รายงานวิจัยฉบับสมบูรณ์

โครงการ "ประสิทธิภาพตลาดเกษตรและกำไรต่อเกษตรกร: การส่งผ่านราคาที่สมมาตรของสินค้าเกษตรที่สำคัญของประเทศไทย"

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มหาวิทยาลัยเชียงใหม่

เมษายน 2557

สัญญาเลขที่ BRG5380024

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สนับสนุนโดยสำนักงานกองทุนสนับสนุนการวิจัย

(ความคิดเห็นในรายงานนี้เป็นของผู้วิจัย สกว. ไม่จำเป็นต้องเห็นด้วยเสมอไป)

บทสรุปผู้บริหาร

1. ที่มาและความสำคัญ

ภาคเกษตรยังคงเป็นสาขาการผลิตที่มีความสำคัญต่อประเทศไทยในด้านเป็นแหล่งรองรับแรงงาน แหล่งวัตถุดิบสำหรับอุตสาหกรรมเกษตรในประเทศและเป็นตลาดสำหรับสาขาการผลิตอื่นๆ โดยเฉพาะอย่างยิ่งสำหรับนโยบายที่ไทยจะเป็นประเทศที่มีความมั่นคงทางอาหารและพลังงานรวมถึงการส่งออกสินค้าเกษตรที่มีคุณภาพและมีมูลค่าสูง ซึ่งนโยบายนี้ควรจะเกิดประโยชน์ต่อเกษตรกรด้วย ในปัจจุบันเกษตรกรประสบปัญหาความเสี่ยงด้านราคาเป็นอย่างยิ่ง นอกจากนั้นยังประสบปัญหาราคาต่ำจนเกิดการขาดทุน ทำให้รัฐบาลต้องเข้าช่วยเหลือโดยการใช้นโยบายประกันรายได้ นโยบายราคาขั้นต่ำและการจำนำผลผลิตในผลผลิตเกษตรหลักหลายชนิด ปัญหาความผันผวนของราคาเกิดจากการเงื่อนไขที่ไม่สามารถควบคุมได้ของอุปสงค์และอุปทาน ที่ส่วนหนึ่งเกิดขึ้นจากการวางแผนการผลิตที่มีข้อมูลไม่เพียงพอและส่วนหนึ่งเกิดจากการทำหน้าที่ของกลไกตลาดที่ขาดประสิทธิภาพ เนื่องจากผู้เกี่ยวข้องในตลาดบางระดับมีอำนาจการตลาด วิธีการหนึ่งที่สามารถทดสอบระดับของอำนาจการตลาดคือ การวิเคราะห์ประสิทธิภาพของระบบตลาดที่เกี่ยวข้องกับการเชื่อมโยงกันของตลาดและการส่งผ่านราคาอย่างสมบูรณ์ระหว่างตลาดระดับต่างๆ ทั้งนี้ตลาดที่มีประสิทธิภาพจะช่วยป้องกันการหากำไรเกินควรของผู้เล่นในตลาดและช่วยให้ทุกฝ่ายได้รับประโยชน์อย่างยุติธรรม

การศึกษาการเชื่อมโยงราคาและประสิทธิภาพของตลาดผลผลิตเกษตรในประเทศไทยเท่าที่ผ่านมาส่วนใหญ่เป็นการศึกษาโดยใช้วิธี Cointegration ของ Engel และ Granger (1987) และแบบจำลอง Error Correction (ECM) ซึ่งวิธีการเหล่านี้บางครั้งไม่เหมาะสมกับลักษณะของข้อมูลราคาสินค้าในปัจจุบันซึ่งมีความแปรปรวนสูงและรวดเร็วจึงส่งผลต่อการสรุปผลการวิเคราะห์และการกำหนดนโยบายราคาและตลาดได้

การศึกษาครั้งนี้จึงมุ่งวิเคราะห์ประสิทธิภาพของตลาดสินค้าเกษตร ซึ่งรวมถึงความเชื่อมโยงของตลาดสินค้าเกษตรที่สำคัญของประเทศไทยและการพยากรณ์ราคาสินค้าเกษตรโดยใช้วิธีวิเคราะห์ที่เหมาะสมกับลักษณะข้อมูลเพื่อการวิเคราะห์ประสิทธิภาพของตลาดที่ชัดเจนมากขึ้น อันนำไปสู่ข้อเสนอแนะเชิงนโยบายของตลาดสินค้าเกษตรที่มีนัยยะทางปฏิบัติและการขยายมุมมองของการวิจัยเรื่องประสิทธิภาพการตลาดเกษตรของประเทศอีกด้วย

2. วัตถุประสงค์ของการศึกษา

งานวิจัยเรื่องประสิทธิภาพตลาดเกษตรและกำไรต่อเกษตรกร: การส่งผ่านราคาที่สมมาตรของสินค้าเกษตรที่สำคัญของประเทศไทยนี้ มีวัตถุประสงค์หลักเพื่อหาวิธีวิเคราะห์ที่มีประสิทธิภาพและให้นัยยะทางนโยบายโดยมีวัตถุประสงค์ย่อยดังนี้

1) วิเคราะห์สถานการณ์การตลาดและกลไกของราคาสินค้าเกษตรที่สำคัญของประเทศไทย
2) วิเคราะห์ความเชื่อมโยงของตลาดสินค้าเกษตรที่สำคัญของประเทศไทย
3) ใช้เทคนิค VAR-VEC และ QRM ในการวิเคราะห์ตลาดสินค้าเกษตร
4) เสนอแนะนโยบายราคาสินค้าเกษตร

3. กรอบการศึกษา

จากการที่โครงการดังกล่าวเป็นโครงการที่มุ่งเขียนบทความ นำเสนอและตีพิมพ์ การดำเนินงานของโครงการวิจัยประกอบด้วยกิจกรรมที่เกี่ยวข้องกับวัตถุประสงค์ของโครงการดังนี้

1) ทบทวนงานวิจัยและบทความเกี่ยวกับการส่งผ่านราคาสินค้าเกษตร เพื่อทบทวนองค์ความรู้ที่ได้มีผู้ทำการวิจัยมาก่อนหน้านี้ รวมทั้งวิธีการและเครื่องมือที่ใช้ในการวิจัยเรื่องการส่งผ่านราคาสินค้าเกษตร อันนำมาสู่การพัฒนากรอบการวิเคราะห์และแบบจำลองที่ใช้ในการศึกษา การทบทวนเอกสารในช่วงปีแรกของโครงการ เป็นการทบทวนเอกสารที่เกี่ยวข้องในเบื้องต้นเพื่อประกอบการเขียนบทความ ซึ่งคณะวิจัยยังคงทำการทบทวนเอกสารต่อไปเพื่อความสมบูรณ์ของบทความที่ได้

2) เก็บรวบรวมข้อมูลทุติยภูมิเช่น สถิติราคาสินค้าเกษตรที่สำคัญ นโยบายของภาครัฐ เป็นต้น ซึ่งได้ทำการรวบรวมจาก web site และหน่วยงานต่างๆ ที่เกี่ยวข้อง เพื่อใช้ในการประมาณค่าแบบจำลองการส่งผ่านราคาของสินค้าเกษตรที่สำคัญของประเทศไทยอันได้แก่ (1) พืชอาหาร (2) พืชอาหารสัตว์/พลังงานทางเลือกเช่น ข้าวโพดเลี้ยงสัตว์ และมันสำปะหลัง (3) พืชเศรษฐกิจเช่น ยางพารา และ (4) สินค้าที่เป็นผลิตภัณฑ์ทางเกษตรเช่น น้ำมันปาล์มและน้ำตาล

3) เขียนบทความจำนวน 10 เรื่อง การเขียนบทความดังกล่าวเป็นความร่วมมือระหว่างคณะวิจัย นักวิจัยจากต่างประเทศและนักศึกษาในระดับปริญญาโทและปริญญาเอก ประกอบด้วย 1) บทความเรื่อง “Spatial Market Integration of Cassava Market and Causality Relationship in Thailand” โดยมีนักศึกษาระดับบัณฑิตศึกษาร่วมโครงการ 2) ร่างบทความการวิเคราะห์ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ 3) บทความเรื่อง “Predicting price of palm oil using Extreme Value Theory 4) บทความเรื่อง “An Application of EVT to Analyze US Corn Market” 5) บทความเรื่อง “Modeling the Volatility of Rubber Price Return using VARMA GARCH Model” 6) บทความเรื่อง “Modeling Volatility and Dependency of Agricultural Price and Production Indices of Thailand: Static versus Dynamic Copulas” 7) บทความเรื่อง “Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH model” 8) บทความเรื่อง “Modeling volatility and interdependencies of Thai rubber spot price return with climatic factors, exchange rate and crude oil markets” 9) บทความเรื่อง “Application of Extreme Value copulas to palm oil prices analysis” และ 10) บทความเรื่อง “Factors affecting palm oil price based on Extremes Value Approach” โดยบทความที่ 3-10 เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอก

4) เพื่อเป็นการเผยแพร่ผลงาน คณะผู้วิจัยได้เสนอบทความที่เขียนเสร็จแล้วในที่ประชุมนานาชาติ 2 แห่งคือ 1) งานประชุมนานาชาติ “The 4th International Conference of the Thailand Econometric Society” ที่คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ วันที่ 13 มกราคม 2554) และ 2) งานประชุมนานาชาติ “The 5th International Conference of the Thailand Econometric Society” ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ ระหว่างวันที่ 12-13 มกราคม 2555

5) แสวงหาเทคนิควิธีการวิเคราะห์โดยเชิญผู้เชี่ยวชาญต่างประเทศให้คำแนะนำและหารือเกี่ยวกับเครื่องมือการวิเคราะห์ และเพื่อให้การเขียนบทความมีประสิทธิผลมากขึ้น คณะวิจัยจึงได้เชิญนักวิจัยต่างชาติมาร่วมปรึกษาและเขียนบทความ

6) เพื่อให้เกิดความร่วมมือทางวิชาการระหว่างหน่วยงานราชการและมหาวิทยาลัยในการทำวิจัย โครงการวิจัยนี้จึงได้จัดกิจกรรมการวิจัยร่วมกับสำนักงานเศรษฐกิจการเกษตร (สศก.) กระทรวงเกษตรและสหกรณ์ (ภายใต้ความร่วมมือทางวิชาการระหว่างมหาวิทยาลัยเชียงใหม่และสำนักงานเศรษฐกิจการเกษตร (สศก.)) โดยกิจกรรมที่เกิดขึ้นภายใต้โครงการความร่วมมือนี้ได้แก่ การจัดอบรมเรื่องการใช้เครื่องมือเศรษฐมิติในการวิจัยให้แก่เจ้าหน้าที่ของสำนักงานเศรษฐกิจการเกษตรและร่วมกันเขียนบทความเกี่ยวกับการส่งผ่านราคาของสินค้าเกษตรของประเทศไทย

4. ผลการศึกษา

จากกิจกรรมที่ได้ดำเนินการดังกล่าวข้างต้นนักวิจัยเน้นการเขียนบทความทางวิชาการเพื่อตีพิมพ์บทความในวารสารต่างประเทศ นอกจากนี้ยังนำผลงานไปใช้ให้เกิดประโยชน์สูงสุดด้วยการแสวงหาความร่วมมือทางวิชาการกับหน่วยงานในประเทศและนักวิชาการจากต่างประเทศ และเข้าร่วมนำเสนอผลงานในงานประชุมนานาชาติ ผลที่ได้รับจากการดำเนินการตลอดระยะเวลาที่ผ่านมามีทั้ง output และ outcome ดังนี้

1) บทความและร่างบทความ จำนวน 10 เรื่อง ประกอบด้วย

1.1) บทความเรื่อง “Spatial Market Integration of Cassava Market and Causality Relationship in Thailand” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาโทของคณะเกษตรศาสตร์ มหาวิทยาลัยเชียงใหม่ บทความดังกล่าวเป็นการวิเคราะห์ความเชื่อมโยงราคาหัวมันสำปะหลังสดโดยพิจาณาจากแหล่งผลิตที่สำคัญของประเทศไทย 7 ตลาด ใน 3 ภูมิภาค เพื่อแสดงประสิทธิภาพของตลาดเชิงพื้นที่ โดยพิจารณาจากความเชื่อมโยงของตลาดและกฎราคาเดียว ด้วยวิธี directed acyclic graph (DAG) with Johansen multivariate cointegration บทความนี้ได้เผยแพร่ให้สำนักงานเศรษฐกิจการเกษตรนำไปใช้ประโยชน์ในการกำหนดนโยบายมันสำปะหลังแล้ว

1.2) บทความการวิเคราะห์ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคาฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. ราคา F.O.B และราคาซื้อขายล่วงหน้าตลาดชิคาโก โดยใช้วิธีวิเคราะห์ที่คล้ายคลึงกับบทความแรกกล่าวคือ ใช้วิธี Johansen multivariate cointegration แต่พิจารณาความเชื่อมโยงที่ต่างกันคือ วิเคราะห์การเชื่อมโยงราคาข้าวโพดเลี้ยงสัตว์โดยพิจาณาจากระดับตลาดที่แตกต่างกัน เพื่อแสดงประสิทธิภาพของตลาดเชิงระดับของตลาด บทความดังกล่าวจะถูกเขียนให้สมบูรณ์และส่งไปตีพิมพ์ในวารสารต่อไป

1.3) บทความเรื่อง “Predicting Price of Palm Oil Using Extreme Value Theory” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ บทความดังกล่าวเป็นการพยากรณ์ราคาโดยพิจารณาใช้ข้อมูลที่มีลักษณะ extreme value ถูกละเลยโดยในการศึกษาก่อนหน้านี้ และวิธีการวิเคราะห์ Block Maxima Model และ Peaks-Over-Threshold Model ที่สอดคล้องกับลักษณะข้อมูลราคาที่รวบรวมได้ โดยวิธีการวิเคราะห์ที่ใช้อยู่นี้เป็นวิธีการที่เพิ่งถูกนำมาใช้กับการพยากรณ์ราคาเมื่อไม่นานมานี้ บทความนี้ถูกส่งไปเพื่อตีพิมพ์ใน International Journal of Agricultural Management และได้รับการตีพิมพ์ใน Volume 2, Number 2, January 2013, pp. 91-99(9)

1.4) บทความเรื่อง “An Application of EVT to Analyze US Corn Market” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ โดยบทความดังกล่าวเป็นการวิเคราะห์ราคาข้าวโพดในตลาดสหรัฐอเมริกาในลักษณะของ extreme value โดยใช้วิธีวิเคราะห์หลายวิธีเพื่อเปรียบเทียบผลที่ได้โดยวิธีวิเคราะห์ในบทความนี้ประกอบด้วย Block Maximum Method (BMM), Peaks Over Threshold (POT) และ GARCH (1,1)-EVT (Conditional-EVT) แม้บทความนี้เป็นการวิเคราะห์ราคาข้าวโพดของสหรัฐแต่ความรู้ที่ได้จะเป็นประโยชน์ต่อผู้วางนโยบายราคาของไทยในการเข้าใจพฤติกรรมราคาของผู้ผลิตสำคัญของโลก

1.5) บทความเรื่อง “Modeling the Volatility of Rubber Price Return Using VARMA GARCH Model” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ โดยบทความดังกล่าวเป็นการวิเคราะห์ความผันผวนของราคายางพารา โดยใช้วิธีวิเคราะห์ VARMA-GARCH และ VARMA-AGARCH เพื่อระบุความสัมพันธ์ระหว่างความผันผวนของราคายางพาราของประเทศไทยกับความผันผวนในอัตราแลกเปลี่ยนที่แตกต่างกัน บทความนี้ถูกส่งตีพิมพ์ใน the Chiang Mai University Journal of Social Sciences and Humanities และอยู่ในระหว่างการตีพิมพ์

1.6) บทความเรื่อง “Modeling Volatility and Dependency of Agricultural Price and Production Indices of Thailand: Static versus Dynamic Copulas” เป็นความร่วมมือระหว่างคณะวิจัยนักวิจัยต่างประเทศ (Prof.Dr. Hung T. Nguyen จาก Department of Mathematical Sciences, New Mexico State University, USA) กับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ โดยบทความดังกล่าวเป็นการวิเคราะห์ความเป็นอิสระระหว่างเปอร์เซ็นต์การเปลี่ยนแปลงราคาผลผลิตเกษตรและดัชนีผลผลิตเกษตรของประเทศไทย โดยวิเคราะห์ conditional volatilities GARCH model และ copula-based multivariate บทความนี้ถูกส่งตีพิมพ์ใน International Journal of Approximate Reasoning และได้รับการตีพิมพ์ทางเว็ปไซต์ 1 กุมภาพันธ์ 2556

1.7) บทความเรื่อง “Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH model” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ บทความนี้ถูกส่งตีพิมพ์ใน International Journal of Intelligent Technologies and Applied Statistics และได้รับการตีพิมพ์ใน Vol.5 No.3 (2012/09), pp. 251-266

1.8) บทความเรื่อง “Modeling volatility and interdependencies of Thai rubber spot price return with climatic factors, exchange rate and crude oil markets” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ บทความนี้ถูกส่งตีพิมพ์ใน 財金論文叢刊 และได้รับการตีพิมพ์ใน No.16 (2012/06), pp. 1-20

1.9) บทความเรื่อง “Application of Extreme Value copulas to palm oil prices analysis” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ บทความนี้ถูกส่งตีพิมพ์ใน Business Management Dynamics และได้รับการตีพิมพ์ใน Vol.2, No.1, Jul 2012, pp.25-31

1.10) บทความเรื่อง “Factors affecting palm oil price based on Extremes Value Approach” เป็นความร่วมมือระหว่างคณะวิจัยกับนักศึกษาระดับปริญญาเอกของคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ และบทความนี้ถูกส่งตีพิมพ์ใน International Journal of Marketing Studies และได้รับการตีพิมพ์ใน Vol. 4, No. 6, 2012

2) การนำผลงานไปใช้ประโยชน์

2.1) ได้ใช้ความรู้ด้านวิชาการเชิงปริมาณให้เกิดประโยชน์ต่อการพัฒนาบุคลากรของรัฐ (สำนักงานเศรษฐกิจการเกษตร (สศก.) กระทรวงเกษตรและสหกรณ์) ในด้านการวิเคราะห์ราคาเพื่อเจ้าหน้าที่สามารถวิเคราะห์ราคาตลาดและพยากรณ์ราคาเพื่อประโยชน์ในการกำหนดนโยบายสำหรับสินค้าเกษตรของประเทศต่อไป โดยกิจกรรมที่เกิดขึ้นภายใต้โครงการความร่วมมือนี้ได้แก่ การจัดอบรมเรื่องการใช้เครื่องมือเศรษฐมิติในการวิจัยให้แก่เจ้าหน้าที่ของสำนักงานเศรษฐกิจการเกษตรและร่วมกันพัฒนาแนวคิดเกี่ยวกับบทความการส่งผ่านราคาของสินค้าเกษตรของประเทศไทยหรือบทความอื่นที่เหมาะสมกับข้อมูลของสำนักงานเศรษฐกิจการเกษตร

2.2) การได้รับเชิญไปเป็นวิทยากรของคณะวิจัยในโครงการ ซึ่งได้รับเชิญในสองลักษณะคือ เป็นวิทยากรบรรยายและผู้นำเสนอบทความ โดยมีรายละเอียดดังนี้

1) คณะวิจัยได้รับเชิญเป็นวิทยากรเรื่อง “การใช้เศรษฐมิติเพื่อการวิจัย” แก่สำนักงานเศรษฐกิจการเกษตร ระหว่างวันที่ 25-29 กรกฎาคม 2554 ที่คณะเกษตรศาสตร์และเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่

2) ได้เข้าร่วมนำเสนอบทความในงานประชุมนานาชาติ 2 แห่งคือ (แสดงในบทที่ 2)

1) งานประชุมนานาชาติ “The 4th International Conference of the Thailand Econometric Society” ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ วันที่ 13 มกราคม 2554 ผลงานวิจัยที่ได้เข้าร่วมในงานประชุมได้แก่บทความเรื่อง “Spatial Market Integration of Cassava Market and Causality Relationship in Thailand” (บทความที่ 1)

2) งานประชุมนานาชาติ “The 5th International Conference of the Thailand Econometric Society” ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ ระหว่างวันที่ 12-13 มกราคม 2555 ผลงานวิจัยที่ได้เข้าร่วมในงานประชุมมีจำนวน 3 บทความ ได้แก่ 1) บทความเรื่อง “Predicting Price of Palm Oil Using Extreme Value Theory” (บทความที่ 3) 2) บทความเรื่อง “An Application of EVT to Analyze US Corn Market” (บทความที่ 4) และ 3) บทความเรื่อง “Modeling the Volatility of Rubber Price Return Using VARMA GARCH Model” (บทความที่ 5)

3) การเชื่อมโยงทางวิชาการอื่นๆ ทั้งในและต่างประเทศ

การดำเนินการโครงการวิจัยดังกล่าว ได้เกิดความเชื่อมโยงทางวิชาการกับหน่วยงานและบุคลากรทั้งจากภายในและต่างประเทศดังนี้

3.1) ความเชื่อมโยงทางวิชาการกับบุคลากรและสถาบันในประเทศ

มีการเชื่อมโยงทางวิชาการในแง่การถ่ายทอดองค์ความรู้และการร่วมมือกันเขียนบทความระหว่างคณะวิจัยและสำนักงานเศรษฐกิจการเกษตร (สศก.)

