Differentiating the optimized version of the DPE with respect to $\mathbf{p}$ and $\mathbf{w}$ yields optimal net investment demand and optimal variable input demand, respectively,

(3) $$\dot{\mathbf{q}}^{o} = (\nabla_{\mathbf{qp}} J)^{-1}(r\nabla_{\mathbf{p}} J - \mathbf{q} - \nabla_{\mathbf{p}t} J)$$

(4) $$\mathbf{x}^{o} = r\nabla_{\mathbf{w}} J - \nabla_{\mathbf{wq}} J \dot{\mathbf{q}}^{o} - \nabla_{\mathbf{w}t} J \, .$$

Equation (2) can be interpreted as the dynamic inter-temporal model of a firm’s cost minimization problem in the presence of perfect efficiency. When a firm neither minimizes its factor inputs given output levels, nor uses the factors according to respective prices and production technology, it is operating inefficiently, both technically and allocatively. A measure of inefficiency can be obtained by adopting a shadow price approach, as described in Kumbhakar and Lovell (2000).

The dynamic efficiency model is constructed by defining the relationship between actual and shadow (behavioral) value functions of the DPE for the firms' inter-temporal cost minimization behavior. The actual value function can be viewed as the perfectly efficient condition, whereas the behavioral value function of the DPE is expressed in terms of shadow input prices, quasi-fixed factors and output. The shadow input prices are constructed to generate an optimality relationship. Moreover, as the shadow input prices will differ from market (actual) prices in the presence of inefficiency, a firm's inefficiency can be estimated and evaluated as the deviation between the actual and behavioral value function.

The behavioral value function of the DPE for the firms' inter-temporal cost minimization behavior that corresponds to the shadow prices and quantities can be expressed as

(5) $$rJ^b(\mathbf{w}^{b\prime},\mathbf{p}',\mathbf{q}',y,t) = \mathbf{w}^{b\prime}\mathbf{x}^b + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^{b\prime}\dot{\mathbf{q}}^b + \gamma^b(y - F[\mathbf{x}^{b\prime},\mathbf{q}',\dot{\mathbf{q}}^{b\prime},t]) + \nabla_t J^b$$

where $\mathbf{x}^b \in R_+^N$ and $\dot{\mathbf{q}}^b \in R_+^Q$ are nonnegative vectors of behavioral variable and quasi-fixed inputs, respectively, $\mathbf{w}^b \in R_{++}^N$ and $\nabla_{\mathbf{q}} J^b \in R_{++}^Q$ are strictly non-negative vectors of behavioral variable input prices and the marginal valuation of behavioral dynamic factors, γ^b is the behavioral Lagrangian multiplier defined as the short-run, instantaneous marginal cost, and $\nabla_t J^b$ is the shift of the behavioral value function.

Following the shadow price approach, $\mathbf{x}^b$ and $\dot{\mathbf{q}}^b$ can be expressed in terms of actual variable and dynamic factors as $\mathbf{x}^b = \boldsymbol{\tau}_x^{-1}\mathbf{x}$ and $\dot{\mathbf{q}}^b = \boldsymbol{\tau}_q^{-1}\dot{\mathbf{q}}$, respectively, where $\boldsymbol{\tau}_x \geq 1$ and $\boldsymbol{\tau}_q \geq 1$ represent inverse producer-specific scalars that provide input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively. Similarly, the behavioral prices can be expressed in terms of actual prices of variable inputs $\mathbf{w}^b = \boldsymbol{\Lambda}_{\mathbf{w}}\mathbf{w}$ and dynamic factors $\nabla_{\mathbf{q}} J^b = \boldsymbol{\Sigma}_{\mathbf{q}}\nabla_{\mathbf{q}} J^a$, where $\boldsymbol{\Lambda}_{\mathbf{w}}$ and $\boldsymbol{\Sigma}_{\mathbf{q}}$ are allocative inefficiencies of the variable and quasi-fixed inputs, respectively.

Differentiating equation (5) with respect to $\mathbf{p}$ and $\mathbf{w}^b$ yields the behavioral conditional demand for the dynamic and variable factors, respectively.

In the presence of technical inefficiency of dynamic and variable factors, the corresponding observed demand for the dynamic and variable factors using the input-oriented approach can be written in terms of the optimized demand for the dynamic and variable factors as

$$(6) \qquad \dot{\mathbf{q}}^o = \boldsymbol{\tau}_q \dot{\mathbf{q}}^b = \boldsymbol{\tau}_q (\nabla_{\mathbf{qp}} J^b)^{-1} (r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)$$

$$(7) \qquad \mathbf{x}^o = \boldsymbol{\tau}_x \mathbf{x}^b = \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (r\nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{wq}} J^b \dot{\mathbf{q}}^b - \nabla_{\mathbf{w}t} J^b)$$

where $\nabla_{\mathbf{w}^b} J^b = \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \nabla_{\mathbf{w}} J^b$.

The value function corresponding to the actual prices and quantities at the optimal level can be defined as

$$(8) \qquad rJ^a(\cdot) = \mathbf{w}'\mathbf{x}^o + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}} J^a{}' \dot{\mathbf{q}}^o + \nabla_t J^a .$$

Inserting equations (6) and (7) in equation (8), the optimized actual value function can be rewritten in terms of the behavioral value function as

$$(9) \qquad \begin{aligned} rJ^a(\cdot) = {} & \mathbf{w}'\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (r\nabla_{\mathbf{w}} J^b - \nabla_{\mathbf{qw}} J^b{}'[(\nabla_{\mathbf{qp}} J^b)^{-1} (r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] - \nabla_{\mathbf{w}t} J^b) \\ & + \mathbf{p}'\mathbf{q} + \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{q}} J^b{}' \boldsymbol{\tau}_q [(\nabla_{\mathbf{qp}} J^b)^{-1} (r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)] + \nabla_t J^a \end{aligned}$$

where $\nabla_t J^a = \nabla_t J^b$ implies that the shift in the behavioral value function is proportional to that in the actual value function.

Differentiating equation (9) with respect to $\mathbf{p}$ (up to second-order derivatives), the optimized actual demand for the dynamic factors in terms of the behavioral value function yields

$$(10) \qquad \begin{aligned} & \left[\mathbf{ii}'/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} (\nabla_{\mathbf{qp}} J^b + \nabla_{\mathbf{qq}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b - \mathbf{ii}'/r) - \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \nabla_{\mathbf{qp}} J^b\right] \dot{\mathbf{q}}^o = \\ & \quad + [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} (\nabla_{\mathbf{wp}} J^b - \nabla_{\mathbf{qw}} J^b{}' (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b)' \mathbf{w} \\ & \quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[r(\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}} J^b - (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}t} J^b\right] \\ & \quad + (\mathbf{i} - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1}) \nabla_{\mathbf{p}t} J^b] \end{aligned}$$

where **i** is a unit vector of appropriate dimension.