3.2) ความเชื่อมโยงทางวิชาการกับบุคลากรและสถาบันในต่างประเทศ

คณะวิจัยได้เชิญนักวิจัยต่างชาติมาร่วมปรึกษาและเขียนบทความ เพื่อให้การเขียนบทความมีประสิทธิผลมากขึ้น โดยคณะวิจัยได้เชิญ Assoc.Prof.Dr. Sanzidur Rahman จาก University of Plymounth ประเทศ United Kingdom มาร่วมปรึกษาและเขียนบทความ เป็นระยะเวลา 2 สัปดาห์ (ระหว่างวันที่ 4-18 สิงหาคม 2554) และคณะวิจัยได้เชิญผู้เชี่ยวชาญต่างประเทศให้คำแนะนำและหารือเกี่ยวกับเครื่องมือการวิเคราะห์ได้แก่ 1) เรื่อง Heavy tail โดย Prof. Dr. Hung 2) เรื่อง Extreme Value โดย Prof. Dr. Berlin Wu และ 3) พบปะหารือเกี่ยวกับการวิจัยและจัด workshop ในระหว่างวันที่ 11 - 15 มกราคม 2555 โดย Prof. Dr. Hung

3.3) การเชื่อมโยงทางวิชาการกับนักวิชาการภายในสถาบันเดียวกัน

จากการที่บทความของโครงการวิจัยที่ใช้เครื่องมือวิเคราะห์ที่มีความซับซ้อน การวิจัยโครงการนี้จึงเกิดจากการทำงานร่วมกันระหว่างภาควิชาเศรษฐศาสตร์เกษตรและส่งเสริมเผยแพร่การเกษตร คณะเกษตรศาสตร์และคณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ นอกจากจะเป็นการทำงานร่วมกันระหว่างนักวิจัยแล้ว ยังได้สนับสนุนให้นักศึกษาปริญญาโท ภาควิชาเศรษฐศาสตร์เกษตร คณะเกษตรศาสตร์ 1 คน และนักศึกษาปริญญาเอก คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ จำนวน 4 คน ร่วมเขียนบทความ อันเป็นการเพิ่มศักยภาพของนักศึกษาด้วย

4) ความก้าวหน้าเชิงวิชาการ

โครงการวิจัยนี้มุ่งศึกษาราคาของสินค้าเกษตรเพื่อให้ได้ข้อเสนอแนะเชิงนโยบายสำหรับปรังปรุงระบบราคาและตลาดสินค้าเกษตรเมื่อพบว่าตลาดขาดประสิทธิภาพ และศึกษาพฤติกรรมราคาเพื่อประเมินความเสี่ยงของราคาและผลตอบแทนให้แก่เกษตรกรตลอดจนพยากรณ์ราคา งานวิจัยที่ผ่านมาสำหรับสินค้าเกษตรของประเทศไทยเกือบทั้งหมดใช้วิธีการและแบบจำลองที่มีข้อสมมติที่ไม่สมจริง (strong assumption) หลายประการ ข้อสมมติเหล่านี้ไม่สอดคล้องกับธรรมชาติของข้อมูลสถิติ และจากการที่ข้อมูลซึ่งใช้ในการศึกษานี้เป็นข้อมูลอนุกรมเวลา จึงมีประเด็นข้อสมมติที่เกี่ยวข้องดังนี้

4.1) แบบจำลองต่างๆ ที่ผ่านมาสมมติว่า ข้อมูลมีการกระจายแบบปกติ (normal distribution) ซึ่งข้อมูลอาจไม่มีการกระจายเช่นนี้

4.2) การวิเคราะห์ราคาในลักษณะ multivariate model มีน้อยและไม่ถูกต้อง เนื่องจากข้อมูลเป็นอนุกรมเวลาจึงควรต้องใช้วิธี VARMA-GARCH หรือ VRAMA-AGARCH แต่ทั้ง 2 วิธีนี้ยังคงมีข้อสมมติที่ไม่สมจริงอยู่เช่นกันคือ

ก. การสมมติ normal distribution หรือ asymptotic normal

ข. สมมติ linear correlation ระหว่างราคา 2 ชนิดขึ้นไป ซึ่งความสัมพันธ์ที่แท้จริงไม่จำเป็นต้องเป็นเชิงเส้น

ค. เมื่อข้อมูลราคาไม่มีการกระจายปกติ ข้อมูลในส่วนปลายอาจมีค่ามาก (เรียกว่า extreme value) แบบจำลองทั่วไปรวมทั้ง VARMA-GARCH และ VARMA-AGARCH ไม่อาจประเมินผลได้ (unable to capture tail dependence)

ง. ไม่สามารถจะหาความเบ้ (skewness) ได้

ทางเลือกใหม่เพื่อแก้ปัญหาข้างต้นคือ การใช้แบบจำลอง Copula ซึ่งจะช่วยผ่อนคลายข้อสมมติ ข. และ ค. ได้ และสามารถจับสัญญาความเบ้ได้โดยอาศัยการทดสอบการกระจายด้วย skewness t-distribution

การผ่อนคลายข้อสมมติที่ไม่สมจริงทำให้สามารถวิเคราะห์ข้อมูลได้ถูกต้องและอธิบายความสัมพันธ์ของราคาได้ดีและแม่นยำกว่าในอดีตที่ผ่านมา โดยเฉพาะเมื่อการค้าและการตลาดมีการเปลี่ยนแปลงของทุนและมีการรับข้อมูลได้รวดเร็ว ราคาจึงมักถูกกระทบด้วยการตัดสินใจที่รวดเร็ว โครงสร้าง/พฤติกรรมราคาเปลี่ยนไปจากอดีตแม้จะเป็นสินค้าเกษตรก็ตาม ดังนั้นการประยุกต์เครื่องมือจากสาขาการเงินจึงคาดว่าจะเป็นแนวทางที่เหมาะสม

คำนำ

รายงานนี้เป็นส่วนหนึ่งของโครงการวิจัย “ประสิทธิภาพตลาดเกษตรและกำไรต่อเกษตรกร: การส่งผ่านราคาที่สมมาตรของสินค้าเกษตรที่สำคัญของประเทศไทย” โดยมีวัตถุประสงค์เพื่อวิเคราะห์ประสิทธิภาพของตลาดสินค้าเกษตรซึ่งรวมถึงความเชื่อมโยงของตลาดสินค้าเกษตรที่สำคัญของประเทศไทยและการพยากรณ์ราคาสินค้าเกษตรหลายชนิด อันนำไปสู่ข้อเสนอแนะเชิงนโยบายของตลาดสินค้าเกษตรที่มีนัยยะทางปฏิบัติที่มากขึ้นและการขยายมุมมองของการวิจัยเรื่องประสิทธิภาพการตลาดเกษตรของประเทศ โครงการวิจัยนี้เป็นงานวิจัยพื้นฐานที่ให้ความสำคัญกับการเขียนบทความและตีพิมพ์ในวารสารต่างประเทศ บทความดังกล่าวได้ใช้แบบจำลองวิเคราะห์การเชื่อมโยงของราคาและประสิทธิภาพของตลาดผลผลิตเกษตรหลายรูปแบบอันได้แก่ การวิเคราะห์ความเชื่อมโยงของราคาโดยวิธี Johensen Cointegration การพยากรณ์โดยราคาโดยวิธี GEV-block maxima และ GDP-threshold u การประมาณค่าความเสี่ยงโดยแบบจำลอง GARCH-EVT-Copula การพยากรณ์ราคาโดยแบบจำลอง GJR-GARCH และการวิเคราะห์ความผันผวนของราคาโดยแบบจำลอง VARMA-GARCH และ VARMA-AGARCH

นอกจากนี้โครงการวิจัยดังกล่าวยังก่อให้เกิดความเชื่อมโยงทางวิชาการกับหน่วยงานและบุคลากรทั้งจากภายในและต่างประเทศ การนำเสนอผลงานในการประชุมนานาชาติของนักวิจัยและการส่งบทความเพื่อตีพิมพ์ในวารสารต่างประเทศ รวมทั้งผลของการดำเนินงานในส่วนต่าง ๆ ถูกแสดงในรายงานฉบับนี้เช่นกัน

คณะผู้วิจัยขอขอบคุณสำนักงานกองทุนสนับสนุนการวิจัย (สกว.) ที่เป็นผู้ให้การสนับสนุนทุนวิจัยสำหรับโครงการนี้มาโดยตลอด รายงานฉบับนี้ไม่อาจเกิดขึ้นได้หากปราศจากการสนับสนุนในครั้งนี้

คณะผู้วิจัย

เมษายน 2557

บทคัดย่อ

งานวิจัยนี้เป็นงานวิจัยพื้นฐานที่ให้ความสำคัญกับการเขียนบทความและตีพิมพ์ในวารสารต่างประเทศ บทความที่ได้เป็นการวิเคราะห์ความเชื่อมโยงของราคามันสำปะหลังและข้าวโพดเลี้ยงสัตว์ โดยวิธี Johensen Cointegration เพื่อแสดงให้เห็นถึงประสิทธิภาพของตลาด โดยพิจารณาจากความเชื่อมโยงของตลาดและกฎราคาเดียว การพยากรณ์ราคาปาล์มน้ำมันที่มีลักษณะข้อมูลแบบ extreme value ด้วยวิธีการวิเคราะห์ Block Maxima Model และ Peaks-Over-Threshold Model การพยากรณ์โดยราคาข้าวโพดในตลาดสหรัฐอเมริกาโดยวิธี GEV-block maxima และ GDP-threshold u การวิเคราะห์ความผันผวนของราคายางพารา โดยใช้วิธีวิเคราะห์ VARMA-GARCH และ VARMA-AGARCH และการวิเคราะห์ความเป็นอิสระระหว่างเปอร์เซ็นต์การเปลี่ยนแปลงราคาผลผลิตเกษตรและดัชนีผลผลิตเกษตรของประเทศไทย โดยวิเคราะห์ conditional volatilities GARCH model และ copula-based multivariate ซึ่งผลที่ได้จากการศึกษาถือเป็นการพัฒนาองค์ความรู้ด้านการวิเคราะห์ความเชื่อมโยงของราคาและประสิทธิภาพของตลาดผลผลิตเกษตรให้มีความสมบูรณ์และสอดคล้องกับสถานการณ์จริงมากขึ้น ซึ่งเป็นสิ่งที่ใหม่สำหรับการศึกษาการความเชื่อมโยงของราคาสินค้าเกษตรของประเทศไทย นอกจากนี้ยังเป็นประโยชน์ต่อผู้วางนโยบายอีกด้วย ผลการศึกษาดังกล่าวถูกนำเสนอในรูปบทความที่ถูกนำเสนอทั้งในในวารสารต่างประเทศและการประชุมระดับนานาชาติ

สารบัญ

บทที่ 1
ผลงานวิจัย

ในช่วงระยะเวลาดำเนินงานของโครงการ (15 สิงหาคม 2553 – 14 สิงหาคม 2555) คณะวิจัยได้เขียนและร่างบทความจำนวน 10 เรื่องได้แก่ 1) บทความเรื่อง “Spatial Market Integration of Cassava Market and Causal Relationship in Thailand” เป็นการวิเคราะห์ความเชื่อมโยงของตลาดหัวมันสำปะหลังสดในแหล่งผลิตที่สำคัญของประเทศไทย 7 ตลาด ใน 3 ภูมิภาค เพื่อวิเคราะห์ประสิทธิภาพของตลาดในเชิงพื้นที่ โดยพิจารณาจากความเชื่อโยงของตลาดและกฎราคาเดียว ด้วยวิธี directed acyclic graph (DAG) with Johansen multivariate cointegration (โดยต่อมาในภายหลังได้เพิ่มเติมการวิเคราะห์ราคาด้วย quantile regression ต่อจาก DAG) 2) ร่างบทความการวิเคราะห์ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคา ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาด กทม. ราคา F.O.Bและราคาซื้อขายล่วงหน้าตลาดชิคาโก 3) บทความเรื่อง “Predicting price of palm oil using Extreme Value Theory” เป็นการพยากรณ์ราคาน้ำมันปาล์มในตลาดล่วงหน้าของประเทศมาเลเซีย โดยพยากรณ์ราคาล่วงหน้าในช่วงระยะเวลา 5 ปี 10 ปี 25 ปี 50 ปี และ 100 ปี 4) บทความเรื่อง “An Application of EVT to Analyze US Corn Market” 5) บทความเรื่อง “Modeling the Volatility of Rubber Price Return using VARMA GARCH Model” 6) บทความเรื่อง “Modeling Volatility and Dependency of Agricultural Price and Production Indices of Thailand: Static versus Dynamic Copulas” 7) บทความเรื่อง “Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH model” 8) บทความเรื่อง “Modeling volatility and interdependencies of Thai rubber spot price return with climatic factors, exchange rate and crude oil markets” 9) บทความเรื่อง “Application of Extreme Value copulas to palm oil prices analysis” และ 10) ร่างบทความเรื่อง “Analysis of volatility and dependence between the future price of corn and soybean conditional on energy indices: Dynamic vine copula based ARMAX-GARCH model” ดังรายละเอียดต่อไปนี้

บทความที่ 1

Spatial Market Integration of Cassava Market and Causal Relationship in Thailand

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Spatial Market Integration of Cassava Market and Causal Relationship in Thailand

Abstract This paper investigated cassava marketing efficiency via spatial market integration using directed acyclic graph (DAG) with Johansen multivariate cointegration procedure to test the law of one price (LOP) for regional cassava markets in Thailand. The empirical evidence indicates that the LOP is satisfied by only some markets even though most cassava markets in the seven provinces are integrated. Results of DAG indicated that the largest production province implying largest market played dominant roles in price transmission. Cassava markets that share the same provincial borders exhibited a significantly higher degree of price linkages in the long run due to cost advantages. The recent growth in production and thus high market concentration evidently worsened market integration. This calls for effective measures for information dissemination and promotion of investment and competition in large production areas.

Keywords: spatial market integration, law of one price, directed acyclic graph, market efficiency, cassava.

1. Introduction

Thailand has been the largest cassava exporting country, with a 70% share of export quantities for many years. Despite of price instability in the past two decades, and frequent losses incurred to growers, cassava production and export are expected to grow continuously. The problem of price instability called for intervention policies such as pledging policy, and export quotas to cope with price volatility. Theoretically, intervention policies distort market mechanism and thus induces market inefficiency which essentially affect for resources allocation.

Studies of market efficiency in the context of price efficiency are common. Researchers adopt the frame work of price transmission along a supply chain and concern with function of agents in each market level as information processors, for example, Vavra and Goodwin (2005); Zhou and Buongiorno (2005); Serra and Goodwin (2003). Another framework in the context of market integration, emphasizing on the spatial dimension and often used to assess effects of price intervention on price and farmers' income as well as the influence on market efficiency, such as in Ravallion (1986); McNew (1996); Onyuma *et al.* (2006); Asche *et al.* (2004); Lohano and Mari (2006) etc. The underlying theory of these frame works is "law of one price" (LOP). Among others, Ardeni (1989); Yang *et al.* (2000); and Nanang (2000); Liu and Wang (2003) test price efficiency in the context of spatial market integration based on the LOP. If market integration does not exist, these policies are potentially effective, since price levels may respond accordingly. On the contrary, such policies are ineffective if market integration is strong because price levels can be affected marginally. Empirical evidences in Thailand show that the pledging programs could not effectively raise prices of cassava and rice (Pongpoorsakorn, et al. , 2000; Sriboonchitta, 2000).

Spatial (horizontal) market integration studies of Thailand was found in various agricultural product such as pig (Lapboonruang, 2004), rice (Trakulphonnimit, 2002), banana (Visansirikul, 2003), fruit (Issariyathip, 2002), feed corn (Kuntum, 2003), and palm (Kaewchuey, 2007) etc., but not in cassava. Previous studies on cassava market in Thailand focused on price transmission along supply chain of various cassava products include Sittikul (1997); Sanguanchur (2002); Apihakit (2004); Poomprasert (2005) and Punkla (2008). These studies employed cointegration approach based on Engle and Granger framework with Granger causality. To our knowledge, this study is the first attempt to test for spatial market integration of cassava in Thailand.

In recent studies, the measurement of pricing efficiency in agricultural commodity markets has overcome methodological flaws due to spurious relationship and heteroscedasticity residuals in the regression. For example, Ravallion (1986) proposed a dynamic model of spatial price differentials, Timmer (1987), suggested the index of market connection (IMC) which based on Ravallion's model and other approaches, such as Switching Regime Model (Fackler, 1996). A growing body of the spatial market integration literature has emphasized the importance of transfer cost, such that the Parity Bounds Model (PBM) developed by Sexton *et al.* (1991) and Baulch (1997) explicitly take into account of the non-linear price relationship in spatially distributed markets that is caused by transfer cost.

Most recently researchers use the cointegration approach as the empirical method for investigating a long run equilibrium relationship. If two spatially separated price series are cointegrated, there is a tendency for them to co-move in the long run according to a linear relationship. In the short run, the prices may deviate, as shocks in one market may not be instantaneously transmitted to other markets or due to delays in shipping, however, regional trading opportunities ensure that these divergences from the underlying long run relationship are transitory and not permanent (Rapsomanikis *et al*. 2003). The recent research works are based on Engle and Granger (1987) method of cointegration, for example, Alexander and Wyeth *et al.* (1991). Although the Engle and Granger (1987) procedure is easily implemented, it does have several important defectives i.e. the procedure is sensitive to the choice of the variable selected for normalization and this problem is obviously compounded when using three or more variables since any of variables can be selected as an endogenous variable. If there may be more than one cointegrating vector, this method has no systematic procedure for the separate estimation of the multiple cointegrating vectors including other defectives (Enders, 2004: pp.370-372). The Johansen and Juselius (1990) maximum likelihood estimator overcomes the use of two step estimators of Engle and Granger (1987) and can test for the presence of multiple cointegrating vectors. Furthermore, this test allows the researcher to test restricted versions of cointegrating vectors, speed of adjustment parameters and it is possible to verify a theory by testing restrictions on the magnitudes of the estimated coefficients (Enders, 2004). Alternatively, the directed acyclic graph (DAG), a data-determining approach has been adopted to identify directional relationship among markets (Bessler et al. 2003; Awokuse, 2007)

This study investigated cassava spatial market integration using DAG with Johansen multivariate cointegration procedure to test the law of one price (LOP) for seven provincial markets of 3 regions of major producing cassava markets.

The rest of the paper is organized as follows: next 2 sections describe conceptual framework and description of the data and back ground, sections 4 and 5 report the empirical results and conclusions and implications.

2. Conceptual framework

Market efficiency has been very popular in both theoretical and empirical research. Market efficiency can be considered in the context of either operational efficiency or price efficiency. For the latter, the approach that uses market integration to measure market efficiency is based on the concept by Bessler and King (1970) that an efficient commodity market will establish prices that are interrelated spatially by transaction cost, intertemporally by storage costs and in terms of form by processing cost. In spatially integrated markets, competition among arbitragers will ensure that a unique equilibrium is achieved where local prices in regional markets differ by no more than transfer cost. Information of spatial market integration, thus, provides indication of competitiveness, the effectiveness of arbitrage, and the efficiency of pricing. In theory, markets are said inefficient if profitable arbitrage opportunities persist. Thus, spatial price determination models suggest that, if two markets are linked by trade in a free market regime, excess demand or supply shocks in one market will have and equal impact on price in both markets and thus these prices move up and down together. This is called the law of one price, it has been the basic for test of market efficiency and market integration (Tomek with Robinson, 2003: 168; Rapsomanikis *et al.* 2003). Factors that prevent the existence of efficient agricultural markets or decrease market integration degree are poor infrastructure, intervention policies, non-competitive behavior of traders (oligopoly and collusion), and high transfer cost and marketing margin. (Rapsomanikis *et al*. 2003; He, 2003; Onyuma *et al*. 2006). Spatial market integration could be investigated via the transmission of price shocks from one regional market to other horizontally related markets.

There are three forms in which the efficient market hypothesis is stated: weak form, semi-strong form and strong form. The weak form of the LOP of market efficiency is more commonly observed in the real world than the strong form. This concept for spatial arbitrage relationship between regions X and Y shown in eq.(1), represents the strong form if $\alpha = \beta_2 = 0$ and represents the weak form when this restriction is removed. The parameter $\beta_1 = 1$ indicates perfect transmission of a price change in one market to the second market for both forms.

$$Px_t = \alpha + \beta_1 Py_t + \beta_2 Z_t + e_t \tag{1}$$

Where Px_t and Py_t are prices for homogenous goods at time t in markets X and Y, α is transfer costs between markets X and Y and Z_t denotes non-stochastic factors. Most of recent works employ cointegration modeling to capture long run price relationship and to avoid problem of spurious relationship due to nonstationarity of prices series (Bessler et al., 2003; Awokuse, 2007). This study adopted the approach outlined by Awokuse (2007) and Bessler et al. (2003)

for investigating spatial market integration and causal analysis with directed acyclic graphs (DAG).

To investigate market integration as modeled in equation (1) the procedure of this study takes 5 steps as follow: 1) test for structural change using recursive residual developed by Brown *et al.* (1975) and Chow test 2) test for seasonal unit roots for each series, using procedure developed by Beaulieu and Miron (1993) under structural change 3) test for Johansen's multivariate cointegration 4) conduct innovation accounting analysis (impulse response function and forecast error variance decomposition) and 5) investigate of causal relationships among seven markets using directed acyclic graph (DAG). The analysis process in step 1) to 5) employ Eviews 6, and causality test by DAG, uses Tetrad IV. All of variables are in logarithms. It is hypothesized that relative to other markets, contiguous cassava producing provinces engaged in arbitrage should exhibit a higher degree of market integration due to effect of relative lower transportation costs, and better access to information. Econometric formulation for essential tests for Johansen's cointegration and DAG procedure are briefly presented below.

2.1 Johansen's cointegration test

The main advantage of the Johansen approach in testing for market integration and the law of one price (LOP) is that it allows hypothesis testing on the coefficients of both α and β using likelihood ratio test. The Johansen cointegration test is based on a vector autoregression (VAR) system. Given a price vector Pt, VAR is carried out using eq. (2) and short term adjustment be written in vector error correction form (VEC) as eq. (3)

$$P_t = A_1 P_{t-1} + A_2 P_{t-2} + \ldots + A_k P_{t-k} + \varepsilon_t \tag{2}$$

$$\Delta P_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-1} + \varepsilon_t , \qquad t = 1,\ldots, T \tag{3}$$

where $\Gamma = -\left[I - \sum_{j=1}^{i} A_j \right]$ and $\Pi = -\left[I - \sum_{i=1}^{k} A_i \right]$

P_t is (nxn) column vector of m variables, μ is an (nx1) vector of constant terms, Γ and Π represent coefficient matrices, Δ is a difference operator, k denotes the lag length, and ε_t is independently and identically distributed (i.i.d.). The coefficient matrix Π is known as the impact matrix, and it contains information about the long run relationships. The following three relevant hypotheses are rank test for number of cointegrating vectors, test of LOP for perfect market and test for weak version of LOP of eq.(1).

1) Cointegration rank (r) test

Rank of Π , r determines the number of stationary linear combinations of P_t, There are three possibilities: (1) if r = n, the price variables are stationary in level, (2) if r = 0, there exists no linear combination of P_t that are stationary, and (3) 0< r <n, there exists r stationary linear combinations of P_t. A rank of r = n -1 in a multivariate system with n price series would imply that there is only one stochastic trend driving the behavior of prices in the system. Cointegration rank test under hypothesis $H_0 : \Pi = \alpha\beta'$. There are two alternative tests that used to identify the number of significant cointegrating vector r, the trace test (λ_{trace}) and maximum eigenvalue test (λ_{max}) as in eq.(4) and (5).

$$\lambda_{Trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}) \qquad (4)$$

Trace test (λ_{trace}) hypothesis is H_0: cointegration vector $\leq$ r

H_a: cointegration vector $\geq$ r

$$\lambda_{max} = -T \ln(1-\hat{\lambda}) \qquad (5)$$

Maximum eigenvalue test (λ_{max}) hypothesis is H_0: cointegration vector = r

H_a: cointegration vector = r+1

2) Test of the law of one price (LOP)

Testing for the law of one price (LOP), restrictions R' can be placed and tested on the parameters in the β matrix under hypothesis $H_0 : R'\beta = 0$. If rank of the multivariate system is n-1, the LOP test becomes a test of whether the row in the β matrix sum to zero. The hypothesis that the LOP holds for all prices simultaneously is determined by the rank of the system. If r = n (full rank), then the LOP holds for all prices simultaneously. If r < n, then the LOP is rejected for all prices simultaneously, in which case, the second testable hypothesis is that the LOP holds between any two prices (Nanang, 2000)

3) Weak exogeneity test

Adjustment parameters are related to the concept of weak exogeneity. If all adjustment parameters for one variable are zero, then this variable is said to be weakly exogenous to the long run parameters in the remaining equations. This implies that the coefficients on the levels of the remaining price series in the system is zero in this particular equation which would mean other price variables are not influencing this variable in the long run. The null hypothesis is that each variable does not respond to shock or disequilibrium in the long run relationship ($H_0 : \beta'\alpha = 0$), the ith row of the Π matrix is zero. That is the ith row of α has its element equal to zero. (Bessler *et al*., 2003)

2.2 Directed acyclic graph (DAG)

The majority of past investigations of causal relationships among economic variables use the Granger causality framework that builds on the knowledge that a cause precedes its associated effect thus an effect does not precede its cause. Recently, Spirtes *et al.* (2000) and Pearl (2000) proposed DAG, which based on a non-time sequence asymmetry in causal relations. DAG represents a conditional independence relationship (for details application of DAG to VAR see Awokuse and Bessler, 2003) as given by the recursive decomposition as eq. (6) Awokuse *et al.* (2009)

$$\Pr\left(v_1, v_2, v_3, \ldots, v_n\right) = \prod_{i=1}^{n} \Pr\left(v_i \middle| pa_i\right) \tag{6}$$

Where Pr (.) is the joint probability of variables $\nu_1, \nu_2, \nu_3, \ldots, \nu_n$ and pa_i represents some subsets of the variables that precede (come before in a causal sense) v_i in order ($\nu_1, \nu_2, \nu_3, \ldots, \nu_n$). DAG employed PC algorithms, that proceeds step wise testing. The process of causal determination begins with a complete undirected graph which shows an undirected edge between variables in the system, then remove edges between variables and the assign causal flows on the remaining edges. Fisher's z is used to test whether conditional correlations are significantly different from zero, Fisher's z show as eq. (7) (Bessler, 2004).

$$z\left[\rho(i, j|k), n\right] = \left[\frac{1}{2}\sqrt{n - |k| - 3}\right] \ln\left\{\frac{|1 + \rho(i, j|k)|}{|1 - \rho(i, j|k)|}\right\}, \tag{7}$$

Where n is the number of observations used to estimate the correlations, $\rho(i, j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and $|k|$ is the number of variables in k. If i, j, and k are normally distribution of $z\left[\rho(i, j|k), n\right] - z\left[r(i, j|k), n\right]$ is standard normal.

MIM, Tetrad and WinMine are alternative software for DAG estimation to identify the causal flow among the variables. Although each package uses a different algorithm, the results are to some extent similar. All three packages are free and easy to use (Haughton, *et al.,* 2006). This study use Tetrad IV which located on the internet at www.phil.cmu.edu/projects/tetrad/.

3. Data and Background

The data used for analysis are monthly farm prices during January 1989 - March 2009 obtained from Office of Agricultural Economics (OEA), Ministry of Agriculture and Agricultural Cooperatives (MAAC). Prices were deflated by CPI to reflect real price received by growers. Seven provinces were selected to represent major markets of 3 regions (northeast, east and west) on the basis of their production areas and availability of data. Nakronrachasima (Nak), Chaiyapoom (Cha) and Konkhaen (Kon), are 3 top rank of the northeastern region which rank 1, 3 and 12 of the country. Nak is apparently the largest market both for cassava and processed products of the whole kingdom. Chacheongsao (Cha), Chonburi (Cho) and Rayong (Ray) rank 5, 7 and 10 of the country production representing the eastern region and Kanchanaburi (Kan) represents central-western region as it holds the sixth largest production of the country.

The average market absorption of cassava drying place-merchants (merchants who own drying compound and transform cassava to dry chips) ranged from 7,028 rai (1acre=6.25 rai) of production area in Cha to 30,580 rai in Ray. These capacities of absorption can somewhat reflect the local competition in individual provinces. Apparently merchants in Nak are relatively large (absorption capacity = 22,482 rai) and likely to have higher market power. The overall picture of cassava prices in 7 provinces seems to move in concert to each other (Figure 1). However, the average prices, maximum and minimum prices of Nak appeared to lay above all others while all price statistics of Kan were found the least.