Similarly, differentiating equation (9) with respect to $\mathbf{w}$ (up to second-order derivatives), the optimized actual demand for the variable inputs in terms of the behavioral value function yields

$$(11) \qquad \begin{aligned} \mathbf{x}^o = {} & \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \begin{bmatrix} r[\nabla_{\mathbf{ww}} J^b - \nabla_{\mathbf{qw}} J^b{}' (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{wp}} J^b{}']\mathbf{w} + r\nabla_{\mathbf{w}} J^b \\ -\nabla_{\mathbf{w}t} J^b + \nabla_{\mathbf{qw}} J^b{}' (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{p}t} J^b \end{bmatrix} \\ & + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[r\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}} J^b - \nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}t} J^b\right] \\ & + \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \left[\nabla_{\mathbf{qw}} J^b{}' - \nabla_{\mathbf{qw}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} (\nabla_{\mathbf{qp}} J^b - \mathbf{i}/r) + \boldsymbol{\tau}_q \nabla_{\mathbf{qw}} J^b{}'\right] \dot{\mathbf{q}}^o \\ & + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_{\mathbf{q}}^{-1} \left[\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{qq}} J^b\right] \dot{\mathbf{q}}^o \end{aligned} .$$

Equations (10) and (11) form the system equations of the dynamic efficiency model for inter-temporal cost minimization. When all inefficiency parameters in the model are equal to one, the dynamic efficiency model reduces to the dynamic inter-temporal model of a firm's cost minimization problem in the presence of perfect efficiency as presented in Epstein and Denny (1983).

By using an econometric approach based on the dynamic optimization behavior developed by Treadway (1974), the optimal investment demand function can be expressed as

$$(12)\qquad \dot{\mathbf{q}}^* = \dot{\mathbf{q}}^b = \mathbf{M}(\mathbf{q} - \mathbf{q}^*)$$

where $\mathbf{M} = (r\mathbf{ii}' - \nabla_{\mathbf{qp}} J^b)^{-1}$ is the partial adjustment coefficient that indicates how quickly the gap between the current level of quasi-fixed factors stock ($\mathbf{q}$) and the optimal capital stock levels($\mathbf{q}^*$) is closed in a given instant.

The stock of quasi-fixed factors evolves over time at an endogenous rate and the steady state or optimal quasi-fixed factors stock is defined as

$$(13)\qquad \mathbf{q}^* = \mathbf{q} - \mathbf{M}^{-1}(\nabla_{\mathbf{qp}} J^b)^{-1} \cdot (r\nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{p}t} J^b)\,.$$

2.2 Econometric model

An econometric model of the dynamic efficiency model for inter-temporal cost minimization is presented in this section. This study focuses on a production technology with two quasi-fixed factors (capital and land), i.e. $\mathbf{q} \in (k, l)$. When farmers decide to increase farm land, capital will not be simultaneously affected. Rather, it might take several periods for net investment to adjust. Therefore, the decision to increase farm land is not fully dependent on the decision to increase a farm's capital. When both capital and land are independent, the off-diagonal elements of the $\nabla_{\mathbf{qp}} J^b$, $\nabla_{\mathbf{qq}} J^b$ and $\nabla_{\mathbf{pp}} J^b$ matrices, i.e. $J^b_{kp_l}$, $J^b_{lp_k}$, J^b_{kl}, and $J^b_{p_k p_l}$ are each equal to zero.

The optimized actual demand for the dynamic factors in equation (10) can be written as

$$(14)\qquad \begin{aligned} &[1/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}(J^b_{kp_k} + J^b_{kk}(J^b_{kp_k})^{-1} J^b_{p_k p_k} - 1/r) - \boldsymbol{\Sigma}_k^{-1} J^b_{kp_k}]\dot{k} \\ &\quad = [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J^b_{\mathbf{w}p_k} - J^b_{k\mathbf{w}}{}'(J^b_{kp_k})^{-1} J^b_{p_k p_k})'\mathbf{w} \\ &\quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}[r(J^b_{kp_k})^{-1} J^b_{p_k p_k} J^b_k - (J^b_{kp_k})^{-1} J^b_{p_k p_k} J^b_{tk}] + (1 - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1}) J^b_{p_k t}] + \varepsilon_1 \end{aligned}$$

$$(15)\qquad \begin{aligned} &[1/r + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}(J^b_{lp_l} + J^b_{ll}(J^b_{lp_l})^{-1} J^b_{p_l p_l} - 1/r) - \boldsymbol{\Sigma}_l^{-1} J^b_{lp_l}]\dot{l} \\ &\quad = [r\boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1}(J^b_{\mathbf{w}p_l} - J^b_{l\mathbf{w}}{}'(J^b_{lp_l})^{-1} J^b_{p_l p_l})'\mathbf{w} \\ &\quad + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}[r(J^b_{lp_l})^{-1} J^b_{p_l p_l} J^b_l - (J^b_{lp_l})^{-1} J^b_{p_l p_l} J^b_{tl}] + (1 - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1}) J^b_{p_l t}] + \varepsilon_2 \end{aligned}$$

where $\boldsymbol{\tau}_x$ and $\boldsymbol{\tau}_q$ are inverse producer-specific scalars providing input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively, $\boldsymbol{\Lambda}_{\mathbf{w}}$ represents the allocative inefficiencies of variable inputs, $\boldsymbol{\Sigma}_k$ and $\boldsymbol{\Sigma}_l$ are allocative inefficiencies of capital and land inputs, respectively, ε_1 and ε_2 are the two-sided error terms representing random errors that $\varepsilon_1 : \text{iid}\, N(0,\sigma_1^2)$ and $\varepsilon_2 : \text{iid}\, N(0,\sigma_2^2)$. Further, ε_1 and ε_2 are distributed independently of each other, and of the regressors.