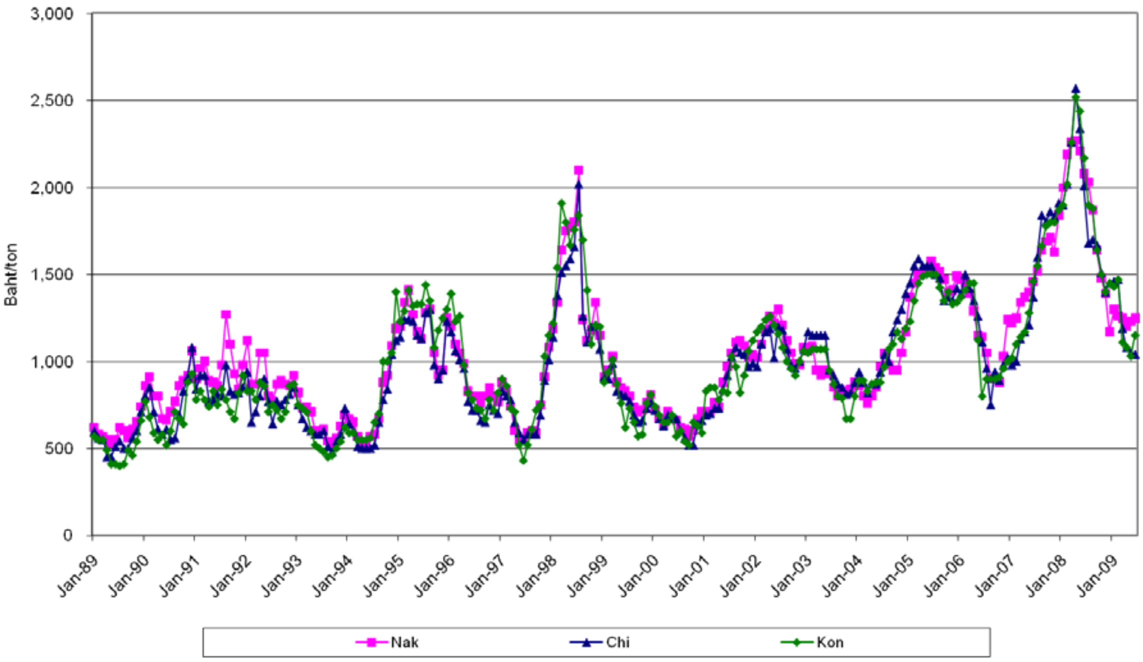
“Insert Table I Here”.

Historically, cassava was used almost entirely for feed. Only in the past 3 years (2008) when all economies faced with high visa in oil price, cassava has been shared for bio fuel production. Cassava as raw material for feed still has dominated the total demand since Europe was Thailand’s largest market during 1980’s and 1990’s. Due to the Common Agricultural Policy (CAP policy) and CAP reform (1992), European’s demand for pellets drastically declined and obviously affected prices paid to cassava growers. To reduce risk and restore volume of export, Thailand export markets have been diverted. As the consequent, China recently became the largest market for chip. The Thai-China free trade agreement (October 2003) boosted export of chips which compensated for decline of pellets export to other market). Furthermore, domestic demand for cassava in biofuel has gradually expanded in 2008.

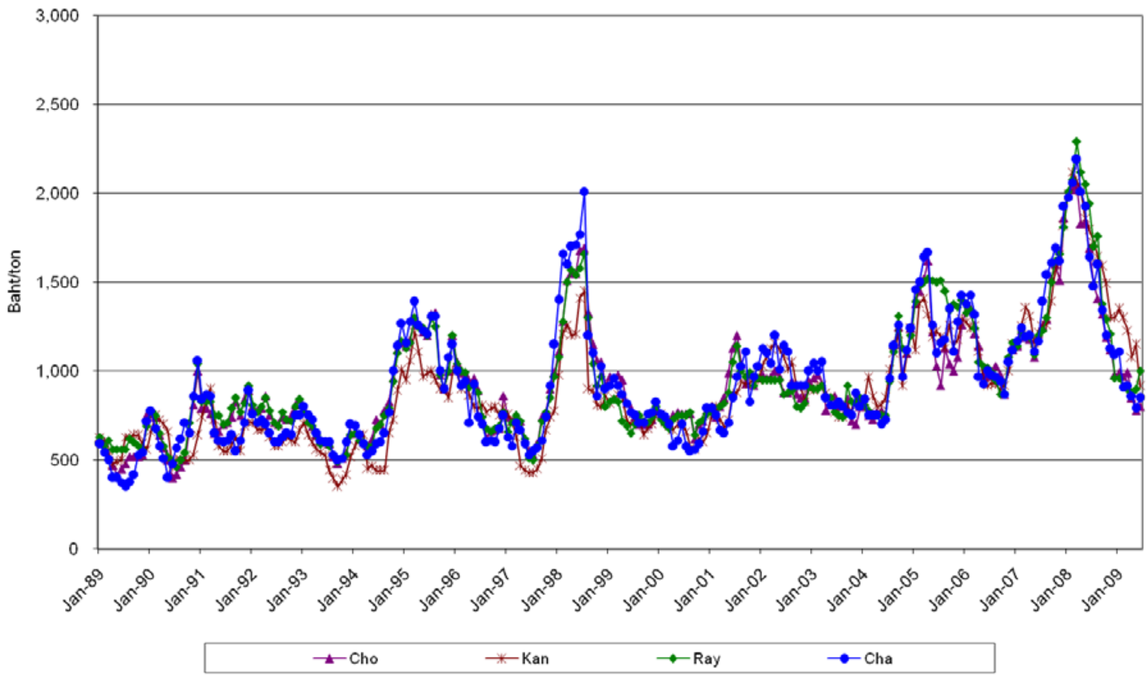
Despite of positive trend in market demand, cassava prices after 1998 on average were relatively lower than the past (Figure 1). As being a major cash crop, frequent market intervention policies were implemented for export expansion and presentation of price falls. More specifically, the pledging policy was employed to reduce price volatility and to maintain desirable farm price levels. In contrast to the past, the most recent income guarantee program

(2009) has allowed market mechanism to operate freely while the certain level of farm income has been ensured. Although previous research did not confirm the success of price intervention programs, we employ test for structural change to ensure the presence of a single pattern of price series. The recursive residual test procedure for structural break suggested by Brown *et al*. (1975) was applied to the price series of Nak (the largest market).

The null hypothesis of no structural change was rejected at .05 and this result was confirmed by Chow test. The existence of structural break appears around January 2003. Hereafter, all prices analyses are applied to 2 sub periods (i.e. 1989: 01 – 2002: 12 and 2003: 01-2009: 06). Before moving to the next section, we applied Beaulieu and Miron (1993) procedure at the known break points. The results indicate existence of non-stationary in all seven series in both sub periods. Thus the seasonal differencing filter is applied to the series.



Farm prices of cassava in Northeastern provinces



Farm prices of cassava in Eastern and Western provinces

Figure 1

4. Empirical Result

Johansen cointegration test and the LOP test

The results of standard rank tests using λ_{trace}(and λ_{max}) reveal 6 (and 2) cointegration vectors in sub period 1 and only vector normalized by Ray was selected for further analysis (based on AIC and SIC criteria). For sub period 2, both λ_{trace} and λ_{max} indicate existence of only one stable long run equilibrium relation in the series.

For sub period 1, the estimation results of cointegrating vector (β) and adjustment parameter (α) after normalization for each period are shown (in Table II) that 4 markets (Kan, Cho, Cha, Nak) determine price in Ray and having long term relationship. As implied by β_s, (0.23 to 1.00) the market exhibit poor to high degree of integration. In sub period 2, most markets are moderately integrated (β_s range from 0.35 to 0.7). Surprisingly Nak, the largest market did not determine the price in Ray as did in the sub period 1.

"Insert Table II Here".

The test for the LOP $(\beta'\alpha = 0)$of cointegration equation in sub period 1 can not be rejected for all of pairs while sub period 2, the LOP hold for some pairs (pkon-pkan and pkon-pcha) but multivariate test for the LOP, shows that LOP hold for all market except Ray (pray) and Nak market (pnak).

"Insert Table III Here".

Results of testing hypothesis $H_0 : \beta'\alpha = 0$ for weak exogeneity of α in sub period 1 and 2 are summarized in Table III. In sub period 1, $\alpha_2, \alpha_4, \alpha_7$ are significantly different from zero, indicated that only Ray (high concentrated market) Cho (closet to the port) and Nak (largest market) responded to shock in the long run relationship (cointegrating vector). In sub period 2, only Kon (the smallest market) and Cho market that responded to perturbations in the long run relations.

Result of causality test using directed acyclic graph (DAG)

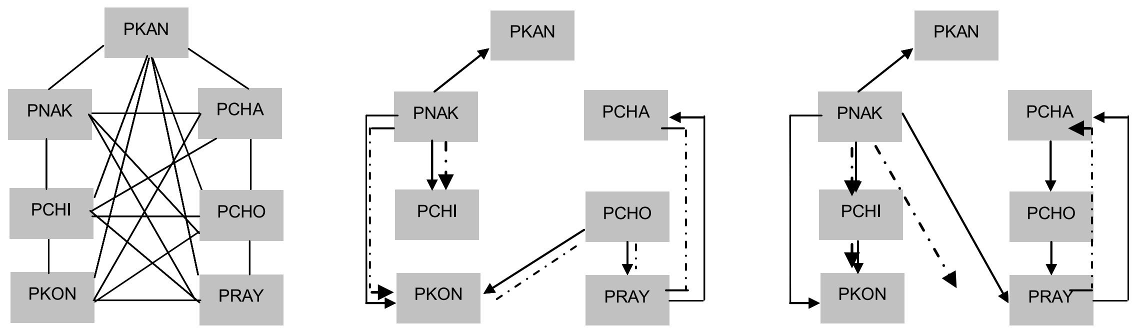
To visualize the dynamic price relationship among 7 provincial markets, the DAG was employed. Based on innovations from error correction model, the correlation matrices for periods 1 and 2 are presented in Figure 2. The DAG depicts casual flows among the set of markets based on observed correlation.

$$
\text{corr}_{\text{sub1}} = \begin{array}{c} \begin{array}{ccccccc} \text{pkon} & \text{pray} & \text{pkan} & \text{pcho} & \text{pcha} & \text{pchi} & \text{pnak} \end{array} \\ \begin{bmatrix} 1.00 & & & & & & \\ 0.51 & 1.00 & & & & & \\ 0.33 & 0.35 & 1.00 & & & & \\ 0.55 & 0.86 & 0.39 & 1.00 & & & \\ 0.40 & 0.45 & 0.37 & 0.41 & 1.00 & & \\ 0.44 & 0.52 & 0.48 & 0.53 & 0.40 & 1.00 & \\ 0.50 & 0.52 & 0.57 & 0.53 & 0.44 & 0.88 & 1.00 \end{bmatrix} \end{array}
$$

$$
\text{corr}_{\text{sub2}} = \begin{array}{c} \begin{array}{ccccccc} \text{pkon} & \text{pray} & \text{pkan} & \text{pcho} & \text{pcha} & \text{pchi} & \text{pnak} \end{array} \\ \begin{bmatrix} 1.00 & & & & & & \\ 0.27 & 1.00 & & & & & \\ 0.12 & 0.36 & 1.00 & & & & \\ 0.20 & 0.59 & 0.44 & 1.00 & & & \\ 0.33 & 0.69 & 0.35 & 0.76 & 1.00 & & \\ 0.70 & 0.31 & 0.10 & 0.33 & 0.47 & 1.00 & \\ 0.47 & 0.56 & 0.21 & 0.40 & 0.50 & 0.60 & 1.00 \end{bmatrix} \end{array}
$$

Panel as in Figure 2 shows complete undirected graph. In sub period 1 (panel b), the general findings indicate integration between cassava markets within the same region (especially, market in contiguous provinces) implied the causal link from a larger to the other smaller markets. In the Northeast region, Nak sends instantaneous price information to Chi (pchi), and Kon (pkon). Similarly to markets in Eastern region showing causal flow of price information Cho (pcho) to Ray (pray) and ambiguous relationship between Ray (pray) and Cha (pcha) in sub period 1. The cross regional appears strongly for Nak and Kan and less from Cho to Kan. In sub period 2 (panel c), in the eastern region, Ray, the highest concentrated market, sent out signals to Cha (the largest market and least concentrated) which in turn signaled price to Cho (smallest market/closet to the port). The causality with in the northeastern markets became stronger in period 2. Furthermore, there exists a close link between northeastern and eastern regions (Nak-Ray).

This analysis revealed the dominant position of the Nakhonratchasrima (the largest cassava producing province) in cassava trade. It was sends instantaneous price information to all other provincial cassava markets in each period, except Cho (pcho) and Cha (pcha). This empirical evidence suggests that markets in contiguous provinces (province that share same border) exhibit instantaneous transmission of price information. Close geographical proximity of cassava markets could be assumed to be raising trade as it relatively lowers transactions costs.



at 5 % level at 10 % level

(a) Complete undirected graph (b) DAG (1989:01-2002:12) (c) DAG (2003:01-2009:06)

Figure 2 Causality test by directed acyclic graphs (DAGs)

Source: Analyze by Tetrad IV

5. Conclusion and policy implication

The empirical evidence indicates existence of structural break around 2003 when export of pellets switched to chips and starch and the free trade agreement between Thailand and China began. The findings reveal cointegrating vectors in periods 1 and 2 can not reject the multivariate test for law of one price in periods 1 and 2. However, the pair wise tests in period 2 can reject H_0 of LOP only for 2 out of 6 pairs. Causal direction results from DAG clearly indicate that the largest market (Nak) with relatively high market concentration is the price leader and plays dominant roles in price transmission not only to within the region but possibly to major markets of other regions. The geographical proximity among contiguous provinces and between each province to the main port exhibit significant price links. A possible reason is relative lower transportation costs allow trades of fresh cassava and dry chips among contiguous provincial markets. The recent market structure change has reduced market intervention. The growth of cassava production and business expansion of merchants owning drying places (chip processors) lead to high market concentration and market power. Proximity to the main port no longer has information and cost advantages. It is possible that these advantages were dominated and offset by market power.

Generally, spatial market integration analysis has been widely used for assessing the effectiveness of government policies (especially, intervention policies) in developing countries. For this empirical result, intervention policy for cassava market of Thailand (pledging policy) found not to impede market integration. The income guarantee program by itself generates compensation to growers based on prevailing market price and thus the program has no effect on price distortion. Evidently, the concentrated (Ray) and/or large (Nak) markets as well as Cho (close to the main port) responded to price perturbation in period 1 but not in period 2. Only the small markets (Kon and Cho) adapted to respond to price shock in period 2. This further confirms existence of significant role of large markets.

To reinforce spatial market integration and pricing efficiency among producing provinces, it require investment promotion for more drying places-merchants (or chip processors) as well as other intermediate processing. The existing information of futures price of chip in the relevant form should be made available widely to growers in all provinces. The government should closely monitor marketing practices of merchants in large markets especially Nak to improve price information distribution and their pricing strategies. Because transportation costs were not available, distance among markets should be served as proxy exogenous variable. Lastly, response to perturbations of each market should be presented to identify direction and magnitude of response such that specific policy implications could be drawn.

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Appendix

Table I: Price statistics and characteristics of the selected provinces

	Northeast			East			West
Stat.	Nak	Chi	Kon	Cha	Cho	Ray	Kan
mean	1,309.4	1,251.4	1,257.4	1,179.5	1,183.3	1,200.5	1,117.4
median	1,256.0	1,204.6	1,197.6	1,091.8	1,134.3	1,124.2	1,071.3
maximum	2,539.3	2,442,6	2,386.4	2,430.5	2,043.5	2,206.2	2,054.3
minimum	677.0	617.6	574.6	654.5	704.8	664.9	563.6
Production area country rank	1	3	12	5	7	10	6
Absorption rank* (rai/merchant)	2 (22,482)	4 (12,469)	3 (20,514)	7 (7,028)	5 (8,619)	1 (30,580)	6 (8,066)
Proximity to pert rank	4	6	7	2	1	3	5

Note * Absorption capacity = total production area ÷ number of merchants.

Table II: Normalized cointegrating vectors (β) and short run adjustment parameter (α) from unrestricted cointegration model

variables	Sub period 1 (1989:01-2002:12)		Sub period 2 (2003:01-2009:06)	
	cointegration equation	(normalized by Pray)	cointegration equation	(normalized by Pkon)
	β	α	β	α
Pkon	0	0.044	1	-1.009***
Pray	1	0.121	0.066	0.552*
Pkan	0.478***	0.412***	0.695***	0.185
Pcho	1.048***	0.363***	0.630***	1.069***
Pcha	0.234***	0.152	0.711**	0.467*
Pchi	0.095	-0.138	0.352***	-0.140
Pnak	0.737***	-0.223*	0.039	0.193
constant	0.015	-	-	-

Note: *,**,*** indicates significance at 10% 5% and 1% level

Source: Analysis by Eviews 6

Table III: Test of hypotheses for sub period 1 and sub period 2

hypothesis		χ^2 statistic	result
Test of hypotheses of LOP and weak exogeneity test in sub period 1			
H_0: test of market integration hypothesis or LOP $(H_0 : R'\beta = 0)$			
$\beta_2 + \beta_3 = 0$	[pray=1, pkan= -1]	4.60	F
$\beta_2 + \beta_4 = 0$	[pray=1, pcho= -1]	0.10	F
$\beta_2 + \beta_5 = 0$	[pray=1, pcha= -1]	4.064	F
$\beta_2 + \beta_6 = 0$	[pray=1, pchi= -1]	3.13	F
$\beta_2 + \beta_7 = 0$	[pray=1, pnak= -1]	7.16	F
$\beta_2 + \beta_3 + \beta_4 + \beta_6 + \beta_7 = 0, \beta_1 = \beta_5 = \beta_7 = 0$		8.33	F
H_0: test of weak exogeneity of adjustment coefficients $(H_0 : \beta'\alpha = 0)$			
$\alpha_{1j} = 0$ for j = 1, 2	$(\alpha_1 = \mathrm{pkon})$	4.76	F
$\alpha_{2j} = 0$ for j = 1, 2	$(\alpha_2 = \mathrm{pray})$	10.22	R
$\alpha_{3j} = 0$ for j = 1, 2	$(\alpha_3 = \mathrm{pkan})$	5.48	F
$\alpha_{4j} = 0$ for j = 1, 2	$(\alpha_4 = \mathrm{pcho})$	10.18	R
$\alpha_{5j} = 0$ for j = 1, 2	$(\alpha_5 = \mathrm{pcha})$	4.80	F
$\alpha_{6j} = 0$ for j = 1, 2	$(\alpha_6 = \mathrm{pchi})$	7.038	F
$\alpha_{7j} = 0$ for j = 1, 2	$(\alpha_7 = \mathrm{pnak})$	10.49145	R

Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis

Source: Analysis by Eviews 6

Table III: continued

hypothesis		χ^2 statistic	result
Test of hypothesis $H_0 : R'\beta = 0$ and $H_0 : \beta'\alpha = 0$ in sub period 2			
H_0: test of market integration hypothesis $(H_0 : R'\beta = 0)$			
$\beta_{11} + \beta_{13} = 0$	[pkon=1, pkan= -1]	2.897311	F
$\beta_{11} + \beta_{12} = 0$	[pkon=1, pray= -1]	13.66343	R
$\beta_{11} + \beta_{14} = 0$	[pkon=1, pcho= -1]	17.82320	R
$\beta_{11} + \beta_{15} = 0$	[pkon=1, pcha= -1]	1.142098	F
$\beta_{11} + \beta_{16} = 0$	[pkon=1, pchi= -1]	19.33641	R
$\beta_{11} + \beta_{17} = 0$	[pkon=1, pnak= -1]	17.39124	R
$\beta_{11} + \beta_{13} + \beta_{14} + \beta_{15} + \beta_{16} = 0, \quad \beta_{12} = \beta_{17} = 0$		9.902597	F
H_0: test of weak exogeneity of adjustment coefficients $(H_0 : \beta'\alpha = 0)$			
$\alpha_{1j} = 0$ for j = 1	$(\alpha_1 = \text{pkon})$	14.64515	R
$\alpha_{2j} = 0$ for j = 1	$(\alpha_2 = \text{pray})$	4.321000	F
$\alpha_{3j} = 0$ for j = 1	$(\alpha_3 = \text{pkan})$	0.559749	F
$\alpha_{4j} = 0$ for j = 1	$(\alpha_4 = \text{pcho})$	9.918984	R
$\alpha_{5j} = 0$ for j = 1	$(\alpha_5 = \text{pcha})$	3.807929	F
$\alpha_{6j} = 0$ for j = 1	$(\alpha_6 = \text{pchi})$	0.184414	F
$\alpha_{7j} = 0$ for j = 1	$(\alpha_7 = \text{pnak})$	0.447487	F

Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis

Source: Analysis by Eviews 6

ร่างบทความที่ 2

ร่างบทความนี้เป็นการวิเคราะห์ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคา ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. ราคา F.O.B และราคาซื้อขายล่วงหน้าตลาดชิคาโก ข้อมูลที่ใช้ในการศึกษาเป็นข้อมูลรายเดือนตั้งแต่เดือนมกราคม 1999 - มิถุนายน 2012 แบบจำลองที่ใช้และผลการศึกษาเบื้องต้นมีรายละเอียดดังนี้

1. ที่มาและความสำคัญ

ข้าวโพดเลี้ยงสัตว์เป็นพืชเศรษฐกิจที่สำคัญของประเทศไทยและยังเป็นพืชอาหารที่มีความสำคัญต่ออุตสาหกรรมการผลิตอาหารสัตว์อย่างมาก ในอดีตข้าวโพดเลี้ยงสัตว์ผลิตเพื่อการส่งออกจนกระทั่งความต้องการภายในประเทศมีแนวโน้มสูงขึ้นจากการขยายการเลี้ยงสัตว์ ทำให้ผลผลิตในประเทศไม่เพียงพอ เพื่อตอบสนองความต้องการของอุตสาหกรรมการผลิตอาหารสัตว์จึงต้องนำเข้าจากต่างประเทศ โดยในปี 2553 ประเทศไทยมีการนำเข้าข้าวโพดเลี้ยงสัตว์จำนวน 366.75 ตัน คิดเป็นมูลค่า 1,339.58 ล้านบาท เพิ่มขึ้นจากปีที่ผ่านมา 74.89 ล้านตัน คิดเป็นมูลค่า 312.15 ล้านบาท (Office of Agricultural Economics, 2011)

ในปีการผลิต 2553/2554 มีเนื้อที่เพาะปลูกข้าวโพดเลี้ยงสัตว์รวมทั้งประเทศ 7.12 ล้านไร่ เพิ่มขึ้นจากปีที่ผ่านมา 16,639 ไร่ ผลผลิตรวมทั้งประเทศ 4.45 ล้านตัน ลดลงจากปีที่ผ่านมา 0.16 ล้านตัน และมีผลผลิตต่อไร่ 626 กิโลกรัม ลดลงจากปีที่ผ่านมา 24 กิโลกรัม พื้นที่เพาะปลูกข้าวโพดเลี้ยงสัตว์ส่วนใหญ่จะอยู่ทางภาคเหนือของประเทศ โดยจังหวัดเพชรบูรณ์เป็นจังหวัดที่มีการปลูกข้าวโพดเลี้ยงสัตว์มากที่สุด (Office of Agricultural Economics, 2011) อย่างไรก็ตามเกษตรกรยังคงต้องประสบปัญหาต้นทุนสูง ผลผลิตต่อไร่ต่ำ นอกจากนี้ยังมีค่าขนส่งไปยังแหล่งรับซื้อสูง รวมถึงพ่อค้าคนกลางหรือนายทุนกดราคาลัรับซื้อน้อย นอกจากนี้ยังมัปัจจัยเสี่ยงเรื่องภูมิอากาศที่แปรปรวนและปัญหาการลักลอบนำเข้าข้าวโพดเลี้ยงสัตว์จากประเทศเพื่อนบ้านซึ่งราคาถูกกว่า ซึ่งปัญหาเหล่านี้ส่งผลกระทบต่อราคาข้าวโพดเลี้ยงสัตว์ที่เกษตรกรได้รับสาเหตุเหล่านี้ทำให้เกษตรบางส่วนลดการปลูกข้าวโพดเลี้ยงสัตว์ลงและหันไปปลูกพืชอื่นทดแทน เช่น อ้อยและมันสำปะหลัง ซึ่งเป็นพืชที่ดูแลรักษาง่ายกว่า นอกจากนั้นยังมีปัญหาด้านคุณภาพผลผลิตอยู่ในเกณฑ์ที่ต่ำกว่ามาตรฐาน เมล็ดมีความชื้นสูงทำให้เกิดเชื้อรา เป็นอีกสาเหตุหนึ่งที่ทำให้เกษตรกรไม่มีสิ่งจูงใจในการผลิต ทำให้ปริมาณผลผลิตข้าวโพดเลี้ยงสัตว์ของประเทศลงลด ดังนั้นรัฐบาลจึงออกนโยบายและมาตรการช่วยเหลือเกษตรกรผู้ปลูกข้าวโพดเลี้ยงสัตว์ ภายใต้โครงการประกันรายได้เกษตรกรผู้ปลูกข้าวโพดเลี้ยงสัตว์ โดยในปี 2553 ได้กำหนดราคาขั้นต่ำโครงการประกันรายได้ที่เกษตรกรได้รับไว้ที่กิโลกรัมละ 7.14 บาท (Office of Agricultural Economics, 2011) ซึ่งถือว่าอยู่ในเกณฑ์ดี แต่ในระยะยาวหากโครงการประกันรายได้สิ้นสุดลงอาจจะส่งผลกระทบทางลบต่อการปลูกข้าวโพดเลี้ยงสัตว์

ดังนั้นผู้วิจัยจึงมุ่งศึกษาการส่งผ่านราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคาที่เกษตรกรได้รับ ราคาขายส่ง ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโก เพื่อให้เกษตรกรได้ทราบแนวโน้มของราคาข้าวโพดเลี้ยงสัตว์เมื่อราคาในตลาดมีการเปลี่ยนแปลง และใช้เป็นแนวทางในการวางแผนการผลิตเพื่อให้สอดคล้องกับแนวโน้มระดับราคาในตลาด นอกจากนี้ยังช่วยลดความเสี่ยงเรื่องการขาดทุนซึ่งเป็นปัญหาหลักของเกษตรกรได้อีกด้วย

2. กรอบแนวคิดและทฤษฎี

ข้อมูลอนุกรมเวลาส่วนมากจะมีลักษณะไม่นิ่ง (non-stationary) กล่าวคือ ค่าเฉลี่ยและค่าความแปรปรวนจะมีค่าไม่คงที่เปลี่ยนแปลงตามกาลเวลาทำให้ความสัมพันธ์ระหว่างตัวแปรของสมการมีความสัมพันธ์ไม่แท้จริง โดยสังเกตได้จากค่าสถิติบางอย่าง เช่น t-statistic จะไม่เป็นการแจกแจงที่เป็นมาตรฐานและค่า R2 ที่สูง ขณะที่ค่า Durbin-Watson (D.W.) อยู่ในระดับต่ำ จึงเป็นการยากที่จะยอมรับได้ในทางเศรษฐศาสตร์ ดังนั้นในการใช้ข้อมูลอนุกรมเวลาจึงมีความจำเป็นต้องทำการทดสอบว่าตัวแปรแต่ละตัวมีลักษณะนิ่ง (stationary) หรือไม่ ซึ่งสามารถทำได้โดยการทดสอบ unit root

2.1 การทดสอบ unit root

การทดสอบ unit root นั้นสามารถทดสอบได้โดยใช้การทดสอบ ADF (Augmented Dicky-Fuller (ADF) test) มีรูปแบบสมการดังต่อไปนี้

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{\rho} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(without intercept and trend)}$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{\rho} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(intercept)}$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{P} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(intercept and trend)}$$

สมมุติฐานว่าง (null hypothesis) ของการทดสอบคือ $\mathrm{H}_0 : \theta = 0$ การยอมรับสมมติฐานว่าง $H_0 : \theta = 0$ หมายความว่า y_t มีลักษณะไม่นิ่ง (non-stationary) หรือมี unit root นั่นเอง (Enders, 1995 และ Gujarati, 2003)

2.2 การทดสอบ seasonal unit root

ข้อมูลรายเดือนแสดงให้เห็นถึงรูปแบบที่แตกต่างกันตามฤดูกาล ดังนั้นการทดสอบ unit root เพียงอย่างเดียวจึงไม่เพียงพอ ข้อมูลรายเดือนจึงมีความจำเป็นต้องทำการทดสอบด้วยการทดสอบ seasonal unit root (Franses, 1991, Beaulieu and Miron, 1993 และ Maddala and Kim, 1998) โดยมีรูปแบบสมการดังต่อไปนี้

$$\begin{aligned}
\varphi^*(L) y_{8,t} \quad = \quad & \pi_1 y_{1,t\text{-}1} + \pi_2 y_{2,t\text{-}1} + \pi_3 y_{3,t\text{-}2} + \pi_4 y_{3,t\text{-}1} + \pi_5 y_{4,t\text{-}2} \\
+ \quad & \pi_6 y_{4,t\text{-}1} + \pi_7 y_{5,t\text{-}2} + \pi_8 y_{5,t\text{-}1} + \pi_9 y_{6,t\text{-}2} + \pi_{10} y_{6,t\text{-}1} \\
+ \quad & \pi_{11} y_{7,t\text{-}2} + \pi_{12} y_{7,t\text{-}1} + \mu_t + \varepsilon_t
\end{aligned}$$

สมมติฐานหลักในการทดสอบ มีดังนี้

1. H_0: $\pi_1 = 0$, H_1: $\pi_1 < 0$

สมมติฐานนี้ใช้ทดสอบ unit root แบบมาตรฐาน พิจารณาผลการทดสอบโดยเปรียบเทียบค่าสถิติ t ที่คำนวณได้กับค่าที่เหมาะสมที่อยู่ในตาราง critical values tabulated by Franses (1990) ถ้าไม่สามารถปฏิเสธสมมติฐานหลัก H_0: $\pi_1 = 0$ หมายความว่าข้อมูลนั้นมี unit root แบบมาตรฐาน (unit root at the zero frequency) หรือ ไม่มี seasonal unit root ในชุดข้อมูลนั้น แสดงว่า ข้อมูลมีลักษณะไม่นิ่งที่ระดับ level

2. H$_0$: $\pi_i = 0$, H$_1$: $\pi_i < 0, i = 2,3,...,12$,

สมมติฐานนี้ใช้ทดสอบ seasonal unit root ซึ่งแต่ละ π_i จะแทนความถี่ที่แตกต่างกัน พิจารณาผลการทดสอบโดยเปรียบเทียบค่าสถิติ t ที่คำนวณได้กับค่าที่เหมาะสมที่อยู่ในตาราง critical values tabulated by Franses (1990) ถ้าไม่สามารถปฏิเสธสมมติฐานหลัก H$_0$: $\pi_i = 0$ โดยที่ i = 2, 3, 4,…,12 หมายความว่าข้อมูลมี seasonal unit root ที่ความถี่ต่างๆ

3. H$_0$: $\pi_i = \pi_{i+1} = 0$, H$_1$: $\pi_i \neq 0$ and/or $\pi_{i+1} \neq 0, i = 3,5,7,9,11$ และ H$_0$: $\pi_3 ... \pi_{12} = 0$, H$_1$: $\pi_3 ... \pi_{12} \neq 0$

สมมติฐานนี้ใช้ทดสอบ frequency seasonal unit root แต่ละคู่จะแทนความถี่ที่แตกต่างกัน พิจารณาผลการทดสอบโดยเปรียบเทียบค่าสถิติ F ที่คำนวณได้กับค่าที่เหมาะสมที่อยู่ในตาราง critical values tabulated by Franses (1990) ถ้าไม่สามารถปฏิเสธสมมติฐานหลัก H$_0$: $\pi_i = \pi_{i+1} = 0$ โดยที่ i = 3, 5, 7, 9, 11 หมายความว่าข้อมูลมี frequency seasonal unit root และการยอมรับสมมติฐานหลัก H$_0$: $\pi_3 = \pi_4 = \pi_5 = \pi_6 = \pi_7 = \pi_8 = \pi_9 = \pi_{10} = \pi_{11} = \pi_{12} = 0$ หมายความว่า ข้อมูลมี seasonal unit root ทุกความถี่ (Maddala and Kim, 1998)

ในการทดสอบ frequency seasonal unit root แต่ละคู่จะแทนความถี่ของ seasonal unit root ดังนี้

π_i	ความถี่
π_1	0
π_2	π
π_3, π_4	$\frac{\pi}{2}$
π_5, π_6	$\frac{2\pi}{3}$
π_7, π_8	$\frac{\pi}{3}$
π_9, π_{10}	$\frac{5\pi}{6}$
π_{11}, π_{12}	$\frac{\pi}{6}$
$\pi_3, \pi_4, \pi_5, \pi_6, \pi_7, \pi_8, \pi_9, \pi_{10}, \pi_{11}, \pi_{12}$	ทุกความถี่

เมื่อพิจารณาผลการทดสอบ seasonal unit root แล้ว หากพบว่าข้อมูลไม่มีทั้ง unit root และ seasonal unit root สามารถใช้ y_t ในการประมาณค่าแบบจำลอง หากผลการทดสอบพบว่า ข้อมูลไม่มี unit root แต่มี seasonal unit root ข้อมูลที่จะนำไปใช้ประมาณค่าแบบจำลองต้องปรับให้อยู่ในรูป $(\Delta_{12})y_t$ และถ้าพบว่า ข้อมูลเพียงมี unit root แต่ไม่มี seasonal unit root ต้องปรับให้อยู่ในรูป $(\Delta)y_t$ ในการประมาณค่าแบบจำลอง แต่ถ้าข้อมูลมีทั้ง unit root และ seasonal unit root ข้อมูลที่จะนำไปใช้ต้องปรับให้อยู่ในรูป $(\Delta_1\Delta_{12})y_t$

2.3 การทดสอบ cointegration ตามวิธีของ Johansen

การทดสอบความสัมพันธ์เชิงดุลยภาพระยะยาวตามวิธีของ Johansen เป็นการทดสอบโดยสร้างแบบจำลองอนุกรมเวลาในรูป reduced rank regression และประมาณค่าด้วย maximum likelihood ในแบบจำลอง cointegration หลายตัวแปร โดยอิงกับแบบจำลอง VAR แสดงดังสมการ (1)

$$P_t = A_1 P_{t-1} + A_2 P_{t-2} + \ldots + A_k P_{t-k} + \varepsilon_t \qquad (1)$$

นำ P_{t-1} ไปลบออกจากสมการ (3.7) ทั้งสองข้างจะได้ดังสมการ (2)

$$\Delta P_t = (A_1 - I)P_{t-1} + A_2 P_{t-2} + \ldots + A_k P_{t-k} + \varepsilon_t \qquad (2)$$

นำ $(A_1 - I)P_{t-2}$ บวกเข้าและลบออกทางขวามือของสมการ (2) จะได้ดังสมการ (3)

$$\Delta P_t = (A_1 - I)\Delta P_{t-1} + (A_2 + A_1 - I)P_{t-2} + A_3 P_{t-3} + \ldots + A_k P_{t-k} + \varepsilon_t \qquad (3)$$

ทำต่อไปจนถึง k lag จะได้สมการ (4)

$$\Delta P_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-1} + \varepsilon_t \qquad (4)$$

เมื่อ P_t คือ column vector ของตัวแปรที่มี n ตัวแปร จำนวน T ค่าสังเกต ขนาด nx1

μ คือ เวคเตอร์ของค่าคงที่ (constant term) ขนาด nx1

Γ, Π คือ เมทริกซ์ของค่าสัมประสิทธิ์ (coefficient matrices)

k คือ จำนวนความล่า (lag length)

ε_t คือ error term ที่มีการกระจายตัวปกติ มีค่าเฉลี่ยเท่ากับศูนย์ และความแปรปรวนคงที่ $[\varepsilon_t \sim N(0,\Sigma)]$

โดย Π เป็นเมทริกซ์ที่แสดงถึงผลกระทบ (impact matrix) ซึ่งประกอบไปด้วยข้อมูลเกี่ยวกับความสัมพันธ์ระยะยาว โดย rank (r) ของ Π มีค่าเป็นจำนวนเต็มบวก ถ้า r < n แสดงว่าต้องมีเมทริกซ์ของ α กับ β ขนาดมิติ nxr นั่นคือ $\Pi = \alpha\beta'$ โดยเมทริกซ์ α แสดงถึงการปรับตัวในระยะสั้นเพื่อเข้าสู่ดุลยภาพในระยะยาว (adjustment parameter) ส่วนเมทริกซ์ β แสดงถึง cointegrating vectors ใน ECM โดย linear combination ของ $\beta' P_t$ ต้อง stationary แม้ว่า P_t จะไม่ stationary ก็ตาม หาก rank (r) เท่ากับศูนย์ สมการ (4) จะกลายเป็นสมการ VAR การทดสอบ cointegration ตามวิธีของ Johansen ประกอบด้วย 4 ขั้นตอนคือ

ขั้นที่ 1: ทดสอบหาจำนวน lag ที่เหมาะสม เนื่องจากการกำหนดจำนวน lag มีผลต่อความสามารถในการอธิบายพฤติกรรมเชิงพลวัตร ซึ่งในการศึกษานี้จะใช้วิธี AIC SC FPE และ HQC ในการตัดสินนัยสำคัญ โดยเลือก lag ที่ให้ค่า AIC, SC, FPE, HQC ต่ำที่สุด

ขั้นที่ 2: ประมาณค่าแบบจำลองและหา cointegrating vectors ระหว่างตัวแปรต่างๆ ในแบบจำลอง โดยการประมาณค่า rank ของเมทริกซ์ Π ซึ่งก็คือ จำนวนความสัมพันธ์ระยะยาวของตัวแปรในเวคเตอร์ของสมการ (4) สถิติที่ใช้ทดสอบประกอบด้วย trace test (λ_{trace}) และ maximal eigenvalue test (λ_{max}) ดังสมการ (5) และ (6) ตามลำดับ

$$\lambda_{Trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}) \tag{5}$$

สมมติฐานที่ใช้ทดสอบ Trace test (λ_{trace}) คือ H_0: cointegrating vector $\leq$ r

H_1: cointegrating vector $\geq$ r

$$\lambda_{max} = -T \ln(1-\hat{\lambda}) \tag{6}$$

สมมติฐานที่ใช้ทดสอบ Maximum eigenvalue test (λ_{max}) คือ H_0: cointegrating vector = r

H_1: cointegrating vector = r+1

ขั้นที่ 3: ประมาณค่าแบบจำลอง VEC (สัมประสิทธิ์ของ cointegrating vector (s) ที่ปรับแล้ว (normalized) และสัมประสิทธิ์ของความเร็วในการปรับตัว (speed of adjustment))

ขั้นที่ 4: innovation accounting เป็นการใช้ stochastic disturbance term จากแบบจำลอง VEC หรือ VAR มาอธิบายผ่านการทดสอบการตอบสนองของตัวแปร (impulse response function, IRFs) และการแยกส่วนประกอบของความแปรปรวน (variance decomposition)

2.4 ทดสอบกฎราคาเดียว (law of one price, LOP)

การทดสอบกฎราคาเดียว (LOP) ทำได้ด้วยการทดสอบใส่ข้อจำกัดใน beta matrix (β) ภายใต้สมมติฐานหลัก $H_0 : R'\beta = 0$ การใส่ข้อจำกัด (1, -1) กับ cointegrating vector (กรณี 2 ตัวแปร) สำหรับกรณีหลายตัวแปร (multivariate) ผลรวมของความสัมพันธ์ (cointegrating vector) ใดใดต้องเท่ากับศูนย์ สมมุติว่าพิจารณาตลาดทั้งหมด n ตลาด กฎราคาเดียวระหว่างตลาดที่พิจารณาทั้งหมดเกิดขึ้นเมื่อราคาในทุกตลาดถูกกำหนดขึ้นพร้อมกัน ซึ่งก็คือกรณี full rank (r = n) แต่หากข้อมูลไม่นิ่งและมีลักษณะเคลื่อนไปด้วยกันแล้ว การกำหนดราคาในแต่ละตลาดที่เกิดขึ้นพร้อมกัน (เป็นไปตามกฎราคาเดียว) จะมีได้สูงสุดเท่ากับ n-1 ตลาด (r=n-1) แต่หาก r < n-1 แล้ว กฎราคาเดียวจะปฏิเสธการเกิดขึ้นพร้อมกันของชุดราคาทั้งหมด ในกรณีเช่นนี้ สมมติฐานที่สามารถทดสอบได้ก็คือ การทดสอบกฎราคาเดียวระหว่าง 2 ตัวแปรใดใด (Nanang, 2000)

2.5 ทดสอบความเป็นนอกระบบ (weak exogeneity)

α เป็นพารามิเตอร์ที่แสดงถึงการปรับตัว (adjustment parameter) ซึ่งสัมพันธ์กับแนวคิดความเป็นนอกระบบ (weak exogeneity) ถ้า adjustment parameter (α) ทั้งหมดของตัวแปรหนึ่งๆเป็นศูนย์ แสดงว่าตัวแปรนั้นเป็น weak exogeneity ของพารามิเตอร์ในระยะยาว (ตัวแปรนั้นไม่ได้มีอิทธิพลต่อ

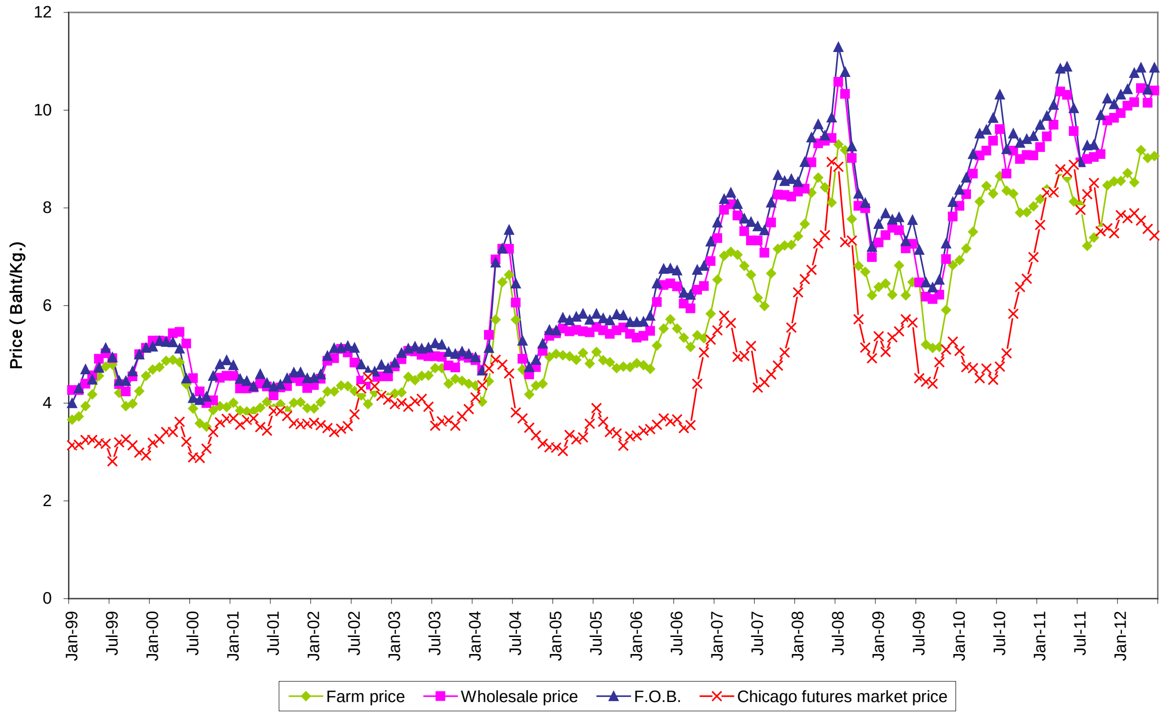
พารามิเตอร์ในระยะยาว) การทดสอบความเป็นนอกระบบทำได้โดยทดสอบใส่ข้อจำกัดในเมทริกซ์ α ภายใต้สมมติฐานหลัก $H_0 : \beta'\alpha = 0$ (Bessler *et al.*, 2003)

3. ข้อมูลที่ใช้ในการศึกษา

ข้อมูลที่ใช้ในการศึกษาครั้งนี้ประกอบด้วย ข้อมูลราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มเกษตรกร (PF) ราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. (PW) และราคาซื้อขายล่วงหน้าตลาดชิคาโก (PC) เป็นข้อมูลรายเดือนตั้งแต่ January 1999 - June 2012 ค่าสถิติพื้นฐานที่สำคัญของข้อมูลแสดงในตารางที่ 1 และเมื่อพิจารณาลักษณะการเคลื่อนไหวของราคาข้าวโพดเลี้ยงสัตว์ทั้ง 3 ตลาด พบว่า ราคาทั้ง 3 ตลาดมีการเคลื่อนไหวไปในทิศทางเดียวกันตลอดช่วงเวลาที่ศึกษา (ภาพที่ 1)

ตารางที่ 1: สถิติข้อมูลที่ใช้ศึกษา

ตัวแปร	ค่าสูงสุด	ค่าต่ำสุด	ค่าเฉลี่ย	ส่วนเบี่ยงเบนมาตรฐาน
farm price (Baht/Kg.)	9.30	3.52	5.74	1.68
wholesale price (Baht/Kg.)	10.58	4.00	6.50	1.96
F.O.B price (Baht/Kg.)	11.29	4.00	6.74	2.09
Chicago futures market price (Baht/Kg.)	8.94	2.81	4.69	1.64

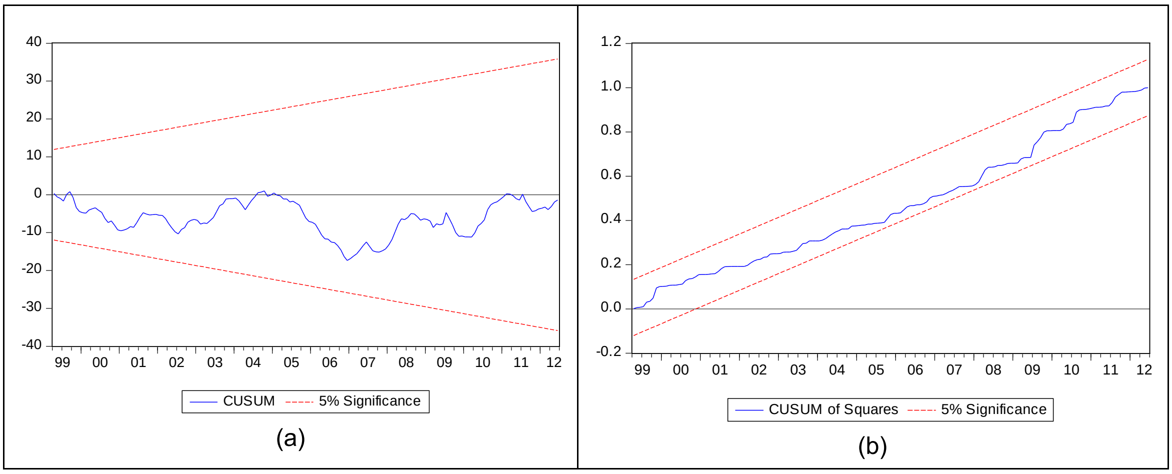


ภาพที่ 1 การเคลื่อนไหวของราคาข้าวโพดเลี้ยงสัตว์ในช่วงเดือนมกราคม 1999 – มิถุนายน 2012

4. ผลการศึกษา

4.1 การทดสอบจุดเปลี่ยนโครงสร้าง

การทดสอบจุดเปลี่ยนโครงสร้างด้วยวิธี recursive residual ตามแนวคิดของ Brown *et al.* (1975) ภายใต้สมมติฐานหลักที่ว่า ไม่มีการเปลี่ยนแปลงทางโครงสร้าง (ค่าพารามิเตอร์มีเสถียรภาพ) โดยพิจารณาจากกราฟ CUSUM และ CUSUM square และเมื่อพิจารณารูปกราฟ ที่ได้พบว่า ข้อมูลราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มเกษตรกร (PF) ราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. (PW) ราคาส่งออก (PFOB) และราคาซื้อขายล่วงหน้าตลาดชิคาโก (PC) ในช่วง January 1999 - June 2012 ไม่มีการเปลี่ยนแปลงทางโครงสร้างเกิดขึ้น (ภาพที่ 2)



ภาพที่ 2 ผลทดสอบจุดเปลี่ยนโครงสร้างด้วยวิธี recursive residual

4.2 การทดสอบ unit root และ seasonal unit root

หลังจากทดสอบจุดเปลี่ยนโครงสร้างพบว่า ข้อมูลราคาราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มเกษตรกร (PF) ราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. (PW) ราคาส่งออก (PFOB) และราคาซื้อขายล่วงหน้าตลาดชิคาโก (PC) ในช่วงเดือนมกราคม 1999 – มิถุนายน 2012 ไม่มีการเปลี่ยนแปลงทางโครงสร้างเกิดขึ้น ขั้นตอนต่อไปคือการทดสอบความนิ่งของข้อมูลราคาทั้ง 4 ตลาด ด้วยการทดสอบ Unit Root ตามวิธี Augmented Dicky-Fuller (ADF) test และ seasonal unit root ตามวิธีของ Franses

ผลการทดสอบ unit root

การทดสอบความนิ่งของข้อมูลด้วยการทดสอบ unit root ตามวิธี Augmented Dicky-Fuller (ADF) test โดยเปรียบเทียบค่าสถิติ ADF test ที่ได้ กับค่า MacKinnon Critical Value ถ้าค่าสถิติ ADF test ที่ได้ มีค่ามากกว่าค่า MacKinnon Critical Value หมายถึง การยอมรับสมมติฐานว่าง ซึ่งอธิบายได้ว่า ข้อมูลมี unit root หรือข้อมูลมีลักษณะไม่นิ่ง (non-stationary)

ผลการทดสอบ unit root ในระดับ level พบว่า ตัวแปรทุกตัวยอมรับสมมติฐานว่าง ที่ระดับนัยสำคัญ 10% แสดงว่า ข้อมูลราคาทั้ง 4 ตลาดมี unit root หรือมีลักษณะไม่นิ่ง (non-stationary) ดังนั้นจึงต้องทำการแปลงข้อมูลโดยการหาผลต่างระดับที่ 1 (first difference) แล้วทดสอบ unit root อีกครั้ง

ผลการทดสอบ unit root ในระดับ first difference พบว่า ตัวแปรราคาทุกตลาดปฏิเสธสมมติฐานว่างที่ระดับนัยสำคัญ 1% แสดงว่า ข้อมูลราคาทั้ง 4 ตลาดไม่มี unit root หรือมีลักษณะนิ่ง (stationary) นั่นหมายความว่า ข้อมูลราคาทั้ง 4 ตลาดมี integration of order 1 หรือ $X_t \sim I(1)$ (ตารางที่ 2)

ตารางที่ 2: ผลการทดสอบ unit root

Augmented Dickey-Fuller Test	PF	PW	PFOB	PC
level				
- with intercept and trend	-2.93	-2.68	-2.92	-2.38
- with intercept	-1.0052	-0.66	-0.82	-1.11
- without intercept and trend	0.80	1.041	1.0054	0.49
first difference				
- with intercept and trend	-9.25***	-8.62***	-9.23***	-10.15***
- with intercept	-9.27***	-8.63***	-9.25***	-10.17***
- without intercept and trend	-9.25***	-8.59***	-9.20***	-10.16***

Notes: ***, ** and * indicates that the seasonal unit root null hypothesis is rejected at 1% 5% and 10% statistical level.