In addition, the optimized actual demand for the variable inputs in equation (11) is given by

$$
\begin{aligned}
(16)\qquad x^o = {} & \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} \begin{bmatrix} (rJ_{\mathbf{ww}}^b \mathbf{w} - rJ_{k\mathbf{w}}^b{}'(J_{kp_k}^b)^{-1} J_{\mathbf{w}p_k}^b{}'\mathbf{w} - rJ_{l\mathbf{w}}^b{}'(J_{lp_l}^b)^{-1} J_{\mathbf{w}p_l}^b{}'\mathbf{w} \\ +rJ_{\mathbf{w}}^b - J_{\mathbf{w}t}^b + J_{k\mathbf{w}}^b{}'(J_{kp_k}^b)^{-1} J_{p_k t}^b + J_{l\mathbf{w}}^b{}'(J_{lp_l}^b)^{-1} J_{p_l t}^b \end{bmatrix} \\
& + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1} [rJ_{\mathbf{w}p_k}^b (J_{kp_k}^b)^{-1} J_k^b - J_{\mathbf{w}p_k}^b (J_{kp_k}^b)^{-1} J_{kt}^b] \\
& + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1} [rJ_{\mathbf{w}p_l}^b (J_{lp_l}^b)^{-1} J_l^b - J_{\mathbf{w}p_l}^b (J_{lp_l}^b)^{-1} J_{lt}^b] \\
& - \begin{bmatrix} \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} [J_{k\mathbf{w}}^b{}' - J_{k\mathbf{w}}^b (J_{kp_k}^b)^{-1} (J_{kp_k}^b - 1/r) + \boldsymbol{\tau}_q J_{k\mathbf{w}}^b{}'] \\ + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_k^{-1} [J_{\mathbf{w}p_k}^b (J_{kp_k}^b)^{-1} J_{kk}^b] \end{bmatrix} \dot{k} \\
& - \begin{bmatrix} \boldsymbol{\tau}_x \boldsymbol{\Lambda}_{\mathbf{w}}^{-1} [J_{l\mathbf{w}}^b{}' - J_{l\mathbf{w}}^b (J_{lp_l}^b)^{-1} (J_{lp_l}^b - 1/r) + \boldsymbol{\tau}_q J_{l\mathbf{w}}^b{}'] \\ + \boldsymbol{\tau}_q \boldsymbol{\Sigma}_l^{-1} [J_{\mathbf{w}p_l}^b (J_{lp_l}^b)^{-1} J_{ll}^b] \end{bmatrix} \dot{l} + \boldsymbol{\varepsilon}
\end{aligned}
$$

where $\boldsymbol{\varepsilon}$ is a linear disturbance vector with mean vector $\mathbf{0}$ and variance-covariance matrix Σ.

Equations (14) to (16) present an econometric model of the dynamic efficiency model with a two quasi-fixed factors case. To estimate this model, it is necessary to specify the functional form of the behavioral value function. A quadratic behavioral value function assuming symmetry of the parameters can be expressed as

$$(17)\qquad J^b(\cdot) = \beta_0 + \mathbf{w}'\boldsymbol{\beta} + \frac{1}{2}\mathbf{w}'\mathbf{B}\mathbf{w}$$

where $\mathbf{w}' = (\mathbf{w}^b\ p_k\ p_l\ k\ l\ y\ t)$, $\boldsymbol{\beta}$ denotes a vector of parameters, and $\mathbf{B}$ is a symmetric matrix of parameters, each of the appropriate dimension.

In addition, all producer- and input-specific estimates of technical and allocative efficiencies must be specified to implement the estimation of all coefficient parameters of the behavioral value function. The system of equations (14) to (16) is recursive, with the endogenous variables of net investment demands in capital and land serving as explanatory variables in the variable input demand equations. The estimation can be accomplished in two stages. In the first state, the optimized actual investment demands in capital and land are estimated by using the maximum likelihood estimation (MLE). Given that the optimized actual variable input demand equations are over-identified, the system of variable input demand equations is estimated in the second stage by using a generalized method of moments (GMM) estimation with all parameter values as determined in the first stage. All predetermined variables, including exogenous and dummy variables from each equation in the variable input demand equations, are defined as the instrumental variables of the system equation in the second stage. The details of the econometric approach used in the dynamic efficiency model are presented in Rungsuriyawiboon and Stefanou (2007).

2.3 Dynamic structure of production

Dynamic structures of production can be investigated using the parameter estimates of the behavioral value function obtained from the procedure of estimation in section 2.2. This section presents the derivations of two measures of farm scale, e.g. scale and cost elasticities. The scale elasticity is associated with the technology represented by the production, while the cost elasticity involves analyzing the movement along the cost curves. With the presence of adjustment costs, the scale elasticity is no longer equivalent to the inverse of the cost elasticity.

2.3.1 Scale elasticity

The scale elasticity is defined as the percentage that change in output responds to a percentage change in all inputs. Following Stefanou (1989), the dynamic theory of cost allows for the selection of dynamic and variable factor demands. The long-run scale elasticity is defined as the ratio of long-run average variable shadow cost (*LRAVC*) to short-run marginal cost (*SRMC*), whereas the short-run scale elasticity is defined as the ratio of short-run average variable shadow cost (*SRAVC*) to short-run marginal cost (*SRMC*). Values of scale elasticity greater than one imply increasing returns to scale, while values less than one imply decreasing returns to scale, and values equal to one imply constant returns to scale.

The optimized actual dynamic programming in equation (9) can be viewed as the long-run cost function associated with the actual quantities. The short-run cost function associated with the actual quantities is defined as the summation of variable costs and fixed costs. The long-run average cost (*LRAC*) at time t is calculated by dividing equation (9) with output, while the short-run average cost (*SRAC*) at time t is calculated by dividing the short-run cost function with output. The long-run marginal cost (*LRMC*) at time t is calculated by differentiating equation (9) with respect to output while the short-run marginal cost (*SRMC*) at time t is calculated by differentiating the short-run cost function with output.

The short-run scale elasticity associated with the actual quantities yields

$$(18) \qquad SE^{SR} = \frac{SRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*}}{\gamma^{a*} y}$$

where $\gamma^{a*} = \nabla_y (\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l)$ is the SRMC at time t.

The long-run scale elasticity associated with the actual quantities yields

$$(19) \qquad SE^{LR} = \frac{LRAVC}{SRMC} = \frac{\mathbf{w}'\mathbf{x}^{o*} + J_k^a \dot{k}^* + J_l^a \dot{l}^* + J_t^a}{\gamma^{a*} y}$$

where $J_k^a = \Sigma_k^{-1} J_k^b$, $J_l^a = \Sigma_l^{-1} J_l^b$ and $J_t^a = J_t^b$.

2.3.2 Cost elasticity

The cost elasticity is defined as the percentage change in costs given a percentage change in outputs. The instantaneous or short-run cost elasticity (CE^{SR}) is the ratio of short-run marginal cost (*SRMC*) to the short-run average total cost (*SRAC*), whereas the long-run cost elasticity (CE^{LR}) is defined as the ratio of long-run marginal shadow cost (*LRMC*) to the long-run average total cost (*LRAC*). Values of cost elasticity greater than one imply decreasing returns to scale, while values less than one imply increasing returns to scale and values equal to one imply constant returns to scale.