ผลการทดสอบ seasonal unit root

การทดสอบ seasonal unit root คือ การทดสอบนัยสำคัญของพารามิเตอร์ในสมการช่วย ด้วยการถดถอยแบบกำลังสองน้อยที่สุด (ordinary least square: OLS) องค์ประกอบในสมการช่วยประกอบด้วย ตัวแปรช่วย (auxiliary variables) และส่วนที่เป็น deterministic term ได้แก่ ค่าตัดแกน (intercept) ตัวแปรหุ่นเกี่ยวกับฤดูกาล (seasonal dummies) 11 ตัว ได้แก่ $S_1, S_2, \ldots, S_{11}$ และตัวแปรแนวโน้ม (time trend)

$$
\begin{aligned}
\varphi^*(L)y_{8,t} \;=\;& \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \pi_5 y_{4,t-2} \\
&+ \pi_6 y_{4,t-1} + \pi_7 y_{5,t-2} + \pi_8 y_{5,t-1} + \pi_9 y_{6,t-2} + \pi_{10} y_{6,t-1} \\
&+ \pi_{11} y_{7,t-2} + \pi_{12} y_{7,t-1} + \mu_t + \varepsilon_t
\end{aligned}
$$

การทดสอบ season unit root แสดงดังตารางที่ 3 ผลการทดสอบ พบว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มเกษตรกร (PF) ปฏิเสธการมี seasonal unit root ณ ความถี่ 0, (π), ($\pm\frac{2\pi}{3}$), ($\frac{\pi}{3}$), ($\pm\frac{5\pi}{6}$) และ ($-\frac{\pi}{6}$) เมื่อทดสอบด้วยสถิติ t และปฏิเสธการมี seasonal unit root ทุกคู่ความถี่ เมื่อทดสอบด้วยสถิติ F แสดงว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มเกษตรกรไม่มี unit root แบบมาตรฐานหรือที่ความถี่ 0 และไม่มี seasonal unit root ส่วนราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. (PW) นั้นพบว่า สามารถปฏิเสธการมี seasonal unit root ณ ความถี่ (π), ($\pm\frac{\pi}{2}$), ($\pm\frac{2\pi}{3}$), ($\frac{\pi}{3}$), ($\pm\frac{5\pi}{6}$) และ ($-\frac{\pi}{6}$) เมื่อทำการทดสอบด้วยสถิติ t และสามารถปฏิเสธการมี seasonal unit root ทุกคู่ความถี่ เมื่อทดสอบด้วยสถิติ F อธิบายได้ว่า ราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. นั้นมี unit root แบบมาตรฐานหรือที่ความถี่ 0 แต่ไม่มี seasonal unit root สำหรับราคาส่งออก (PFOB) นั้นพบว่า สามารถปฏิเสธการมี seasonal unit root ณ ความถี่ (π), ($\pm\frac{\pi}{2}$), ($\pm\frac{2\pi}{3}$), ($\frac{\pi}{3}$), ($\pm\frac{5\pi}{6}$) และ ($-\frac{\pi}{6}$) เมื่อทดสอบด้วยสถิติ t และเมื่อทดสอบด้วยสถิติ F พบว่า สามารถปฏิเสธการมี seasonal unit root ในทุกคู่ความถี่ แสดงว่า ราคาส่งออกมี unit root แบบมาตรฐานหรือที่ความถี่ 0

แต่ไม่มี seasonal unit root เช่นกัน และเมื่อพิจารณาผลการทดสอบราคาซื้อขายล่วงหน้าตลาดชิคาโก (PC) ด้วยสถิติ t พบว่า สามารถปฏิเสธการมี seasonal unit root ณ ความถี่ (π), ($\frac{\pi}{2}$), ($\pm\frac{2\pi}{3}$), ($\pm\frac{5\pi}{6}$) และ ($-\frac{\pi}{6}$) และสามารถปฏิเสธการมี seasonal unit root ในทุกคู่ความถี่ เมื่อทดสอบด้วยสถิติ F แสดงว่า ราคาซื้อขายล่วงหน้าตลาดชิคาโกนั้นมี unit root แบบมาตรฐานหรือที่ความถี่ 0 แต่ไม่มี seasonal unit root เช่นเดียวกับราคาในตลาดอื่น (ตารางที่ 3)

ตารางที่ 3: ผลการทดสอบ seasonal unit root

Null Hypotheses	Frequencies	PF (1)	PW (1)	PFOB (1)	PC (1)
$\pi_1 = 0$	0	-3.75**	-3.22	-3.15	-2.10
$\pi_2 = 0$	π	-5.36**	-4.58**	-4.68**	-5.76**
$\pi_3 = 0$	$\frac{\pi}{2}$	0.37	-3.024**	-2.20**	-2.77**
$\pi_4 = 0$	$-\frac{\pi}{2}$	-2.94	-4.89**	-3.96**	-2.96
$\pi_5 = 0$	$\frac{2\pi}{3}$	-5.0010**	-4.63**	-5.53**	-6.32**
$\pi_6 = 0$	$-\frac{2\pi}{3}$	-4.80**	-4.52**	-5.65**	-5.13**
$\pi_7 = 0$	$\frac{\pi}{3}$	-2.50**	-2.81**	-2.60**	0.17
$\pi_8 = 0$	$-\frac{\pi}{3}$	-0.15	-0.13	-0.060	-2.80
$\pi_9 = 0$	$\frac{5\pi}{6}$	-5.66**	-3.54**	-4.89**	-3.50**
$\pi_{10} = 0$	$-\frac{5\pi}{6}$	-3.39**	-5.57**	-4.78**	-4.25**
$\pi_{11} = 0$	$\frac{\pi}{6}$	0.78	0.12	0.17	0.37
$\pi_{12} = 0$	$-\frac{\pi}{6}$	-4.57**	-4.74**	-4.22**	-4.75**
$\pi_3 = \pi_4 = 0$	$\pm\frac{\pi}{2}$	4.63	16.52**	9.92**	8.038**
$\pi_5 = \pi_6 = 0$	$\pm\frac{2\pi}{3}$	13.063**	11.33**	16.98**	20.46**
$\pi_7 = \pi_8 = 0$	$\pm\frac{\pi}{3}$	24.54**	26.27**	22.81**	14.89**
$\pi_9 = \pi_{10} = 0$	$\pm\frac{5\pi}{6}$	17.49**	18.47**	18.67**	12.19**
$\pi_{11} = \pi_{12} = 0$	$\pm\frac{\pi}{6}$	12.36**	14.999**	11.90**	13.83**
$\pi_3 = \ldots = \pi_{12} = 0$	all frequencies	20.67**	24.10**	21.998**	15.63**

Notes: 1. ** indicate that the seasonal unit root null hypothesis is rejected at 5% statistical level.

2. Numbers in parentheses denote the number of lagged values of the dependent variable.

4.3 การทดสอบความสัมพันธ์เชิงดุลยภาพในระยะยาว (cointegration)

จากผลการทดสอบ unit root และ seasonal unit root แสดงให้เห็นว่า ข้อมูลราคาทั้ง 3 ตลาดไม่มี seasonal unit root และมีลักษณะนิ่งที่ระดับเดียวกัน คือ ระดับ first difference หรืออาจกล่าวได้ว่าข้อมูลมี integration of order 1 หรือ $X_t \sim I(1)$ ดังนั้นจึงสามารถนำมาทดสอบหาความสัมพันธ์ระยะยาว (cointegration) ได้ ในการศึกษาครั้งนี้ใช้การทดสอบ cointegration ตามวิธีของ Johansen เนื่องจากเป็นกระบวนการทดสอบที่ใช้กับแบบจำลองที่มีตัวแปรมากกว่า 2 ตัว ดังสมการ (7) โดยเมทริกซ์ Π เป็นเมทริกซ์ผลกระทบ (impact matrix) ที่ประกอบด้วย $\alpha\beta'$ โดยสัมประสิทธิ์ β ในสมการ cointegration แสดงถึงความยืดหยุ่นในระยะยาว (long-run elasticity) และเมทริกซ์ α แสดงถึงการปรับตัวในระยะสั้น (short run adjustment) ในแต่ละความสัมพันธ์ (cointegration relations)

$$\Delta P_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-1} + \varepsilon_t \qquad (7)$$

ในส่วนนี้ทดสอบทั้งหมด 3 สมมติฐานได้แก่

1) ทดสอบหา cointegration rank (r) จากสมการ (a) ภายใต้สมมติฐาน $H_0 : \Pi = \alpha\beta'$

2) ทดสอบกฎราคาเดียว (law of one price, LOP) ด้วยการทดสอบใส่ข้อจำกัดใน beta matrix (β) ภายใต้สมมติฐานหลัก $H_0 : R'\beta = 0$

3) ทดสอบความเป็นนอกระบบ (weak exogeneity) ด้วยการใส่ข้อจำกัดใน alpha matrix (α) ภายใต้สมมติฐานหลัก $H_0 : \beta'\alpha = 0$

การทดสอบ cointegration ต้องประมาณค่าแบบจำลอง VAR เพื่อกำหนดจำนวนความล่าที่เหมาะสม โดยพิจารณาจากค่า LR test statistic, Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) และ Hannan-Quinn information criterion (HQ) และเลือกแบบจำลองที่เหมาะสม โดยพิจารณาจากค่า Akaike information criterion (AIC) และ Schwarz information criterion (SC) แบบจำลองที่เหมาะสมคือ แบบจำลองที่มีค่า AIC และ SC น้อยที่สุด ขั้นตอนต่อไปคือ การทดสอบหาจำนวน cointegrating vector โดยพิจารณาจากค่าสถิติ trace test (λ_{trace}) และ maximal eigenvalue test (λ_{max}) เมื่อได้จำนวนความล่าที่เหมาะสม แบบจำลองที่เหมาะสม และจำนวน cointegrating vector ที่เหมาะสมแล้ว ขั้นตอนต่อไปคือ การประมาณค่าแบบจำลอง cointegration

เมื่อพิจารณาจากค่า Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) และ Hannan-Quinn information criterion (HQ) พบว่า จำนวน lag ที่เหมาะสม คือ 2 (ตารางที่ 4)

ตารางที่ 4: ผลการทดสอบเพื่อเลือก lag ที่เหมาะสม

Lag	LogL	LR	FPE	AIC	SC	HQ
0	673.03	NA	1.98e-09	-8.69	-8.61	-8.66
1	1141.22	905.98	5.58e-12	-14.56	**-14.17***	-14.40
2	1177.71	**68.71***	**4.27e-12***	**-14.83***	-14.12	**-14.54***
3	1185.51	14.28	4.76e-12	-14.72	-13.70	-14.30
4	1199.97	25.73	4.87e-12	-14.70	-13.36	-14.16
5	1206.62	11.48	5.51e-12	-14.58	-12.92	-13.91
6	1218.33	19.63	5.85e-12	-14.52	-12.55	-13.72
7	1225.89	12.26	6.58e-12	-14.41	-12.13	-13.48
8	1237.91	18.90	6.99e-12	-14.36	-11.76	-13.31

Notes: * indicates lag order selected by the criterion.

LR is sequential modified LR test statistic (each test at 5% level).

FPE is Final prediction error.

AIC is Akaike information criterion .

SC is Schwarz information criterion.

HQ is Hannan-Quinn information criterion.

เมื่อเลือก lag ที่เหมาะสมได้แล้ว ขั้นตอนต่อไปคือการเลือกแบบจำลองที่เหมาะสมและหาจำนวน cointegrating vector จากตารางที่ 5 แสดงให้เห็นว่า แบบจำลองที่ 1 (no intercept or trends) มีค่า AIC และ SC น้อยที่สุด ดังนั้นแบบจำลองที่เหมาะสม คือ แบบจำลองที่ 1 นั่นคือ แบบจำลองที่ไม่ปรากฏค่าคงที่และแนวโน้มเวลา จากนั้นทำการทดสอบหาจำนวน cointegrating vector โดยพิจารณาจากค่าสถิติ trace test (λ_{trace}) และ maximal eigenvalue test (λ_{max}) และเมื่อพิจารณาค่าสถิติทั้ง 2 ในตารางที่ 6 พบว่า ค่าสถิติ trace test และ maximal eigenvalue test บ่งชี้ว่า แบบจำลองที่เหมาะสมควรมี 2 cointegrating vectors ขั้นต่อไปเป็นการประมาณค่าแบบจำลองภายใต้จำนวน cointegrating vector ที่เหมาะสม (ในกรณีนี้คือ 2 cointegrating vectors) เพื่อทำการทดสอบกฎราคาเดียวและความเป็นนอกระบบ (ใส่ข้อจำกัดในเมทริกซ์ β และ α) และนำ residual ที่ได้จากแบบจำลองอธิบายความสัมพันธ์ระหว่างตัวแปรด้วยการทดสอบการแยกองค์ประกอบของความแปรปรวน (forecast error variance decomposition) และการวิเคราะห์ฟังก์ชันการตอบสนองต่อความแปรปรวน (impulse response function) ซึ่งจะนำเสนอในส่วนต่อไป

ตารางที่ 5: ค่า Akaike Information Criteria (AIC) และ Schwarz Criteria (SC) ของแบบจำลองทั้ง 5 รูปแบบ

Model	AIC	SC
1. no intercept or trends	**-14.53**	**-13.58**
2. restricted intercepts, no trends	-14.50	-13.54
3. unrestricted intercepts, no trends	-14.48	-13.48
4. unrestricted intercepts, restricted trends	-14.52	-13.48
5. unrestricted intercepts, unrestricted trends	-14.50	-13.41

ตารางที่ 6: ผลการทดสอบหาจำนวน cointegrating vector

H_0	H_1	Trace Statistic	Critical Value	H_0	H_1	Max-Eigen Statistic	Critical Value
r=0	r>1	77.252**	47.856	r=0	r=1	38.028**	27.584
r≤1	r>2	39.224**	29.797	r=1	r=2	25.796**	21.132
r≤2	r>3	13.428	15.495	r=2	r=3	12.008	14.265
r≤3	r>4	1.419	3.841	r=3	r=4	1.419	3.841

Notes: ** indicate that the seasonal unit root null hypothesis is rejected at 5% statistical level.

4.4 การทดสอบกฎราคาเดียว (law of one price, LOP) และความเป็นนอกระบบ (weak exogeneity)

ผลทดสอบกฎราคาเดียว (law of one price, LOP)

ผลทดสอบกฎราคาเดียว ด้วยการทดสอบใส่ข้อจำกัดใน beta matrix (β) ภายใต้สมมติฐานหลัก $H_0: R'\beta = 0$ ผลการทดสอบพบว่า ความสัมพันธ์ระหว่างราคาข้าวโพดเลี้ยงสัตว์ทุกคู่ความสัมพันธ์สามารถปฏิเสธสมมติฐานหลักที่ทดสอบกฎราคาเดียว ซึ่งอธิบายได้ว่า ทุกความสัมพันธ์ระหว่างราคาใน 4 ตลาดนั้นไม่เป็นไปตามกฎราคาเดียว (LOP) เช่น ความสัมพันธ์ระหว่างราคา ณ ฟาร์มของเกษตรกร (PF) กับราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. (PW) ไม่เป็นไปตามกฎราคาเดียว (LOP) หรือความสัมพันธ์ระหว่างราคา ณ ฟาร์มของเกษตรกร (PF) กับราคาส่งออก (PFOB) ไม่เป็นไปตามกฎราคาเดียว (LOP) เช่นกัน (ตารางที่ 7)

ตารางที่ 7: ผลการทดสอบกฎราคาเดียว (Law of One Price, LOP)

hypothesis ($H_0 = R'\beta = 0$)	χ^2 test statistic
$\beta_{11} + \beta_{12} = 0$ (PF+PW=0)	15.14***
$\beta_{11} + \beta_{13} = 0$ (PF+PFOB=0)	22.74***
$\beta_{11} + \beta_{14} = 0$ (PF+PC=0)	21.46***
$\beta_{12} + \beta_{13} = 0$ (PW+PFOB=0)	21.73***
$\beta_{12} + \beta_{14} = 0$ (PW+PC=0)	22.21***
$\beta_{13} + \beta_{14} = 0$ (PFOB+PC=0)	15.43***

Notes: ***, ** and * indicates that the seasonal unit root null hypothesis is rejected at 1% 5% and 10% statistical level.

ผลทดสอบความเป็นนอกระบบ (weak exogeneity)

ทดสอบความเป็นนอกระบบด้วยการใส่ข้อจำกัดใน alpha matrix (α) ภายใต้สมมติฐาน $H_0: \beta'\alpha = 0$ ผลทดสอบพบว่า ราคาข้าวโพดเลี้ยงสัตว์ทั้ง 4 ตลาดปฏิเสธสมมติฐานหลัก ซึ่งสามารถอธิบายได้ว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโกนั้นมีอิทธิพลต่อราคาข้าวโพด ณ ฟาร์มของเกษตรกรในระยะยาว (ตารางที่ 8)

ตารางที่ 8: ผลทดสอบความเป็นนอกระบบ (weak exogeneity)

H_0: test of weak exogeneity ($H_0 : \beta'\alpha = 0$)	χ^2 test statistic
$\alpha_{11} = 0$, $\alpha_{22} = 0$	4.26**
$\alpha_{21} = 0$, $\alpha_{12} = 0$	18.56***
$\alpha_{31} = 0$, $\alpha_{32} = 0$	6.87**
$\alpha_{41} = 0$, $\alpha_{42} = 0$	7.13**

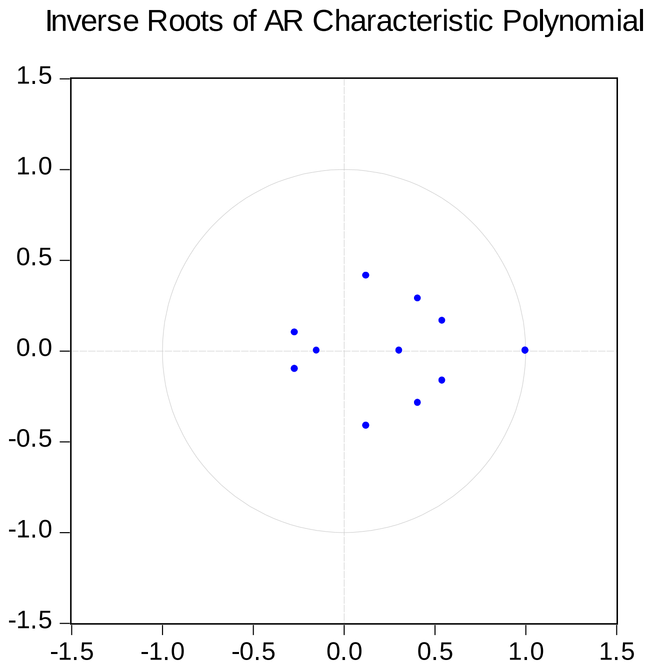
Notes: 1. ***, ** and * indicates that the seasonal unit root null hypothesis is rejected at 1% 5% and 10% statistical level.

2. α_{ij} = adjustment parameters เมื่อ i แสดงถึงตัวแปรที่ i (i = 1-4) ส่วน j แสดงถึงความสัมพันธ์ (cointegrating vectors) ที่ j (j = 1-2)

หลังจากประมาณค่าแบบจำลองและทดสอบกฎราคาเดียวกับความเป็นนอกระบบแล้ว ขั้นตอนต่อไปเป็นการนำ residual จากแบบจำลองเข้ามาช่วยอธิบายความสัมพันธ์ระหว่างตัวแปรด้วยการทดสอบการแยกองค์ประกอบของความแปรปรวน (forecast error variance decomposition, FEVD) และการวิเคราะห์ฟังก์ชันการตอบสนองต่อความแปรปรวน (impulse response function, IRF)

4.5 การทดสอบการแยกองค์ประกอบของความแปรปรวน (forecast error variance decomposition, FEVD)

ก่อนที่จะทำการทดสอบการแยกองค์ประกอบของความแปรปรวนนั้น จำเป็นต้องทดสอบเสถียรภาพของแบบจำลองก่อน ถ้าแบบจำลองไม่มีเสถียรภาพแล้วผลการทดสอบการแยกองค์ประกอบของความแปรปรวนและการวิเคราะห์ฟังก์ชันการตอบสนองต่อความแปรปรวนนั้นจะไม่สามารถใช้ได้ การทดสอบเสถียรภาพทำได้โดยพิจารณาค่า root ของ AR จากแบบจำลอง ซึ่ง inverse roots of AR characteristic polynomial ต้องมี roots ที่มี modulus น้อยกว่า 1 และมีค่าอยู่ในวงกลมหนึ่งหน่วย (lie inside the unit circle) ผลการทดสอบแสดงให้เห็นว่า แบบจำลองที่ได้นั้นมีเสถียรภาพ (stability) และสามารถทดสอบการแยกองค์ประกอบของความแปรปรวนและการวิเคราะห์ฟังก์ชันการตอบสนองต่อความแปรปรวนได้ (ภาพที่ 3)



ภาพที่ 3 ผลทดสอบเสถียรภาพของแบบจำลอง

ผลการทดสอบการแยกองค์ประกอบของความแปรปรวนของราคาข้าวโพดเลี้ยงสัตว์พบว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ถูกกำหนดจากความผันผวนในตัวเองเป็นหลักในเดือนแรก และเริ่มลดลงเหลือประมาณร้อยละ 83-30 ในช่วง 2-12 เดือนต่อมา นอกจากนี้ในช่วง 2-12 เดือนต่อมานั้น ราคาฟาร์มยังถูกกำหนดจากความผันผวนของราคาที่โรงงานอาหารสัตว์รับซื้อด้วยสัดส่วนร้อยละ 13-48 ในขณะที่อิทธิพลจากความผันผวนของราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโกมีน้อยมากกล่าวคือ ความผันผวนของราคาในสองตลาดนี้อิทธิพลต่อราคาฟาร์มในช่วง 2-12 เดือนต่อมาประมาณร้อยละ 1-9 และประมาณร้อยละ 2-11 ตามลำดับ

สำหรับราคาที่โรงงานอาหารสัตว์รับซื้อนั้นพบว่า ความผันผวนส่วนใหญ่ถูกกำหนดมาจากราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกรในช่วง 1-2 เดือนแรก ประมาณร้อยละ 62-57 และลดลงเหลือประมาณร้อยละ 49-23 ในช่วง 3-12 เดือนต่อมา และได้รับอิทธิพลจากความผันผวนในตัวเอง ประมาณร้อยะ 37-53 ตลอดช่วงเวลา 12 เดือน