The short-run cost elasticity associated with the actual quantities in equation (9) yields

$$(20) \qquad CE^{SR} = \frac{SRMC}{SRAC} = \frac{\gamma^{a*} y}{\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l}.$$

The long-run cost elasticity associated with the actual quantities yields

$$(21) \qquad CE^{LR} = \frac{LRMC}{LRAC} = \frac{(\gamma^{a*} + J_{ky}^a \dot{k}^* + J_{ly}^a \dot{l}^* + J_{ty}^a) y}{\mathbf{w}'\mathbf{x}^{o*} + p_k k + p_l l + J_k^a \dot{k}^* + J_l^a \dot{l}^* + J_t^a}.$$

In contrast to the static setting that the scale elasticity is the inverse of the cost elasticity, the inverse of the dynamic cost elasticity is no longer equal to the dynamic scale elasticity. The primary differences between the two scale measures are the terms $J_{ky}^a \dot{k}^*$, $J_{ly}^a \dot{l}^*$ and J_{ty}^a.

3. Data discussion

The data used in this study is drawn from the National Fixed Point (NFP) survey data series, conducted annually by Research Center for Rural Economy (RCRE) of the Ministry of Agriculture, China. The NFP survey is based on a multistage, random-cluster process to attain the rich information of rural reform on agricultural production and rural development.[3] We use individual household data in Zhejiang, Hubei, and Yunnan provinces covering the period from 2003 to 2006. The three provinces were chosen to reflect the different regional economic development and the diversity of China's agricultural production. Zhejiang

[3]Benjamin et al. (2005) provide a detailed description of the data and history of the NFP survey.

Province is one of the richest provinces in East China; Hubei Province represents the central middle-income region and is the traditional heartland of China's agricultural production; located in West China, Yunnan Province is one of the poorest regions in the country.

The agricultural production technology in this study is represented by one output (y), two variable inputs (x_1 = labor, x_2 = intermediate inputs), and two quasi-fixed factors (q_1 = l = land, q_2 = k = capital). Output is the total value of crop production measured at constant 2003 prices. Labor input is expressed as the total number of annual working days of the whole household in crop production. Our dataset contains information on employment in crop production. The wage of labor is hence obtained as the quotient of total expenses paid to employees and their total working days. Intermediate inputs include expenses on seeds, chemical fertilizers, pesticides, and diesel oil for agricultural machinery. The volume of intermediate inputs is calculated as the quotient of the total expenses on intermediate inputs and agricultural productive materials price indices. The Divisia price indices are computed for intermediate inputs with value shares of each component as weights.

Capital input is defined as the fixed-capital assets of the household at the end of each year, including draught animals, production tools, production buildings, and machinery for agriculture. The volume of capital input is calculated as the quotient of the capital input value and the price index of productive agricultural fixed assets (p_{ki}). According to Jorgenson (1963), the rental price for capital is expressed as $p_{ki} * (r + \delta)$, where r is the nominal interest rate and δ is the depreciation rate.[4] Land input is the total utilized arable land area in mu.[5] The rental price for land is calculated as the quotient of expenses for leasing land and leased land area from other households. The descriptive statistics of the variables are listed in Table 1. Households in Zhejiang have a relatively lower output of crop production compared to Hubei and Yunnan. It is not a surprise if we look further into the various inputs of households in the three provinces. The volume of labor input in Zhejiang is 63.59 working days on average, which is roughly 40% of that in Hubei and Yunnan. Actually, rural labors in Zhejiang are more likely to engage in off-farm employment, and non-agricultural income has accounted for a major share of the household total income. At the same time, labor productivity (y/x_1) in Zhejiang is the highest among the three provinces. In comparison to the relatively lower crop output, the capital input in Zhejiang is impressive and much higher than that in Hubei and Yunnan. Regarding land input, the statistics of our sample sufficiently reflect the land endowment of the three provinces. Arable land is scarce in Zhejiang, with an average of 2.42 mu per household; the next is 4.79 mu in Hubei; Yunnan has the highest

[4]The nominal interest rate is approximated using the interest rate of rural credit cooperatives production loan. The depreciation rate is calculated as the quotient of depreciation and fixed assets.
[5] 1 mu = 1/15 hectare.

arable land area per household, which is 7.35 mu. Compared to Hubei and Yunnan, households in Zhejiang have lower capital productivity (y/k) but higher land productivity (y/l). When further comparing input prices across the provinces, it can be seen that the differences in prices have perfectly reflected varying factor endowments of the three in crop production.

Table 1. Descriptive statistics of the variables, 2003-2006

Variable description	***Symbol***	**Zhejiang**		**Hubei**		**Yunnan**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Output of crop production (Yuan)	y	2,262.38	2,020.37	3,716.76	2,741.78	4,356.72	3,151.30
Volume of labor input (working days)	x_1	63.59	64.58	164.88	125.09	151.50	126.86
Wage of labor (Yuan/working day)	w_1	34.29	19.63	22.24	12.33	14.82	10.96
Volume of intermediate input (Yuan)	x_2	611.44	528.93	626.11	522.88	805.03	855.58
Divisia price indices of intermediate input	w_2	1.14	0.10	1.19	0.14	1.10	0.06
Volume of capital input (Yuan)	k	8,864.49	1,2913.47	2,116.49	2,757.61	4,647.75	5,170.73
Rental price indices for capital	p_k	5.29	4.20	12.62	7.12	12.23	4.07
Volume of land input (mu)	l	2.42	1.59	4.79	2.47	7.35	5.75
Rental price for land (Yuan/mu)	p_l	163.83	51.83	70.35	43.35	97.39	87.14
No. of observations		**428**		**2,421**		**1,352**	

4. Results and discussion

The dynamic efficiency model defined in section 2 can be viewed as the perfectly inefficient model. Following Cornwell, Schmidt and Sickles (1990), all allocative and technical efficiencies of the dynamic and variable factors are specified to vary across provinces and through time. A lag of two periods of autocorrelation terms is used to compute the covariance matrix of the orthogonality conditions for the GMM estimation. Assuming a constant discount rate of 5%, the estimated coefficients are shown in Table 2.[6] Most coefficient estimates, particularly the first-order coefficients, are significant at the 95% confidence interval using a two-tailed test, except for the estimated parameters β_l. The R^2 values of net investment demand for the dynamic factors and of variable inputs are 0.345, 0.532 and 0.847, respectively. The test of overidentifying restriction from GMM estimation using the Hansen (1982) *J* test is significant. The null hypothesis fails to reject, implying that

[6]Further, a hypothesis test regarding the presence of the perfect efficiency in production is conducted using the likelihood ratio (LR) test. The LR test is approximately chi-square distributed with the degrees of freedom being equal to the number of restrictions. The LR test of the null hypothesis that farms are perfectly efficient in dynamic and variable factor demands is rejected at the 95% confidence level, implying that the farms in this study operated inefficiently in the production.

additional instrumental variables are valid, given that a subset of the instrumental variables is valid and exactly identifies the coefficient.

Table 2. Estimated parameters of dynamic efficiency model

Parameter[a]	Estimates	Standard Error
β_0	0.559***	0.033
β_{w1}	0.223***	0.026
β_{pk}	0.352***	0.028
β_{pl}	0.047**	0.018
β_k	0.331***	0.038
β_l	-0.058	0.043
β_y	0.073***	0.027
β_t	0.053***	0.016
β_{w1w1}	0.113***	0.040
β_{pkpk}	-0.876***	0.195
β_{plpl}	1.038***	0.153
β_{kk}	-2.068***	0.514
β_{ll}	-1.088**	0.434
β_{yy}	-0.033	0.021
β_{tt}	0.018	0.011
β_{w1pk}	3.083***	0.413
β_{w1pl}	0.478***	0.027
β_{w1k}	-0.124	0.141
β_{w1l}	-0.220***	0.039
β_{w1y}	0.056***	0.015
β_{w1t}	0.609***	0.045
β_{pkk}	21.739***	6.032
β_{pky}	0.403***	0.037
β_{pkt}	-0.291	0.120
β_{pll}	76.207***	5.235
β_{ply}	0.033	0.027
β_{plt}	2.370***	0.574
β_{ky}	2.821***	0.343
β_{kt}	-2.790**	1.270
β_{ly}	0.468***	0.026
β_{lt}	0.072***	0.014
β_{yt}	0.516***	0.028
Equation	**R^2**	**DW**
- Capital	0.345	1.671
- Land	0.532	1.456
- Labor	0.847	1.324
Test of overidentifying restrictions	214.168	

[a] Price of intermediate input (w_2) was normalized.
Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. The regressions also include dummy variables used to calculate all efficiency parameters of dynamic and variable inputs, and the estimates are not reported here.

Table 3 presents the average farm technical and allocative efficiencies of dynamic and variable factors by each province from 2003-2006. An estimate of the technical efficiency of dynamic and variable factors is bounded between zero and unity. The value of technical efficiency scores equal to one implies that a farm can minimize both dynamic and variable factors to produce a given level of output. The estimated technical efficiencies of variable inputs range from 0.325 to 0.910 with an average of 0.694, whereas those of net investment in quasi-fixed factors range from 0.382 to 0.837 with an average of 0.594. These findings imply that the Chinese farms in this study, on average, could have reduced the variable and dynamic factors by 30.6% and 40.6%, respectively, and still produce the same level of output. The average value of the technical efficiency of variable and dynamic factors is 71.0% and 64.2% (for Zhejiang), 69.5% and 60.6% (for Hubei) and 66.5% and 59.2% (for Yunnan). Farms in Zhejiang achieved higher technical efficiencies of dynamic and variable factors than those in Hubei and Yunnan. Farms in Yunnan have the lowest technical efficiency scores in terms of both dynamic and variable factors. When further checking the differences of scores across the three provinces, it can be seen that farms in Yunnan are less efficient at using variable inputs of labor and intermediate input, while farms in Zhejiang are much more efficient at using quasi-fixed inputs of land and capital.

Considering the allocative efficiency scores, the value of the allocative efficiency of dynamic factors is bounded between zero and unity. The value of one implies that farms can use the dynamic factors in optimal proportions given their respective prices and the production technology. Average farm allocative efficiencies of net investments in capital and land are 0.758 and 0.628, respectively. These results suggest that Chinese farms could potentially reduce net investment in capital and land demands by 24.2% and 37.2%, respectively, to their cost-minimizing level of factors. The average value of the allocative efficiency of capital and land inputs is 85.4% and 70.4% (for Zhejiang), 79.7% and 62.9% (for Hubei) and 61.8% and 57.0% (for Yunnan). The results indicate that farms in Zhejiang achieved higher allocative efficiencies of capital and land than those in Hubei and Yunnan. This finding is consistent with the previous observations that factor markets are relatively better functioning in Zhejiang, for example the development of the land rental market. Statistics in Zhang et al. (2011) show that land rental activities are much more important in Zhejiang than in the other two provinces; the share of arable land rented out is, on average, 8.2% in Zhejiang, but only 1.3% in Hubei and 2.3% in Yunnan.

Following the shadow price approach, the price of intermediate input is arbitrarily specified as the numeraire. The value of the allocative efficiency of variable input demands represents price distortions of the labor relative to the intermediate input. An estimate of allocative efficiency of labor input demands less (greater) than one means that the ratio of the shadow price of labor relative to the intermediate input is considerably less (greater) than the corresponding ratio of actual prices. This implies that the farms are overusing (underusing) the labor relative to the intermediate input. Table 3 also reports that average farm allocative efficiencies of labor input demands is 0.395. These results imply that farms in the three provinces are over-utilizing labor relative to the intermediate input in the crop production. The average value of the allocative efficiency of labor input demands is 40.5% (for

Zhejiang), 36.6% (for Hubei) and 37.7% (for Yunnan). This relatively severe price distortion is not particularly surprising since obstacles[7] still hinder the free migration of rural labor, although the controls on rural labor mobility were greatly relaxed after the reform.

Table 3. Average farm technical and allocative efficiency scores of dynamic and variable factor demands, 2003-2006

Efficiency scores*	Zhejiang	Hubei	Yunnan	All provinces
TE(x)	0.710	0.695	0.665	0.694
TE(q)	0.642	0.606	0.592	0.594
AE(k)	0.854	0.794	0.618	0.758
AE(l)	0.704	0.629	0.570	0.628
AE(w_1)	0.405	0.366	0.377	0.395

Note: *TE(x) = technical efficiency of variable inputs; TE(q) = technical efficiency of dynamic factors; AE(k) = allocative efficiency of net investment in capital; AE(l) = allocative efficiency of net investment in land; AE(w_1) = allocative efficiency of labor input.

Table 4 presents average annual technical and allocative efficiency scores of the dynamic and variable factor demands for each province over the period 2003-2006. The findings in Table 4 allow us to examine the performance of crop production farms after three decades of reform. Farms in Zhejiang and Hubei have an average annual technical efficiency of dynamic and variable factors higher than those in Yunnan. During the period 2003-2006, technical efficiency scores of variable inputs in all provinces increase over time. In contrast, technical efficiency scores of dynamic factors in all provinces are decreasing over time. Average annual allocative efficiencies of dynamic factors for both capital and land in Zhejiang and Hubei are higher than Yunnan in every year over the study period. This result suggests that farms in Zhejiang and Hubei could adjust their dynamic factors to the cost-minimizing level of factors easier than those in Yunnan. During the period 2003-2006, allocative efficiency scores of the net investment in capital of farms in Zhejiang are increasing over time. In contrast, allocative efficiency scores of the net investment in the capital of farms in Yunnan are decreasing over time, while the allocative efficiency score of the net investment in capital in Hubei varies considerably over the period. Allocative efficiency scores of the net investment in land by farms in Zhejiang and Hubei are also

[7]For instance, the implementation of Household Registration System (hukou) divided people into those holding a rural hukou and those with an urban hukou. Under the constraints of the hukou system, rural migrants face residence discrimination and lack access to public services like education, health care and public welfare in cities (OECD, 2009).

increasing over time, where the allocative efficiency score of the net investment in capital of farms in Yunnan varies with a decreasing trend over the period. The allocative efficiency estimates of the variable inputs during the 2003-2006 period indicates that farms in Hubei and Yunnan tend to increase over-utilization in labor relative to intermediate input, whereas farms in Zhejiang tend to decrease over-utilization in labor relative to intermediate input.