เมื่อพิจารณาราคาส่งออกข้าวโพดเลี้ยงสัตว์พบว่า ความผันผวนของราคาถูกกำหนดโดยราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ประมาณร้อยละ 59-55 ในระยะสั้นช่วง 1-2 เดือนแรก และลดลงเหลือประมาณร้อยละ 47-22 ในช่วง 3-12 เดือนต่อมา และได้รับอิทธิพลจากความผันผวนของราคาข้าวโพดเลี้ยงสัตว์ที่โรงงานอาหารสัตว์รับซื้อ ประมาณร้อยะ 21-52 ตลอดช่วงเวลา 12 เดือน

ในขณะที่ความผันผวนของราคาซื้อขายล่วงหน้าตลาดชิคาโกนั้นถูกกำหนดจากตัวเองเป็นหลักประมาณร้อยละ 92-89 ตลอดช่วงเวลา 12 เดือน (ตารางที่ 9)

ตารางที่ 9: ผลการทดสอบการแยกองค์ประกอบของความแปรปรวนของราคาข้าวโพดเลี้ยงสัตว์

Month	S.E.	PF	PW	PFOB	PC	Month	S.E.	PF	PW	PFOB	PC
PF						*PW*					
1	0.047	100.000	0.000	0.000	0.000	1	0.048	62.148	37.852	0.000	0.000
2	0.082	83.226	13.141	1.488	2.145	2	0.084	57.232	40.677	0.252	1.839
3	0.109	69.728	23.116	1.272	5.883	3	0.111	49.112	44.107	0.480	6.301
4	0.130	58.852	30.332	1.554	9.262	4	0.132	42.548	46.537	1.245	9.670
5	0.147	51.106	35.435	2.405	11.054	5	0.149	37.693	48.303	2.663	11.341
6	0.161	45.528	39.046	3.703	11.722	6	0.164	34.072	49.605	4.321	12.003
7	0.173	41.364	41.659	5.111	11.865	7	0.177	31.287	50.612	5.869	12.232
8	0.184	38.162	43.618	6.415	11.805	8	0.190	29.105	51.419	7.193	12.282
9	0.194	35.638	45.142	7.546	11.673	9	0.201	27.375	52.074	8.300	12.251
10	0.204	33.609	46.369	8.499	11.523	10	0.211	25.986	52.610	9.219	12.185
11	0.213	31.945	47.382	9.295	11.379	11	0.221	24.855	53.052	9.981	12.112
12	0.222	30.556	48.234	9.960	11.250	12	0.231	23.919	53.422	10.616	12.043
PFOB						*PC*					
1	0.050	59.025	21.695	19.280	0.000	1	0.069	2.104	3.752	1.946	92.198
2	0.085	55.083	30.867	12.014	2.037	2	0.109	1.308	2.807	1.524	94.362
3	0.112	47.235	37.271	9.112	6.382	3	0.143	0.910	2.922	2.115	94.054
4	0.132	40.482	41.682	8.332	9.504	4	0.170	0.678	3.433	2.674	93.215
5	0.150	35.618	44.718	8.705	10.959	5	0.195	0.521	3.965	3.097	92.418
6	0.165	32.103	46.842	9.530	11.525	6	0.216	0.430	4.388	3.424	91.758
7	0.178	29.477	48.377	10.413	11.733	7	0.236	0.386	4.691	3.711	91.211
8	0.191	27.461	49.529	11.215	11.794	8	0.254	0.368	4.904	3.969	90.759
9	0.202	25.884	50.422	11.906	11.789	9	0.270	0.359	5.057	4.194	90.390
10	0.213	24.627	51.133	12.485	11.754	10	0.285	0.353	5.169	4.383	90.094
11	0.224	23.609	51.714	12.965	11.712	11	0.300	0.349	5.256	4.540	89.855
12	0.233	22.768	52.197	13.362	11.673	12	0.314	0.345	5.325	4.668	89.661

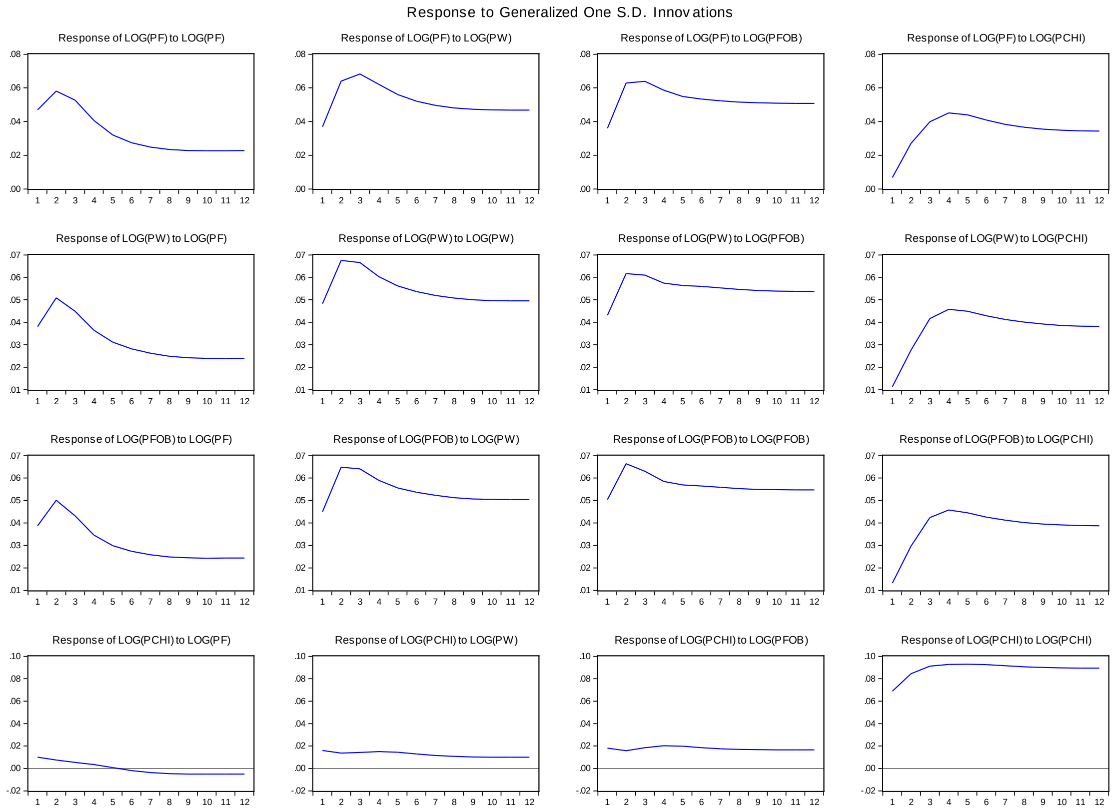
4.6 การวิเคราะห์ฟังก์ชันการตอบสนองต่อความแปรปรวน (impulse response functions: IRFs)

การวิเคราะห์ฟังก์ชันการตอบสนองของตัวแปรเป็นวิธีที่ใช้พิจารณาผลกระทบจาก shock (innovation) ของตัวแปรใดใดในแบบจำลองที่มีต่อตัวแปรอื่นในระบบทั้งในช่วงเวลาเดียวกันและช่วงเวลาในอนาคตโดยวัดในรูปส่วนเบี่ยงเบนมาตรฐานหนึ่งหน่วย (one standard deviation: 1 s.d.) เพื่อทำให้เข้าใจถึงกลไกการส่งผ่านผลกระทบของความผันผวนด้านราคาข้าวโพดเลี้ยงสัตว์ในแต่ละตลาดในรอบ 12 เดือน (1 ปี) ข้างหน้า และเมื่อพิจารณาพิจารณาผลวิเคราะห์การตอบสนองของตัวแปรในดังภาพที่ 4 โดยพิจารณาคอลัมน์แรก (แสดงการตอบสนองของราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโก เมื่อได้รับ shock จากราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร) ซึ่งอธิบายได้ว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อและราคาส่งออกนั้นมีการตอบสนองต่อ shock ในทันทีและเป็นไปในทิศทางเดียวกันกล่าวคือ เมื่อราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อและราคาส่งออกได้รับ shock ที่เกิดจากราคาฟาร์มแล้ว ราคาใน 3 ตลาดนั้นจะมีการตอบสนองเพิ่มขึ้นและเริ่มลดลงในเดือนที่ 2 และเริ่มเข้าสู่เสถียรภาพในเดือนที่ 6 ในขณะที่ shock ที่เกิดจากราคาฟาร์มไม่มีอิทธิพลต่อราคาซื้อขายล่วงหน้าตลาดชิคาโก

ส่วน shock จากราคาที่โรงงานอาหารสัตว์รับซื้อนั้นนอกจากจะมีต่อตัวเองแล้วยังส่งผลต่อราคา ณ ฟาร์มของเกษตรกรและราคาส่งออกในรูปแบบเดียวกัน กล่าวคือ shock ดังกล่าวส่งผลให้ราคาฟาร์ม ราคาที่โรงงานอาหารสัตว์รับซื้อและราคาส่งออกตอบสนองเพิ่มขึ้นในช่วง 1-4 เดือนแรกและค่อยๆ ปรับตัวเข้าสู่เสถียรภาพในเดือนที่ 7 แต่ไม่มีอิทธิพลต่อราคาซื้อขายล่วงหน้าตลาดชิคาโก

สำหรับ shock จากราคาส่งออกนั้นมีอิทธิพลต่อราคาฟาร์ม ราคาที่โรงงานอาหารสัตว์รับซื้อและราคาส่งออกเองแต่ไม่มีอิทธิพลต่อราคาซื้อขายล่วงหน้าตลาดชิคาโก โดยผลจาก shock ที่เกิดขึ้นนั้นส่งผลต่อราคาทั้ง 3 ตลาดในรูปแบบเดียวกันกล่าวคือ shock ที่เกิดจากราคาส่งออกนั้นทำให้ราคาใน 3 ตลาดตอบสนองเพิ่มขึ้นในช่วง 1-3 เดือนแรกและเริ่มลดลงในเดือนที่ 4 จนเข้าสู่เสถียรภาพในเดือนที่ 5

สำหรับ shock จากราคาซื้อขายล่วงหน้าตลาดชิคาโกนั้นพบว่า มีผลกระทบต่อราคาข้าวโพดเลี้ยงสัตว์ในทุกตลาด เมื่อตลาดทั้ง 4 แห่งได้รับ shock ที่เกิดจากราคาซื้อขายล่วงหน้าตลาดชิคาโก ราคาข้าวโพดเลี้ยงสัตว์ทั้ง 4 ตลาดจะตอบสนองเพิ่มขึ้นในช่วงสี่เดือนแรกและเริ่มลดลงจนกระทั่งเข้าสู่เสถียรภาพในเดือนที่ 8 (ภาพที่ 4)



ภาพที่ 4 Generalized impulse response functions

5. สรุป

บทความมีวัตถุประสงค์เพื่อวิเคราะห์ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคา ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโก โดยใช้การทดสอบ cointegration ตามวิธีของ Johansen ผลการทดสอบพบว่าแบบจำลองที่เหมาะสมที่สุดคือ แบบจำลองรูปแบบที่ไม่ปรากฏค่าคงที่และแนวโน้มเวลา และเมื่อพิจารณาผลทดสอบกฎราคาเดียวพบว่า ทุกคู่ความสัมพันธ์ระหว่างราคาข้าวโพดเลี้ยงสัตว์ที่ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโกไม่เป็นเป็นไปตามกฎราคาเดียว ส่วนผลการทดสอบความเป็นนอกระบบแสดงให้เห็นว่า ราคาข้าวโพดเลี้ยงสัตว์ทั้ง 4 ตลาดมีอิทธิพลต่อราคาฟาร์มของเกษตรกรในระยะยาว และเมื่อพิจารณาผลการทดสอบการแยกองค์ประกอบของความแปรปรวนนั้นพบว่า ราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกรถูกกำหนดจากความผันผวนในตัวเองเป็นหลักในเดือนแรกและถูกกำหนดจากความผันผวนของราคาที่โรงงานอาหารสัตว์รับซื้อ ร้อยละ 13-48 ในช่วง 2-12 เดือนต่อมา ส่วนความผันผวนของราคาที่โรงงานอาหารสัตว์รับซื้อและความผันผวนของราคาส่งออกนั้นถูกกำหนดจากความผันผวนในตัวเองเป็นหลักตลอดช่วงเวลา 12 เดือน และถูกกำหนดจากความผันผวนของราคาข้าวโพดเลี้ยงสัตว์ ณ ฟาร์มของเกษตรกรในช่วง 1-2 เดือนแรก เช่นเดียวกัน ในขณะที่ความผันผวนของราคาซื้อขายล่วงหน้าตลาดชิคาโกนั้นถูกกำหนดจากความผันผวนในตัวเองเป็นหลัก ผลจากการศึกษาครั้งนี้สามารถสรุปได้ว่า ความเชื่อมโยงของราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคา ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาดกทม. ราคาส่งออกและราคาซื้อขายล่วงหน้าตลาดชิคาโก มีเพียงสามตลาดที่มีความเชื่อมโยงกันนั่นคือ

ราคาข้าวโพดเลี้ยงสัตว์ระหว่างราคา ณ ฟาร์มของเกษตรกร ราคาที่โรงงานอาหารสัตว์รับซื้อ ณ ตลาด กทม. และราคาส่งออก ดังนั้นเกษตรกรจึงควรพิจารณาแนวโน้มการเปลี่ยนแปลงราคาในสามตลาดดังกล่าวนี้ร่วมกับนโยบายและมาตรการช่วยเหลือเกษตรกรผู้ปลูกข้าวโพดเลี้ยงสัตว์ของรัฐบาลในการวางแผนการผลิตเพื่อลดความเสี่ยงด้านราคาข้าวโพดเลี้ยงสัตว์ที่อาจเกิดขึ้นได้ในระยะยาว

6. บรรณานุกรม

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บทความที่ 3

Predicting price of palm oil using Extreme Value Theory

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Predicting price of palm oil using Extreme Value Theory

Abstract

This paper uses the extreme value theory focusing on the Block Maxima (BM) and Peak-Over-Threshold (POT) modeling to predict extreme price events and forecast extreme value of palm oil price in the future. We fit the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) models to examine growth in the price of palm oil for 25 years (mid-1986 to mid-2011). Both GEV and GPD methods revealed that palm oil price will peak at an incremental rate in the next 5, 10, 25, 50 and 100 year periods. The BM and POT models are two effective approaches for predicting prices caused by extreme events. The results could be useful to the government as well as the buyers (e.g. exporter) and sellers (e.g. farmers) in the palm oil industry for future strategic planning.

Keyword: Extreme Value theory, Block Maxima, Peak-Over-Threshold, Generalized Extreme Value, Generalized Pareto Distribution.

1. Introduction

The last few years have seen an increase in the production of renewable fuels because of rising crude oil prices, limited supplies of fossil fuel and increased concern about global warming. The increase in the oil price has caused many countries to consider using alternative renewable energy from agricultural sector, particularly vegetable oils such as soybean, rapeseed, sugarcane, corn and palm oil. This increase in production reflects the rising global demand for vegetable oils, and palm oil production is the dominant one as compared with other vegetable oils (Carter, 2007). However, there are regional distinctions in the choice of vegetable oils for conversion to biodiesel output. For example, in Europe, the primary production of biodiesel is based on the use of rapeseed oil; in Brazil and the USA, the base is soybean oil, and in Malaysia, palm oil is main source for biodiesel production (Yu et al., 2006).

Palm oil is a type of fatty vegetable oil derived from the fruit of the palm tree. It is used for both food and non-food consumption. Palm oil is a highly efficient and high yielding source of food and fuel. Approximately 80% of the palm oil is used for food such as cooking oils, margarines, noodles, baked goods, etc. (World Growth, 2011). In addition, palm oil is used as an ingredient in non-edible products such as biofuels, soaps, detergents and pharmaceuticals. With such a high range of versatile use, the global demand for palm oil is expected to grow further in the future (USDA, 2011).

Many countries plant oil palm to produce oil to fulfill their local consumption. World trade in palm oil has increased significantly due to increase in global demand. The world production of palm oil has increased rapidly during the last 30 years as a result of the fast expansion of oil palm plantation in the south-east Asian countries. The world palm oil production was 13.01 million tons in 1992 which has increased to 50.26 million tons in 2011, a 286% increase in 19 years (USDA, 2011).

The major world producers and exporters of palm oil are Malaysia and Indonesia. For these countries, palm oil production for export purposes is found to be highly viable, and oil palm has become a favorite cash crop to replace other traditional crops such as rubber. However, high yield of the palm throughout the year is essential to achieve viability for the export market (MPOB, 2010). Indonesia is the largest exporter of palm oil in the world, exporting around 19.55 million tons a year during 2008-2011 (USDA, 2011). Malaysia is the second largest exporter. In the past until 2007, Malaysia was the largest exporter of palm oil in the world, producing about 15 million tons of palm oil a year. Malaysia has been playing an important role to accomplish the needs and to stay competitive in the world's oils and fats market (World Growth, 2011).

The main consumer and business market for the palm oil commodity is the food industry. The major importers of palm oil are India, China and the European Union. India is the largest and leading consumer of palm oil worldwide importing about 7.8 million tons in 2011. China is the second largest importer of palm oil, importing about 6.65 million tons in 2011 (USDA, 2011). World production of palm oil is expected to increase by 32% to almost 60 million tons by 2020 (FAPRI, 2010).

In the international market, the expanding trade, continuous demand and supply, and other relevant factors of palm oil have made the prices of palm oil to fluctuate. Figure 1 presents the fluctuation in Malaysia palm oil futures price over the past 25 years (1986 – 2011). The price was $182.00 per metric ton in July 1986 which has increased to $1,033.57 per metric ton in July 2011, an increase of 468%.

Palm oil price can be significantly affected in two ways, fluctuation in nature and world demand (OECD, 2008). Since nature is unpredictable, thus the main source of palm oil price fluctuation is mainly changing from its demand. However, world demand of palm oil depends on food demand as well as demand for biofuel in the industrial sector. These two types of demand are currently decreasing due to small share of palm oil in food as well as a decline in biofuel usage. Therefore, the price of palm oil remains uncertain in the future.

Instability of palm oil price can create significant risks to producers, suppliers, consumers, and other stakeholders. In risky conditions and between price instability, forecasting is very important in helping to make informed decisions. Forecasting price is quite a challenging effort as its behavior is very unpredictable in nature (MPOB, 2010).

Forecasting of agricultural price has traditionally been carried out by applying an econometric model such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) (Assis et al., 2010) based on historical data. The general linear regression analysis used in the aforementioned models assumes normality of the distribution and, therefore, predicting future prices using such approach ignores the possibility of extreme events. We believe that the palm oil price prediction involves determining the probability of extreme events. And the Extreme Value Theory enables us to describe the performance of the heavy-tail properties of the high frequency time series data (e.g. financial, weather disasters). The extreme value theory can describe the behavior of random variables both at extremely high or low levels.

Since we believe that the palm oil price prediction involves recognition of extreme events, we apply the Extreme Value Theory (EVT) to predict future prices of palm oil. Our modeling approach focuses on the Block Maxima (BM) and Peak-Over-Threshold (POT) methods to analyze the extreme price events and forecast the extreme values of palm oil price in the future, for example, in the next 5, 10, 25, 50 and 100 year periods. Forecasting future prices of palm oil using the most accurate method can help the government, the buyers (e.g. exporter) as well as the sellers (e.g. farmers) of the palm oil industry to plan strategically for the future.

The structure of the paper is as follows. Section 2 presents a brief review of the literature. Section 3 introduces the extreme value theory and the application of the BM and POT model. Section 4 presents the empirical results. The final section concludes.

2. Literature Review

A number of studies exist on forecasting palm oil prices using various techniques. Alias and Tang (2005) have analyzed the supply response of the Malaysian palm oil market using Engle and Granger (1987) cointegration and error correction approach. Abdullah et al., (2007) studied the impact of palm oil based biodiesel demand on palm oil price. They included biodiesel demand in the price equation by using time varying parameter. Fatimah and Roslan (1986) used a univariate ARIMA model developed by Box-Jenkins to forecast the short-run monthly price of crude palm oil. In addition, Rangsan and Titida (2006) applied ARIMA model to forecast three types of palm oil price to estimate the minimum of Mean Absolute Percentage Error (MAPE).

Simple regression and/or moving average technique works better in forecasting if the data is stationary. For non-stationary data, ARIMA is preferred. But both these approaches assume normality of the distribution of the data. All of the above studies, therefore, suffer from this weakness of normality assumption since the price of palm oil is assumed to have a non-normal distribution. This is because palm oil price is characterized by a high degree of volatility and involves occurrance of extreme events (see Figure 1). Therefore, we have decided to apply the EVT to forecast palm oil price which overcomes the limitations inherent in all of the aforementioned studies.

EVT provides a strong theoretical basis with which we can construct statistical models that are capable of describing extreme events (Manfred and Evis, 2003). Extreme value methods were used in environmental science, hydrology, insurance and finance. EVT became a popular method to forecast extreme financial risks. For example, Bensalah (2000) applied EVT to a series of exchange rates of Canadian/U.S. Dollars. Silva and Mendes (2003) used EVT to compute Value at Risk (VaR) estimates and compared with normal VaR for ten Asian stocks. Bekiros and Georgoutsos (2004) conducted a comparative evaluation of the predictive performance of various VaR models using EVT that allowed accurate forecasts of extreme losses with a very high confidence levels. Zuo-xiang et al., (2005) studied forecasting results of the compound index of Shanghai Stock Exchange by applying EVT and GARCH models. They concluded that EVT method is superior to GARCH models in estimating and predicting VaR.

In disaster studies, Li-Hau and Pei-Hsuan (2005) used EVT to evaluate the appropriateness of the upper tail of the data of agricultural output loss due to natural disasters in Taiwan. Xu and Zhang (2010) applied EVT to analyze and evaluate the agricultural catastrophic risk of extreme rainfall in Jilin Province, China.

In general, the work mentioned above used the EVT to analyze and evaluate VaR in finance sector and losses in the agricultural output due to disasters, but not applied to predict agricultural prices. We believe that palm oil price prediction involves determining the probability of extreme events. Therefore, in this paper, we examine the distribution of palm oil price under extreme condition. We look for the existence of heavy-tail in the distribution of palm oil price using original data, and then evaluate the parameters of best fit using the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD).

3. Methodology

3.1 The Extreme Value Theory (EVT)

EVT is a method for modeling extreme values. The main idea of this theory is the concept of modeling and measuring extreme events which occur with very small probability (Erik and Claudia, 2006). It provides methods for quantifying such events and their consequences statistically. Generally, there are two principal approaches to identify extremes in real data. The

BM and POT are central for the statistical analysis of maxima or minima and of exceedances over a higher or lower threshold (Li-Hau and Pei-Hsuan, 2005).

3.2 Block Maxima Model (BM)

The BM studies the statistical behavior of the largest or the smallest value in a sequence of independent random variables (Xu and Zhang, 2010). One approach to working with extreme value data is to group the data into blocks of equal length and fit the data to the maximums of each block: assuming we have identified n blocks let Z_i (i=1,…,n) denote maximum observation in each block(Coles, 2001). Z_n is normalized to obtain a non-degenerated limiting distribution. The BM is closely associated with the use of Generalized Extreme Value (GEV) distribution with c.d.f:

$$G(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

where μ, $\sigma > 0$ and ξ are location, scale and shape parameter respectively. Note that $\xi > 0$ is called Frechet distribution, $\xi < 0$ is called Fisher-Tippet or Weibull distribution and $\xi = 0$ is called Gumble or double-exponential distribution. Under the assumption that $Z_1, \ldots, Z_n$ are independent variables having the GEV distribution, the log-likelihood for the GEV parameters when $\xi \neq 0$ is (Coles, 2001) is given by:

$$\ell(\xi, \mu, \sigma) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right]^{-1/\xi}$$

provided that $1+\xi\left(\frac{Z_i-\mu}{\sigma}\right) > 0$, for i=1,….,n

The case $\xi = 0$ requires separate treatment using the Gumbel limit of the GEV distribution (Coles, 2001). The log-likelihood in that case is:

$$\ell(\mu, \sigma) = -n\log\sigma - \sum_{i=1}^{n}\left(\frac{Z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\exp\left\{-\left(\frac{Z_i-\mu}{\sigma}\right)\right\}$$

The maximization of this equation with respect to the parameter vector (μ, σ, ξ) leads to the maximum likelihood estimate with respect to the entire GEV family (Coles 2001)

3.3 Peaks-Over-Threshold Model (POT)

The POT approach is based on the Generalized Pareto Distribution (GPD) introduced by Pickands (1975) (cited in Xu and Zhang, 2010). These are models for all large observations that exceed a high threshold. It deals with the distribution of excess over a given threshold wherein the modeling is to understand the behavior of the excess loss once a high threshold (loss) is reached. Previous studies have shown that if the block maxima has an approximate distribution of GEV (Li and Pei, 2005, Xu and Zhang, 2010), then for large enough threshold, u, the distribution function of (X-u), conditional on X > u, is approximately

$$H(y) = 1 - \left(1+\frac{\xi y}{\sigma}\right)^{-1/\xi}$$

defined on {y: y > 0 and $\left(1+\frac{\xi y}{\sigma}\right)$ > 0}, where y (growth rate price exceeds) is random variable, σ ($\sigma > 0$) and ξ ($-\infty < \xi < +\infty$) are scale and shape parameters, respectively. The family of distributions defined by this equation is called the GPD family. Having determined a threshold, the parameters of GPD can be estimated by log-likelihood.

Suppose that the values $Y_1,\ldots, Y_n$ are the n excesses of a threshold u. For $\xi \neq 0$ the log-likelihood is (Coles 2001)

$$\ell(\sigma, \xi) = -n\log\sigma - (1+1/\xi) \sum_{i=1}^{n} \log(1+\xi y_i/\sigma)$$

provided that $(1+\xi y_i/\sigma) > 0$ for i=1,…,n

The maximum likelihood procedures can also be utilized to estimate the GPD parameters, given the threshold (Xu and Zhang, 2010).

4. Empirical results

4.1 The results from the BM model

The data in this study are 300 observations on Malaysia Palm Oil Futures price. In the case of BM model, we focus on the statistical behavior of block maximum data. This analysis is based on the series of annual maximum palm oil price growth rate (PPGR) covering a 25 year period (Jul, 1986 to Jul, 2011). Therefore, the source data is a set of 26 records of maximum annual PPGR. Figure 2 shows the scatter plot of annual maximum PPGR. We model these data as independent observations from the GEV distribution.

Maximization of the GEV log-likelihood for these data provides the following estimates of the necessary parameters: $\hat{\xi}$ = 0.2106, $\hat{\sigma}$ = 4.5000, $\hat{\mu}$ = 9.6435. Figure 3 shows the various diagnostic plots for assessing the accuracy of the GEV model fitted to the PPGR data. The plotted points of the probability plot and the quantile plot are nearly-linear and the return level curve converges asymptotically to a finite level as a consequence of the positive estimate, although the estimate is close to zero and the respective estimated curve is close to a straight line. The density plot estimate seems consistent with the histogram of the data. Therefore all four diagnostic plots give support to the fitted GEV model.

In Table 1 we present T-year return levels based on GEV model for the 25 year period to forecast the extreme values in the PPGR for the next 5, 10, 25, 50 and 100 year in the future. We provide the probability of 95% confidence interval for future 5-, 10-, 25-, 50-, 100-years return levels based on profile likelihood method. Empirical results show that the extreme values of the PPGR will increase in the future. Under the assumption of our model, in the future year-5, the extreme value of PPGR will be 17.58% overall with the minimum extreme value of PPGR to be 14.05% and the maximum to be 24.43 %. In year-10 the extreme value of PPGR will be 22.59% (min 17.51, max 37.59). In year-25 the extreme value figures are 30.18% (min 21.86, max 67.37). Similarly, in year-50, the extreme value figures are 36.87% (min 24.96, max 105.35). And finally, in year-100, the extreme value figures for PPGR are 44.57% (min 27.86, max165.68). These figures reveal that the PPGR values are going to be incrementally higher further in the future. For instance, the value of PPGR rising from 17.58% in year-5 to 44.57% in year-100.

4.2 The results from the POT model

In this section, we use the same data, but the model focuses on the statistical behavior of exceeds over a higher threshold. We analyze the data by modeling exceedances of individual observations over a threshold according to the following method. The scatter plot of PPGR data is presented in Figure 4 and the mean residual life plot is presented in Figure 5. In POT model, the selection of a threshold is a critical problem. If the threshold is too low, the asymptotic basis of the model will be violated and the result will be biased. If the threshold is too high, it will generate few observations to estimate the parameters of the tail distribution function, leading to high variance (Eric and Richard, 2005). We make use of the fact that GPD is asymptotically the correct model for all the exceedances. The mean residual life plot for these data suggested a threshold of u=6. Vertical lines in Figure 6 show 95% confidence intervals for correct choice of the threshold value u= 6. This gives 61 records of PPGR. We can estimate the parameters of GPD using MLE approach with threshold value of u =6. The parameters of GPD are estimated at σ =6.0619 and ξ = -0.0435. Figure 7 shows the diagnostic plots for GPD fit to the PPGR data. Neither the probability plot nor the quantile plot presents any doubt on the validity of the fitted model.

In table 2, we provide the probability of 95% confidence intervals based on profile likelihood method to forecast the extreme value of growth rate of palm oil price for the next 5, 10, 25, 50 and 100 years into the future. Table 2 exhibits T-year return level based on GPD model. In the future year-5, the extreme value of PPGR will be 37.62% (min 27.86, max 117.14). In year-10 the extreme value figures are 40.82 % (min 29.35, max 154.66). In year-25 the extreme value figures are 44.91% (min 30.98, max 222.65). In year-50 the extreme value figures are 47.89% (min 32.00, max 292.85). And finally, in year-100 the extreme value of PPGR are 50.78% (min 32.99, max 384.80). Again the value of PPGR increases at an incremental rate further into the future. For example, the value of PPGR increasing from 37.6% in year-5 to 50.78% in year-100.

5. Conclusion

The aim of this study is to predict extreme events in the price of palm oil in the future using the best possible method that overcomes previous shortcomings in the literature dealing with palm oil price predictions. To do this, the paper applies the EVT approach to examine the tail of the growth rate of palm oil price distribution and identified that it possesses a heavy-tail which implies that the distribution is non-normal. Using BM and POT approaches of extreme value modeling technique, we fit GEV and GPD models to the growth rate of the palm oil price covering a 25 year period (Jul, 1986 to Jul, 2011). Both GEV and GPD found that palm oil price will have higher extremes in the next 5, 10, 25, 50 and 100 year period with acceleration in values towards longer future periods. Both BM and POT models are two effective approaches for predicting prices caused by extreme events. We believe that our results will be useful for the government as well as the buyers (e.g. exporter) and sellers (e.g. farmers) involved in the palm oil industry as it will enable them to undertake better strategic planning and mitigate against risk and instability.

6. Acknowledgements

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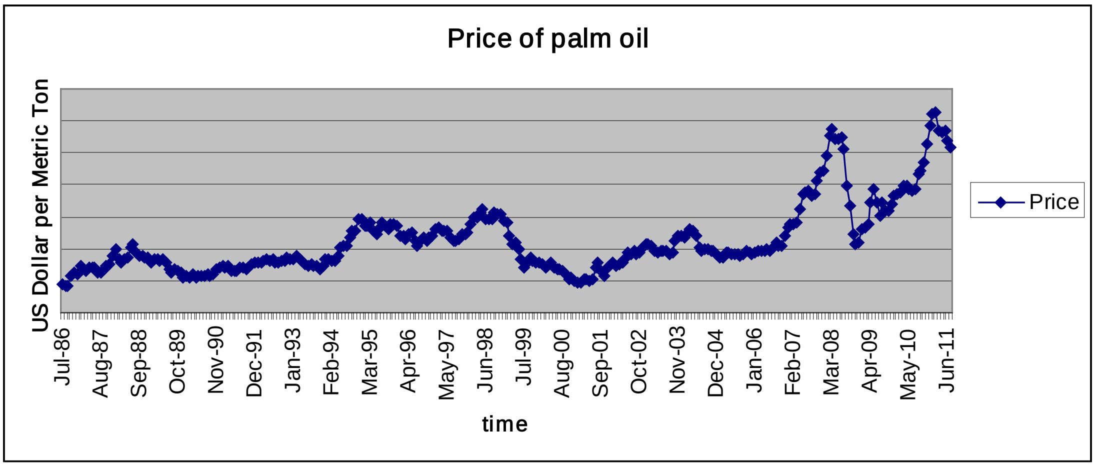


Source: www.indexmundi.com

Figure 1 Palm oil monthly price, Jul 1986 - Jul 2011

Note: The Palm oil price of this paper is Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, US Dollars per Metric Ton.

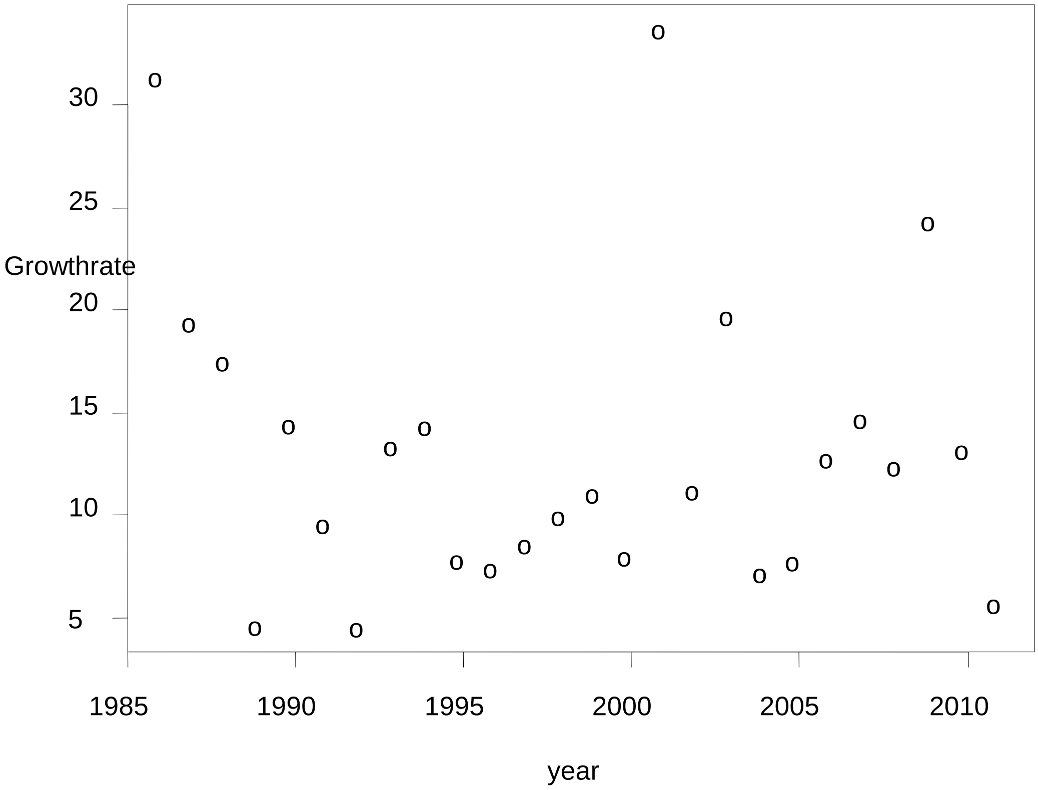


Figure 2 The scatter plot of annual maximum palm oil price growth rate (PPGR)

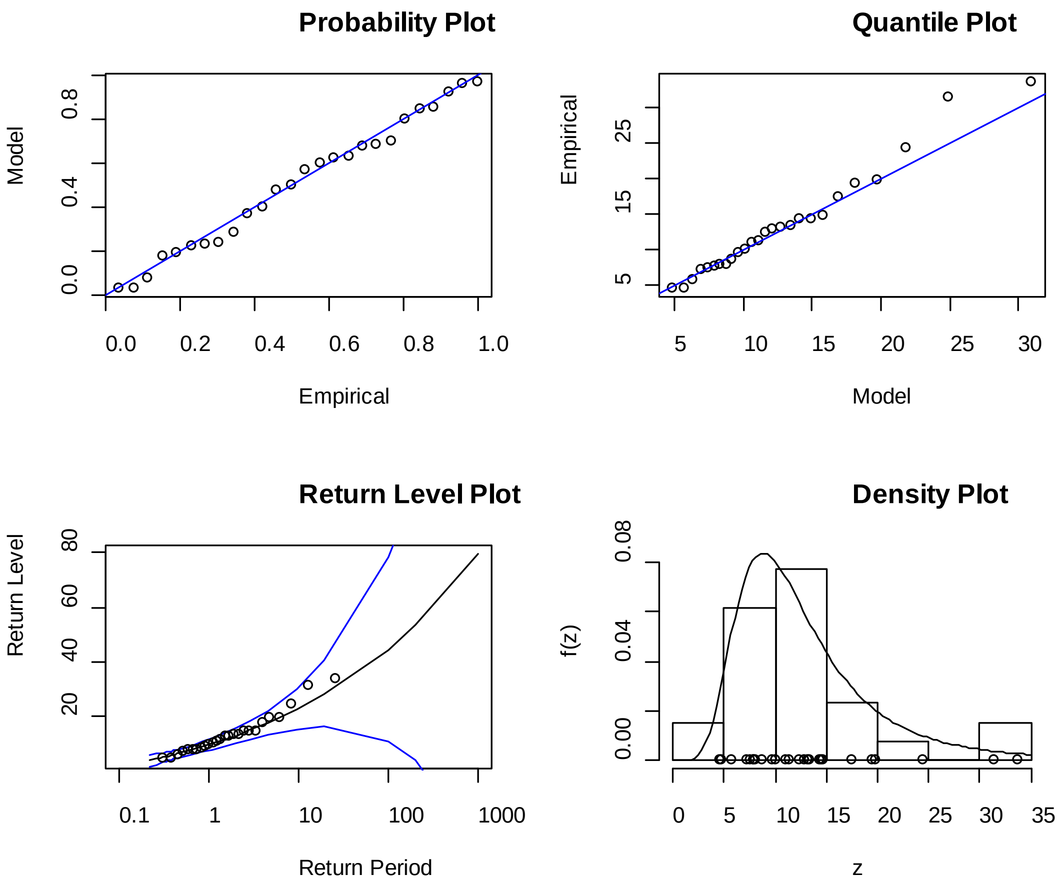


Figure 3 Diagnostic Plots for GEV fit to the annual maximum PPGR

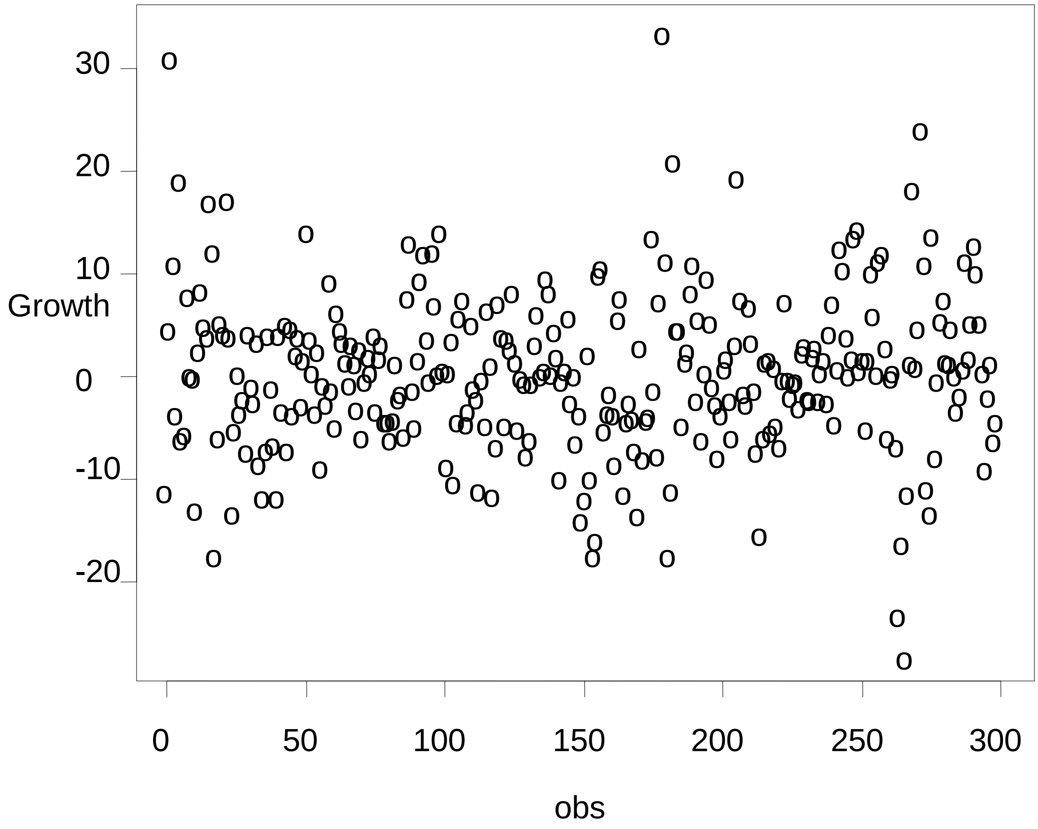


Figure 4 the scatter plot of PPGR

Figure 5 Mean Residual Life Plot of PPGR

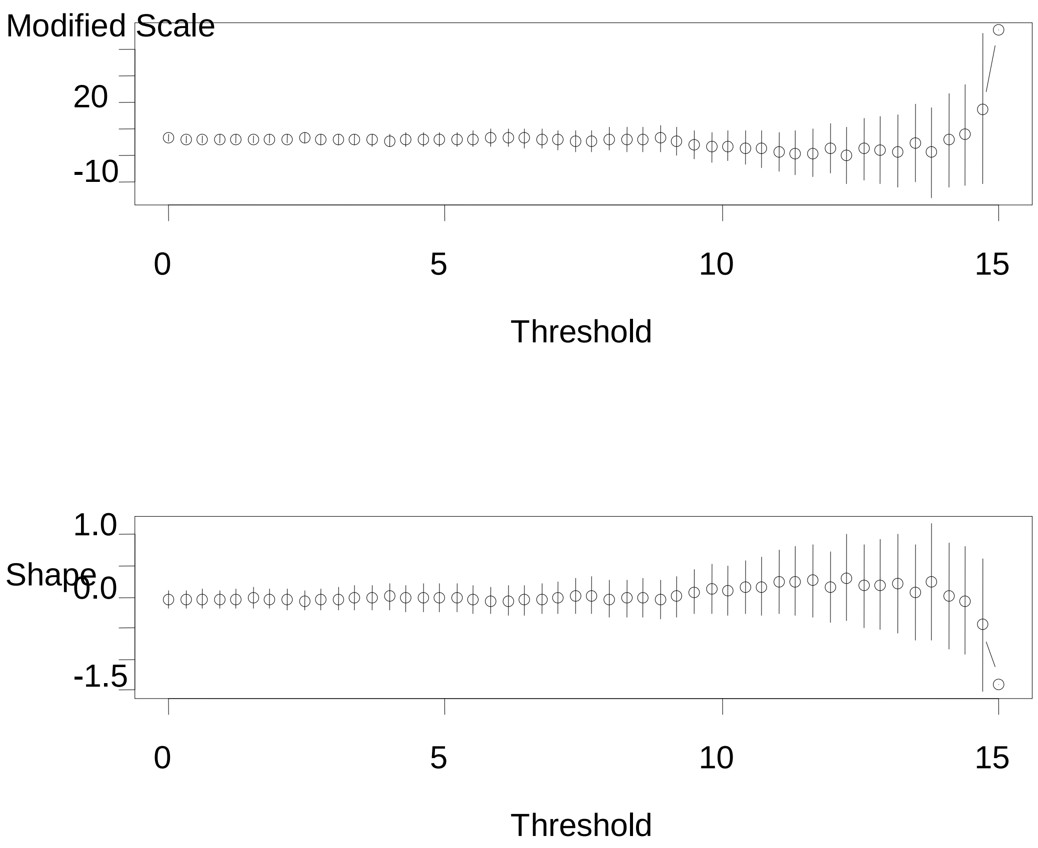


Figure 6 Parameter stability plots for PPGR

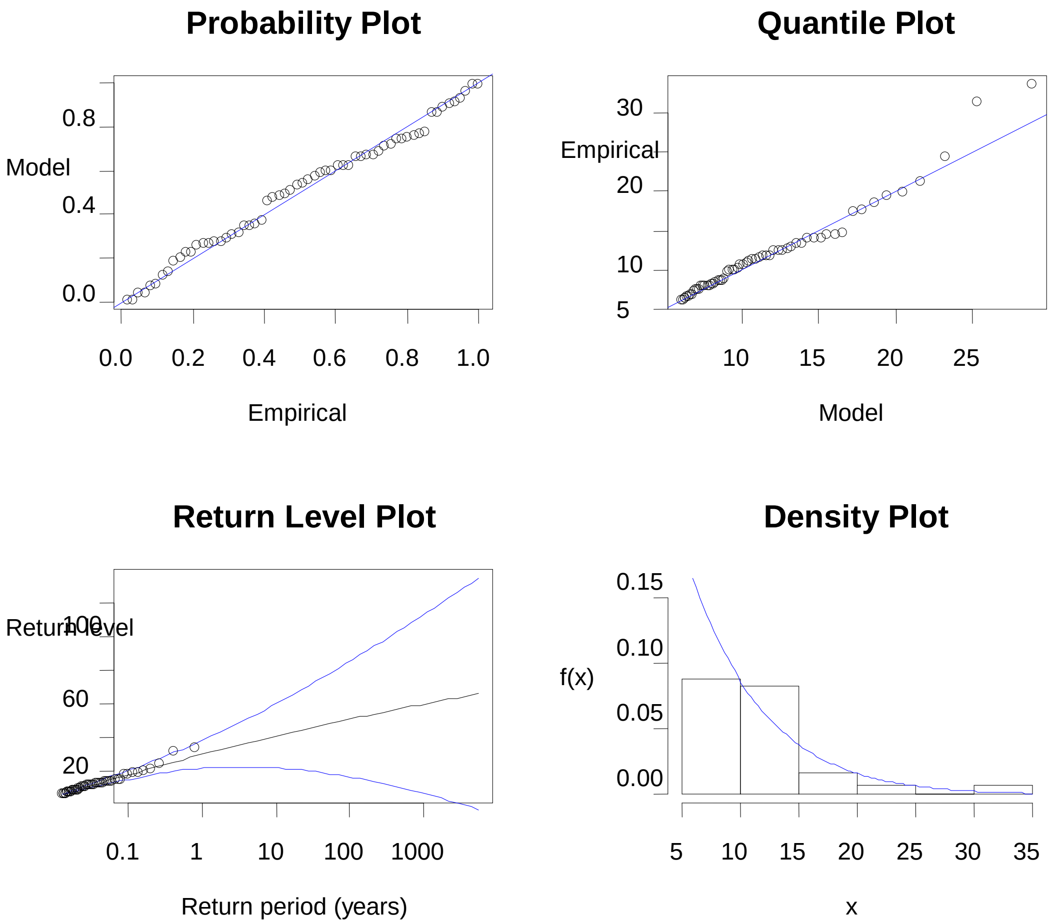


Figure 7 shows diagnostic plots for GPD fit to PPGR

Table 1 T-year return level based on GEV model

Item	GEV fit	95%
ξ	0.2106	
σ	4.5000	
μ	9.6435	
Year-5	17.5810	(14.0515,24.4286)
Year-10	22.5982	(17.5190,37.5984)
Year-25	30.1837	(21.8648,67.3767)
Year-50	36.8748	(24.9560,105.3495)
Year-100	44.5726	(27.8615,165.6797)

Table 2 T-year return level based on GPD model

Item	GPD fit	95 %
ξ	-0.0435	
σ	6.0619	
Year-5	37.6226	(29.1853,76.9672)
Year-10	40.8219	(30.7610,94.3344)
Year-25	44.9058	(32.4901,122.6481)
Year-50	47.8887	(33.5656,149.0050)
Year-100	50.7830	(34.4789,180.5439)

บทความที่ 4

An Application of EVT to Analyze US Corn Market

Abstract

Corn is not only a food source, but also used for ethanol production, and livestock feed. The corn market has been volatile in the last three decades, with price reaching USD 770 per bushel on June 2011. The volatility of corn return is of great importance to the farmers, policy makers and even consumers. Safeguarding them from the risk of volatile corn return is important. In this paper, we apply extreme value theory to predict US corn return series. Two unconditional methods : Block Maximum Method (BMM) and Peaks over threshold (POT) were used. We use BMM to estimate the return level, and POT to calculate the static Value at Risk (VaR) and Expected Shortfall (ES). We also use GARCH (1, 1)-EVT (conditional-EVT) method to estimate dynamic VaR. The results show that compared with the normal-GARCH model and t-GARCH model, the dynamic EVT-GARCH performs better.

Keywords: US Corn Market, Value at Risk, Risk analysis

1. Introduction

Nowadays corn is not only a staple food crop in many regions of the world (Nweke, 2005)[1], but is also used for ethanol production (USAD, 2007)[2] and livestock feed (Leibtag, 2008)[3]. Due to this variety of usages, corn became a very important commodity around the world. As in U.S, corn accounts for over 85 percent of total U.S. feed grain production. The fluctuations of corn price influence everyone’s daily life, higher corn prices motivated farmers to plant corn instead of other crops, such as soybeans, cotton and wheat, therefore raising the their prices as well.[3] Moreover, since corn is the main source of livestock feed, higher feed makes the meat and poultry prices, even all food prices rise.

USA is the largest producer of corn representing about 40 percent of global production, and also the largest exporter of corn, with a world market share over 70 percent in the last decades.[4] The higher corn price will benefit to the domestic famers but hurt the poor and hungry people, in particular the urban poor in low-income countries which import the corn. Therefore, predicting the corn volatility, and measuring the risk of corn is a principal concern for the US farmers, low-income consumers, and both policymakers.