Table 4. Average annual technical and allocative efficiency scores of dynamic and variable factor demands for each province, 2003-2006

Efficiency scores	**Zhejiang**				**Hubei**			
	2003	**2004**	**2005**	**2006**	**2003**	**2004**	**2005**	**2006**
TE(x)	0.642	0.658	0.754	0.787	0.646	0.670	0.720	0.742
TE(q)	0.683	0.667	0.616	0.603	0.666	0.635	0.570	0.551
AE(k)	0.819	0.839	0.864	0.892	0.769	0.808	0.788	0.817
AE(l)	0.675	0.696	0.717	0.727	0.575	0.620	0.655	0.665
AE(w_1)	0.373	0.395	0.412	0.440	0.440	0.350	0.319	0.358
Efficiency scores	**Yunnan**				**All provinces**			
	2003	**2004**	**2005**	**2006**	**2003**	**2004**	**2005**	**2006**
TE(x)	0.627	0.655	0.679	0.698	0.638	0.661	0.718	0.742
TE(q)	0.606	0.644	0.569	0.548	0.652	0.649	0.585	0.567
AE(k)	0.652	0.657	0.596	0.567	0.747	0.759	0.756	0.759
AE(l)	0.626	0.547	0.564	0.534	0.625	0.628	0.637	0.645
AE(w_1)	0.431	0.343	0.398	0.338	0.415	0.362	0.376	0.378

Turning to the role of adjustment costs in Chinese farm crop production, the partial adjustment coefficient of quasi-fixed factors is defined in equation (12) in section 2.1. Given the discount rate of 5%, the findings (Table 2) show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low. The estimated adjustment rate is 4.54% per annum by capital and 3.84% per annum by land, or it may take capital approximately 22 years and land approximately 26 years to adjust fully to its long-run equilibrium level.

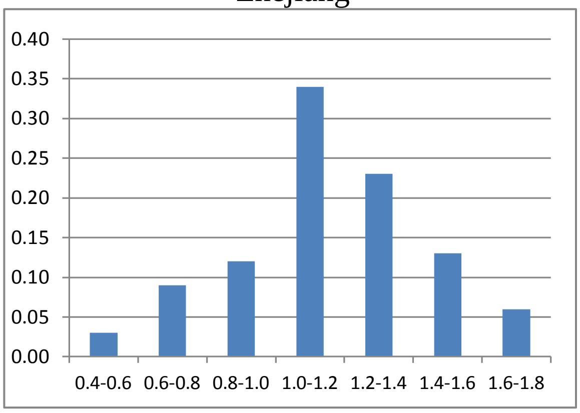
Further, the optimal stocks defined in equation (13) in section 2.1 are calculated and compared to the actual stocks. The ratio of optimal quasi-fixed factors to actual quasi-fixed factors accounts for the capacity utilization, which provides some insights into the efficiency of quasi-fixed factor uses by a farm. Values of the ratio of optimal quasi-fixed factors to actual quasi-fixed factor stocks greater than one imply that a farm is under-utilizing quasi-fixed factors, while values less than one imply that a farm is over-utilizing quasi-fixed factors.

Figure 1 and Appendix Table A1 present the distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors by farm in each province. The findings in Figure 1(a) show that the estimates of the ratio of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745 with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, which is a sign of under-utilization in capital prevailing in crop production. Looking into the statistics of each province, the differences are evident, with 42% of the farms in Zhejiang, 67% in Hubei, and 85% in Yunnan being under-capitalized. The performance of Zhejiang is relatively good, with 34% of the farms nearly optimizing their capital use in the range of 1.0-1.2. On the contrary, most of the farms in Hubei and Yunnan still have the potential to reach the optimal level by increasing their capital stocks.

Turning to land utilization, Figure 1(b) provides some insights into the efficiency of land use by a farm in each province. The estimates of the ratio of optimal land (L^*) to actual land (L) range from 0.124 to 1.354, with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels, which is explained as an over-utilization of land input. This finding is consistent with the common inverse relationship between farm size and productivity in developing country agriculture (Berry and Cline, 1979) where smaller farms tend to more intensively use their labor in the absence of perfect factor markets. As is shown in our results, the area of actual land utilization is higher than that of the optimal level for most of the farms.

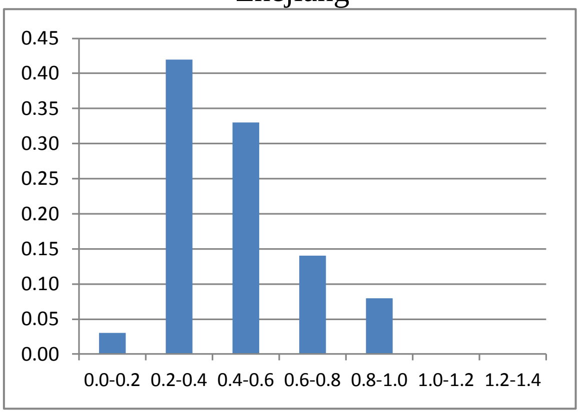
Figure 1. Distribution of the ratio of optimal capital to actual capital

Zhejiang

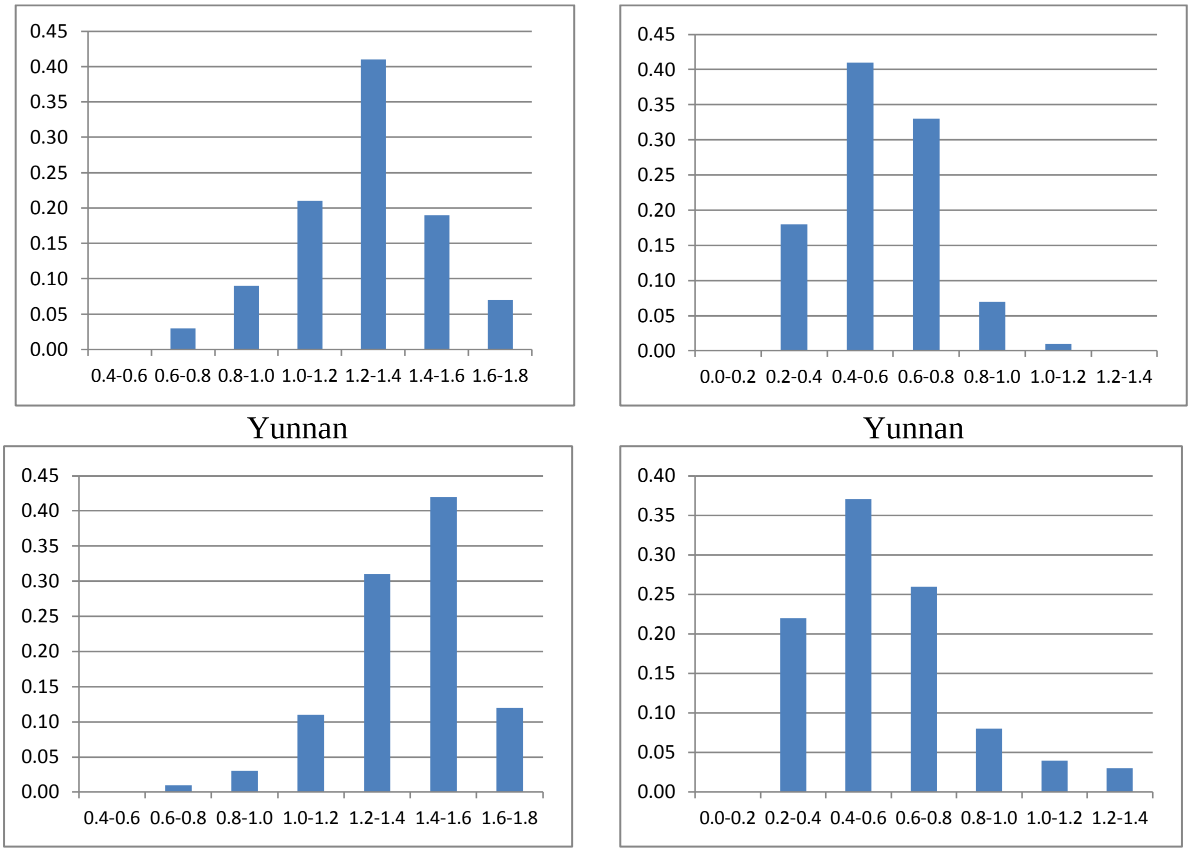


Hubei

Zhejiang



Hubei



(a) K^*/K **(b) L^*/L**

Table 5 presents weighted-average estimates of the short- and long-run dynamic scale and cost elasticities by province and all farms from 2003-2006. The estimates of the short-run scale elasticities range from 0.624 to 0.945 with an average of 0.828, while the long-run scale elasticities range from 0.678 to 0.985 with an average of 0.857. All farms indicate the presence of decreasing returns to scale in both the short and long run. In addition, the weighted-average estimated results of scale elasticities indicate modestly decreasing returns to scale in the long run and considerably higher ones in the short run. The weighted-average estimate of scale elasticities of farms in Zhejiang is higher than those in Hubei and Yunnan in both the short and long run, respectively. The estimates of the short-run cost elasticities range from 1.064 to 1.628, with an average of 1.269, while the long-run cost elasticities range from 1.078 to 1.715, with an average of 1.222. All farms present decreasing returns to scale in both the short and long run. Consistent with the measure of scale elasticity, the results of cost elasticities are hence robust. The estimated results of the short- and long-run dynamic cost elasticities suggests that farms in Yunnan have a higher degree of decreasing returns to scale compared to farms in Zhejiang and Hubei.

Table 5. Short- and long-run scale and cost elasticity (2003-2006)

	Zhejiang	Hubei	Yunnan	All provinces
Scale Elasticity				
- Short-run	0.893	0.865	0.742	0.828
- Long-run	0.945	0.915	0.725	0.857
Cost Elasticity				
- Short-run	1.194	1.215	1.389	1.269
- Long-run	1.025	1.142	1.427	1.222

5. Conclusions

This study contributes to the ongoing debate on the structural transformation of farm production in China. We analyzed this phenomenon by examining the economic performance of Chinese farms. By developing a dynamic frontier-based model using the shadow cost approach in the framework of the dynamic duality model of inter-temporal decision making, the dynamic cost efficiency model allows us to consider the impact of allocative and technical efficiency in Chinese agriculture, as well as the adjustment costs resulting from the change of quasi-fixed input use. The dynamic efficiency model is implemented empirically using a panel data set of 4,201 Chinese farms in three provinces (i.e. Zhejiang, Hubei and Yunnan) from 2003 to 2006. This is the first study to investigate the allocative and technical efficiencies of Chinese agriculture using a dynamic shadow cost approach. With the parameter estimates from the model, we further calculate the partial adjustment coefficients of quasi-fixed factors, the optimal stocks of quasi-fixed factors, and the short- and long-run dynamic scale and cost elasticities.

Our results show that, in terms of technical efficiency, the farms in this study, on average, could have reduced their variable and dynamic factors by 30.6% and 40.6%, respectively, and still have produced the same level of output. Regional differences are evident, indicating that farms in Zhejiang perform the best while farms in Yunnan have the lowest scores. Considering the allocative efficiency scores of net investment in dynamic factors, our results show that farms could potentially reduce their net investments in capital and land demands by 24.2% and 37.2% to reach their cost-minimizing level of factors. Farms in Zhejiang still achieve the highest level compared to those in the other two provinces. The average allocative efficiency of net investment in labor demands is relatively low at 0.395, indicating a severe price distortion of the labor relative to the intermediate input, which implies the over-utilization of labor relative to the intermediate input in crop production.

Turning to the role of adjustment costs in Chinese farm crop production, the findings show that the estimated adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low, which implies a rather sluggish adjustment process and considerably high adjustment costs. The ratios of optimal capital (K^*) to actual capital (K) range from 0.414 to 1.745, with an average of 1.382. More than 70 percent of all farms indicate that their optimal capital stocks are greater than the existing levels, a sign that the under-utilization of capital prevails in crop production. On the contrary, the ratios of optimal land (L^*) to actual land (L) range from 0.124 to 1.354 with an average of 0.527. More than 90 percent of all farms indicate that their optimal land stocks are less than the existing levels. According to these findings, there also exist high degrees of over-utilization in land prevailing in crop production. The estimates of the short- and long-run dynamic scale and cost elasticities are robustly consistent, which indicates the presence of decreasing returns to scale in both the short and long run.

Based on the findings of this study, important policy implications can be derived for the future development of agricultural production in China. The relatively low levels of technical and allocative efficiencies indicate that most farms are unable to catch up with the production frontier under the existing production technology, or to use various inputs in appropriate proportions given their respective prices. Since the inefficiencies are normally associated with motivation, information, and institutional environment problems, policy makers should pay more attention to various factor market reforms as a whole. This statement is reinforced by the relatively low estimated adjustment rates of the quasi-fixed factors, implying high adjustment costs. We introduced adjustment costs in the model to capture those forces or economic situations that impose some penalty on the farm beyond the acquisition cost, and hence slow down the adjustment process of production factors.

Farmers' rights to land should be strengthened and extended so that land tenure is more secure. Possible policy measures could include complete land titling to grant full property rights to farmers and hence establish a foundation for the development of rural rental and credit markets where land could be used as collateral; extending the duration of land-use contracts to perpetuation; this duration is currently 30 years. At the same time, policy measures are needed to encourage rural labor mobility, for instance, the Household Registration System (hukou) needs to be reformed to provide migrant workers with equal access to public services in cities. The migration process will be smoother when farmers' rights to land are protected and secure.

The presence of decreasing returns to scale in both the short and long run also has important policy implications with respect to the government's recent policy focus on supporting the creation of large-scale farms. The simple action of integrating farms will neither increase productivity nor farmers' income. Adjusting the structure of farm production is needed in order to reach the optimal proportion of various input use. The progress of this adjustment will also rely on the successful reform of land and labor markets.

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Appendix

Table A1. The distribution of the ratio of optimal quasi-fixed factors to actual quasi-fixed factors

	Frequency		
K^*/K	**Zhejiang**	**Hubei**	**Yunnan**
0.4-0.6	0.03	0.00	0.00
0.6-0.8	0.09	0.03	0.01
0.8-1.0	0.12	0.09	0.03
1.0-1.2	0.34	0.21	0.11
1.2-1.4	0.23	0.41	0.31
1.4-1.6	0.13	0.19	0.42
1.6-1.8	0.06	0.07	0.12
	1.00	1.00	1.00

	Frequency		
L^*/L	**Zhejiang**	**Hubei**	**Yunnan**
0.0-0.2	0.03	0.00	0.00
0.2-0.4	0.42	0.18	0.22
0.4-0.6	0.33	0.41	0.37
0.6-0.8	0.14	0.33	0.26
0.8-1.0	0.08	0.07	0.08
1.0-1.2	0.00	0.01	0.04
1.2-1.4	0.00	0.00	0.03
	1.00	1.00	1.00

บทความสำหรับการเผยแพร่

ในแวดวงวรรณกรรมนั้น ค่าประสิทธิภาพการผลิตถือเป็นตัววัดที่มีความสำคัญ เพราะนอกจากจะนำมาใช้เปรียบเทียบผลการดำเนินการของหน่วยผลิตในอุตสาหกรรมแล้ว ยังสามารถนำมาใช้เป็นข้อมูลสำคัญสำหรับผู้กำหนดนโยบายของรัฐเพื่อนำมาวางแผนเชิงนโยบายที่เหมาะสมในการกำหนดทิศทางและยุทธศาสตร์การพัฒนาเศรษฐกิจของประเทศ เนื่องจากงานวิจัยที่ศึกษาถึงผลการดำเนินการทางการเกษตรของประเทศเปลี่ยนผ่าน รวมถึงของประเทศสาธารณรัฐประชาชนจีนนั้น ค่าประสิทธิภาพการผลิตที่ถูกวัดจากแบบจำลองนั้นถูกพัฒนาจากแนวคิดในการแก้ปัญหาเชิงสถิตย์ ส่งผลทำให้ค่าประสิทธิภาพการผลิตที่วัดได้เกิดความคลาดเคลื่อน

งานวิจัยชิ้นนี้ได้ท้าทายข้อบกพร่องดังกล่าวด้วยการพัฒนาแบบจำลองการวัดประสิทธิภาพเชิงพลวัต (dynamic efficiency model) สำหรับวัดค่าประสิทธิภาพของหน่วยผลิตภายใต้การตัดสินใจเลือกแบบข้ามเวลาเพื่ออธิบายถึงพฤติกรรมของหน่วยผลิตที่ต้องการแสวงหาต้นทุนต่ำสุดจากการผลิต แบบจำลองเชิงพลวัตนี้สามารถนำไปประยุกต์ใช้ได้กับกระบวนการผลิตที่มีการใช้ปัจจัยกึ่งคงที่หลายชนิดเพื่อผลิตสินค้าเพียงชนิดเดียว นอกจากนั้น แบบจำลองยังสามารถอธิบายความแตกต่างของการผลิตแยกตามลักษณะภูมิศาสตร์ เทคโนโลยีการผลิต และลักษณะเฉพาะของการผลิต แบบจำลองการวัดประสิทธิภาพเชิงพลวัตสามารถวัดและแยกค่าประสิทธิภาพต้นทุนออกเป็นประสิทธิภาพประเภทต่างๆ รวมทั้งสามารถอธิบายถึงต้นทุนในการปรับค่าของปัจจัยกึ่งคงที่ที่เกิดขึ้นในกระบวนการผลิตของหน่วยผลิต

แบบจำลองการวัดประสิทธิภาพเชิงพลวัตในงานวิจัยนี้ถูกนำมาวิเคราะห์กับฐานข้อมูลการผลิตภาคการเกษตรของประเทศสาธารณรัฐประชาชนจีนใน 3 มณฑล ได้แก่ Zhejiang, Hubei และ Yunnan ระหว่างช่วงปี ค.ศ. 2003 ถึง 2006 เพื่อเปรียบเทียบถึงผลการดำเนินการทางการเกษตรที่เกิดขึ้นหลังจากที่ประเทศได้มีการปฏิรูปเศรษฐกิจจากระบบรวมศูนย์มาเป็นระบบที่ขึ้นกับกลไกของตลาด ผลการศึกษาที่ได้แสดงให้เห็นว่าผลการดำเนินการทางการเกษตรในแต่ละมณฑลมีความแตกต่างกันอย่างมาก ค่าประสิทธิภาพการผลิตของมณฑล Zhejiang มีค่าสูงที่สุด ในขณะที่ มณฑล Yunnan มีค่าประสิทธิภาพการผลิตต่ำที่สุด นอกจากนั้น ต้นทุนในการปรับค่าของปัจจัยทุนและที่ดินอยู่ในระดับสูง หน่วยผลิตต้องใช้ระยะเวลานานมากในการปรับการใช้ปัจจัยทั้งสองให้อยู่ในระดับดุลยภาพระยะยาว จากผลการศึกษาที่ได้นี้สามารถกล่าวได้ว่าผู้กำหนดนโยบายควรให้ความสำคัญกับการปฏิรูปตลาดปัจจัยการผลิตต่างๆโดยรวม และสิทธิของเกษตรกรในการครอบครองที่ดินควรมีการเพิ่มและขยายมากขึ้นเพื่อให้การครอบครองที่ดินของเกษตรกรมีความมั่นคงและปลอดภัยมากขึ้น