This price spike in corn market is due to a series of factors, including US energy policy, weather conditions such as droughts, and increased use of feedstock to produce biofuels.[4] The US energy Policy Act can date back to 1992, this policy aims to reduce the US dependence on imported petroleum and improving air quality by alternative energy to replace the crude oil, coal and other traditional energy.[5] Since then, as a main raw material of biofuel, corn price kept increasing and went to a peak in July 15.1996. Later another amendment of energy policy act published in 2005, accompanying with the natural disaster, extreme draught threatens the planting, the corn raised to highest price on July 4 2008.[6] Recently the oil price rose and due to the promotion of biofuels in the USA, the corn price jumped to 770 dollars/bushel on June 9 2011. Also, the trend for the corn price is going up and remains fairly volatile.

Accordingly, farmers, consumers and also governments should be aware of corn market dynamics and apply an effective theory to measure the unexpected risk of corn price. Extreme Value Theory (EVT) has been applied in many fields of economics. Such as the finance (Gilli, KÄellezi, 2006)[7], energy market [8](Marimoutou, Raggad and Trabelsi, 2009), and insurance [9](Vandewalle, Beirlant, 2006). Unlike the traditional theory measure the risk as the standard deviation of returns, EVT is an essential more useful theory to the risk management since it focuses directly on the tail of the return distribution. (Liow, 2008)[10] To predict unexpected extreme price movements in the corn market, theoretically the EVT could perform better.

In this study we implement several tools based on extreme value theory to manage the risk of corn market. The first one is return level estimation, which calculates the return period of the occurrence of the extreme event and predict its magnitude. It answers the question such as to what degree the extreme events will happen again in next few decades. The second one is Value at Risk (VaR), it illustrates how much we can lose with a given probability over a certain time horizon.(Marimoutou.el, 2009)[11] The third tool, Expected Shortfall, also named CVAR which overcome several shortcomings of the VaR and answers how large the expected value of the tail.

In this paper, we will apply three techniques related to the EVT: BMM, POT and GARCH (1,1)-POT method to measure the risk. We call the first two methods unconditional EVT, while the last one is the conditional EVT approach[12](McNeil, Frey, 2000). Backtesting criteria are implemented to test the statistical accuracy of the conditional EVT model with the other kinds of dynamic models, such as GARCH-normal, and GARCH-t models.

The paper is organized as follows: Section 2 presents a brief review. Section 3 discusses various EVT methods that we apply in order to forecast risk measures. Section 4 provides our empirical results and Section 5 concludes the paper.

2. Brief Review of Literature

Within the agricultural products markets, implementing a risk measurement methodology based on the statistical theory of extremes is an important issue. There is a large amount of literatures which successfully use the EVT to estimate market risks. However these literatures only focused on finance, energy and futures markets. Bekiros and Georgoutsos(2005)[13] used two methods in EVT, namely BMM and POT to calculate the VaR of three indices: USD-denominated, daily returns of the Dow Jones Industrial Average (DJIA) and the Cyprus Stock Exchange (CSE). After comparing the results with traditional methods on three different markets, they concluded that EVT-based method produces the most accurate forecasts of extreme losses. McNeil and Frey(2000)[12] first proposed GARCH-EVT models to estimate the conditional quintiles(VaR) and conditional expected shortfalls. Using backtesting by the data of stock market, exchange rate and gold futures price, they concluded that their Garch-EVT two steps procedure gives better estimates than methods which ignore the heavy tails of the innovations (Garch-normal model)or the stochastive nature of the volatility(EVT method). Bystrom(2004)[7] suggested that Garch-EVT models give particularly accurate VaR measures with the data of two different stock indices, the Swedish AFF, and the DOW index.

For the energy market, Marimoutou, Raggad and Trabelsi(2009)[8] applied the Garch-EVT model in the oil market, modeled VaR for long and short trading positions by applying both unconditional and conditional EVT models(Garch-EVT model) to forecast VaR. However the conditional EVT models are not superior to the others. Chan and Gray (2009)[14] suggested that the proposed EVT-based model was a useful technique in forecasting VaR in electricity markets.

Although there has been an extensive research on Extreme value theory to investigate the market risks, the main focus has been on stock and energy markets, with few applications to investigate the agricultural field. Ozaki el(2010)[16] estimated the Brazil agricultural yield data for the insurers with extreme values theory, calculated the probability of loss by modeling the left tail of the chosen distribution. He also compared the results with the values estimated under the normality assumption which commonly used by the Brazilian insurers. The results showed that under the inaccurate assumption, the insurance companies overpricing the risk, therefore increased adverse selection problem happened. Xu and Zhang(2010)[17] used EVT to analyze the agricultural catastrophic risk illustrated by extreme rainfall in Jinlin Province, China.

Though the literature on agriculture is extensive, no formal analyzes have been conducted on the agricultural price return, especial the corn return. Cotter el (2008)[15] applied POT based on EVT to estimate the extreme financial risk measures for corn and soybean US futures market, three tools were used: VaR, ES,and Spectral Risk Measures (SPMs). They compared the estimated risk measures in terms of their size and precision, and find that they are all considerably higher than normal estimates. However they only use the extreme value theory in static context. The conditional VaR was not adopted in their research.

Since the importance to manage corn return risks, this paper adopts both unconditional EVT and conditional EVT methods to evaluate several indices of risk measures in the corn return, and compare the results. Furthermore we will give suggestions for the policymakers of U.S Agriculture and importers from low-income countries.

3. Extreme Value Theory and Extreme Risk Modeling

Extreme value theory has emerged as one of the most important statistical disciplines over the decades. This theory provides asymptotic models which model the tails of a distribution and helps to reveal the extreme behavior information from the return data. There are two kinds of techniques widely used in extreme value theory, namely Block Maxima Method (BMM) and Peaks over Threshold (POT). The BMM method, divides the return data into N blocks, each block has m observations, exacts the largest increases (decreases) to form a maximal (minimal) series, these series could be used to model both tails of the sample return distribution. According to the Jenkinson (1955)[18] , these series, in any case, would converge in distribution to a random variable with a Generalized Extreme Value (GEV) distribution. However the POT method is considered as a more efficient method, which collects all large return beyond a certain threshold to create a series, and fit this series to the Generalized Pareto Distribution (GPD) (Pickands, 1975).[19] Both methods are under the assumption that the series are independent random data. However, when applied to the return data, it is usually unrealistic since the extremes would tend to cluster, therefore we introduce the declustering method to overcome data dependent problem. Several references will be adopted in following subsection when discuss the EVT methods.; Allen el.(2011)[21] , McNeil and Frey (2000)[12] :

3.1 Block Maxima Method (BMM)

As stated above, BMM method extract the maxima and minima from each block and collect all the observations to create a series, then fit the series into a limiting distribution, according to the Fisher and Tippett (1928)[22], Coles (2001)[20], there are at least three limiting distribution alternatives to characterize the distribution of extreme returns, namely Gumbel, Frechet and Weibull distribution. All Three of them can be combined into a single family of models having distribution functions of the form, namely, Generalized Extreme Value(GEV) distribution:

$$G(z) = \exp\left\{ -\left[1 + \xi \left(\frac{z-\mu}{\sigma} \right)^{-1/\xi} \right] \right\}$$

Defined on the set $\{z : 1+\xi(z-\mu)/\sigma > 0\}$, where the parameters satisfy $-\infty < \mu < \infty$, $\sigma > 0$, $-\infty < \xi < \infty$. The difference for the three specific type of distribution is the shape parameter (ξ), which determines the tail shape of the distribution. For the Grumbel, Frechet and Weibull distribution, the shape parameter is equal, less, and greater than zero, respectively. The Frechet distribution ($\xi < 0$), which represents the fat-tail shape, was suggested the best fit in the financial series. (Liow, 2008[10], Pavel et al., 2011[24])

The BMM method based on EVT has following two steps:

First step, we divide the return data into blocks of equal length (such as yearly, quarterly or monthly), and then fit the GEV to the set of block maxima (minima).

Second step, estimate the parameters for the GEV fit ($\hat{\zeta}, \hat{\mu}, \hat{\sigma}$)by maximum likelihood estimation (MLE) method, the confidence interval can be estimated for the parameters are estimated by profile likelihood estimation.

3.2 Peaks over Threshold (POT)

While the traditional method BMM is proper for the large observations of return sample in consecutive periods, the POT method is generally a more efficient way to model the extreme values even the observations are not large. (Coles, 2001)[20] The main idea of the POT is to gather all the large observations over a certain high threshold, since it is not constraint to collect one maxima (minima) from each block, it is considered to draw more information from the tail. POT method require the individual excesses were independent, but in financial return data it is usually not that case, the maxima(minima) extremes return tend to cluster. An approach, namely, declustering is adopted in our study, which filter the dependent returns to obtain a set of threshold excesses that are approximately independent.

Let us define the excess distribution over a threshold u:

$$F_u(y) = P(X-u \le y \mid X > u) = \frac{F(y+u)-F(u)}{1-F(u)} = \frac{F(x)-F(u)}{1-F(u)}$$

For $0 < y < x_F - u$ where $x_F \le \infty$ is the right endpoint of F and $y = x-u$. F_u is the conditional excess distribution function.

It can be shown that the Generalized Pareto distribution (GPD) is the limiting distribution for the $F_u(y)$. The GPD is as followed:

$$H(y) = 1-\left(1+\frac{\xi y}{\tilde{\sigma}}\right)^{-1/\xi}$$

Defined on{y:y>0 and $\left(1+\frac{\xi y}{\tilde{\sigma}}\right) > 0$}, where $\tilde{\sigma} = \sigma + \xi(u-\mu)$

The steps for the declustering method as below:

First step, we find a rule to define independent clusters;

Second step, extract the maximum from each cluster;

Third step fit GPD to clustered maxima.

3.2.2 Return level, Value at Risk (VaR) and Expected Shortfall (ES)

(1) Return Level

When return data are blocked into sequences of observations of lengths n, for some large value of n, generating a series of block maxima, $M_{n,1},\ldots, M_{n,m}$, then the GEV distribution can be fitted. Estimates of extreme quantiles of the annual maximum distribution are obtained by inverting equation:

$$z_p = \begin{cases} \mu - \dfrac{\sigma}{\xi}\left[1-\{-\log(1-p)\}^{-\xi}\right] & \xi \neq 0 \\ \mu - \sigma \log\{-\log(1-p)\} & \xi = 0 \end{cases}$$

Where $G(z_p) = 1-p$, Here is the **return level** associated with **return period** 1/p, the level z_p is expected to be exceeded on average once every 1/p period. We can estimate the return level given a certain p, or estimate the return period for a given return level.

Value at Risk (VaR) is the maximum loss that will be incurred on the portfolio with a given level of confidence over a specified period. The VaR of a long position over a given time horizon t and probability p, while p is one minus the VaR confidence level, $VaR_p(X) = F^{-1}(p)$.

For the GPD modeling, we fix a sufficiently high threshold u. Let $Y_1 \ldots Y_n$ be the excesses above this threshold where $Y_i = X_i - u$. If there is an extreme distribution F with right endpoint x_F, we can assume that $F_u(x) = G_{\xi,\sigma}(x)$ for $0 \le x < x_F - u$ and $\xi \in$ i and $\sigma > 0$, obtained from equation above:

$$F(x) = (1-F(u))G_{\xi,\sigma}(y) + F(u)$$

And the function F(u) can be estimated non-parametrically using the empirical c.d.f:

$$\hat{F}(u) = \frac{n - N_u}{n}$$

The estimate of F(x)

$$\hat{F}(x) = 1 - \frac{N_u}{n}\left(1 + \hat{\xi}\left(\frac{x-\hat{u}}{\hat{\sigma}}\right)\right)^{-\frac{1}{\hat{\xi}}}$$

Where $\hat{\xi}$ and $\hat{\sigma}$ are estimates of ξ and σ, respectively, which can be obtained by the method of maximum likelihood.

VaR_p can be obtained by the equation above:

$$VaR_p = \hat{u} + \frac{\hat{\sigma}}{\hat{\xi}}\left[\left(\frac{n}{N_u}(1-p)\right)^{-\hat{\xi}} - 1\right]$$

Where u is a threshold, $\hat{\sigma}$ is the estimated scale parameter, $\hat{\xi}$ is the estimated shape parameter.[slightly revise sth.]

For $\xi < 1$ the estimated ES is given by

$$E\hat{S}_p = \frac{1}{1-p}\int_p^1 q_x(F)dx = \frac{VaR_p}{1-\hat{\xi}} + \frac{\hat{\sigma} - \hat{\xi}u}{1-\hat{\xi}}$$

The main advantage of unconditional GPD approach is that it focuses attention directly on the tail of the distribution. However, even we apply the declustering method, the result will depend on the "r" we choose, as some paper suggest [add reference, the result varied with the..]

3.3 Conditional EVT (Garch-EVT) Method

In order to overcome the shortcomings of unconditional approach which require the data is i.i.d, and the traditional approach (GARCH modeling) focues on the whole return distribution but not only on the tail part.

We introduce a new conditional EVT method to estimate the VaR. Let R_t the return at time t be defined by the following stochastic volatility (SV) model

$$R_t = \mu_t + \sigma_t Z_t$$

Where μ_t is the expected return on day t and σ_t is the volatility and Z_t is the noise variable with a distribution $F_Z(z)$ (commonly assumed to be standard normal). We assume that R_t is a stationary process.

To estimate the volatility, we accept an autoregressive GARCH(1,1) process given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where $\varepsilon_{t-1} = R_{t-1} - \mu_{t-1}$, $\mu_t = \lambda R_{t-1}$, α_0, $\alpha_1, \beta > 0$, $\beta + \alpha_1 < 1$ and $|\lambda| < 1$

The combined approach, denoted conditional EVT approach constitutes of the following two steps:

-step 1 (GARCH(1,1)): Fit a GARCH model to the return data by quasi-maximum likelihood. Estimate μ_{t+1} and σ_{t+1} from the fitted model and extract the residuals z_t.

-step 2 (EVT method): Consider the standardized residuals and a constant choice of threshold u, use POT method to estimate $VaR(Z)_q$ and $ES(Z)_q$ to calculate the risk measures.

We will apply the above methods in to yellow corn return data to predict the corn market risk, the data is from the U.S. Agricultural Department(USAD).

4. Empirical results and discussions

4.1 Description of Data

The corn market is one of the largest agricultural products market and USA is the largest producer of corn representing about 40 percent of global production. Therefore we chose corn prices: corn U.S No.2 yellow for our analysis. This quotation is the leading benchmark price reported by the USDA on Fridays of each week. The data set contains prices from 1st January 1979 to 29th September 2011 all in U.S. dollar per Bushel. To get a stationary data, we transform the price into the return ($\log P_{t+1}/P_t$). The returns are measured in percentage. We plot it in the following:

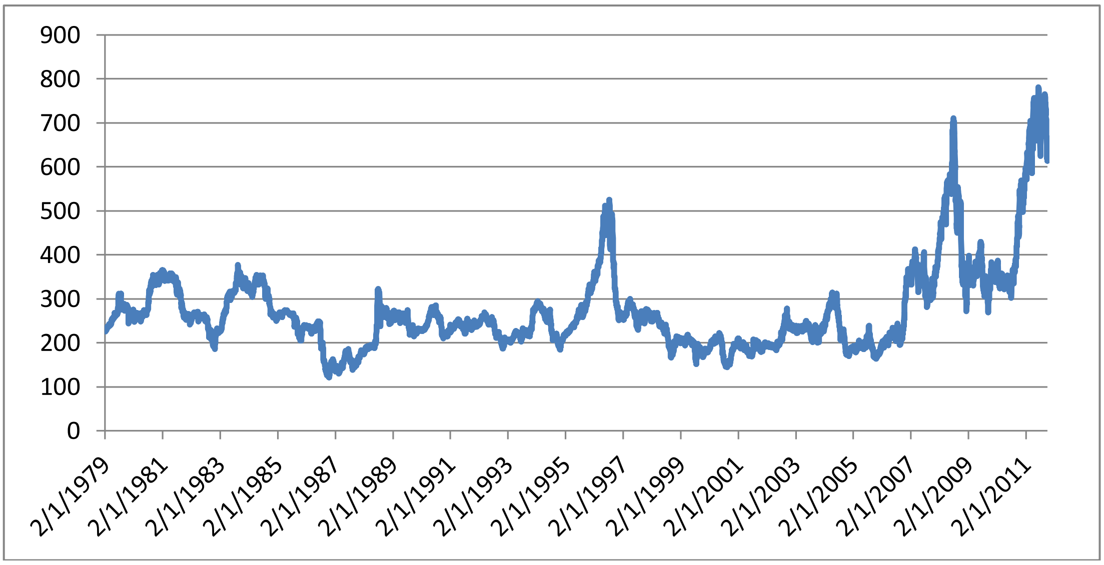


Fig.1 price

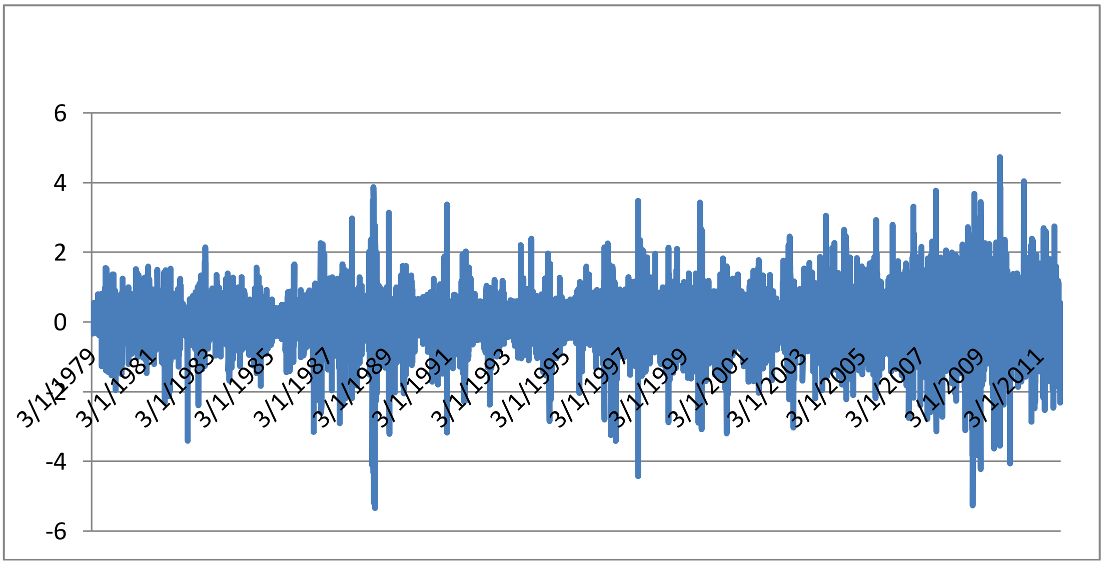


Fig.2 return in percentage

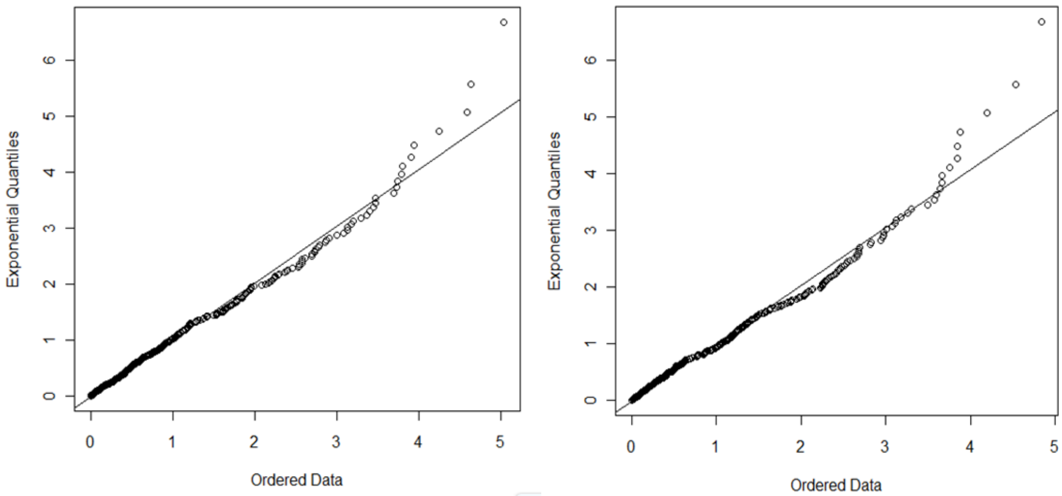
	No. of observations	Min	Median	Mean	Max	Std. Dev	1% quantile	5% quantile	95% quantile
Corn_US	8542	-5.3444	0	0.00507	4.72857	0.72029	-2.1096	-1.1329	1.105392

Table 1: Summary Statistics of Data

4.2 The Block Maxima Method

In this study we apply the BMM method to the left and right tails of our corn return in three calendar block lengths, monthly, quarterly and yearly.

We examine whether our maxima data follow the GEV distribution by the quantile-quantile (Q-Q) plot. The figure shows that the monthly block lengths does not necessarily follow GEV for the both tail of our return data, so does the quarterly block length. The sub figures(4) illustrates that the right tail of quarterly block length does not a good fit to GEV distribution.



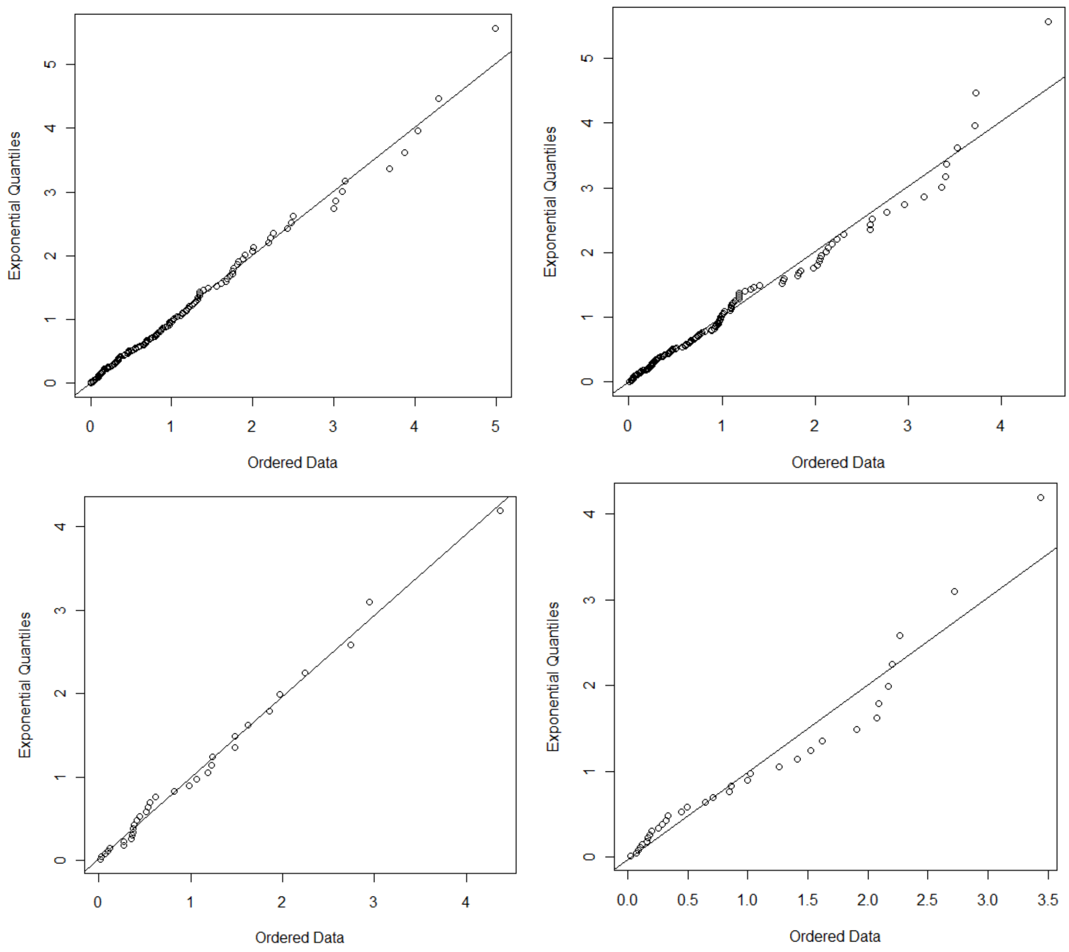


Fig.2 : GEV Fit Plot for the Left and Right Tail of Monthly Data (see the first two sub-figures) And Quaterly data

First of all, the yearly block choice is good for the corn return data because it eliminate seasonal effects. Furthermore as it shows in the fig, the yearly periods are likely to fit the GEV distribution better than other block choices. Therefore, we estimate the yearly block length in details, and compare the results of different block estimations later.

As we divide the corn return into 33 calendar years, sample blocks are not of exactly equal length. Figure 3(a),(b) plots the yearly maxima and minima return.

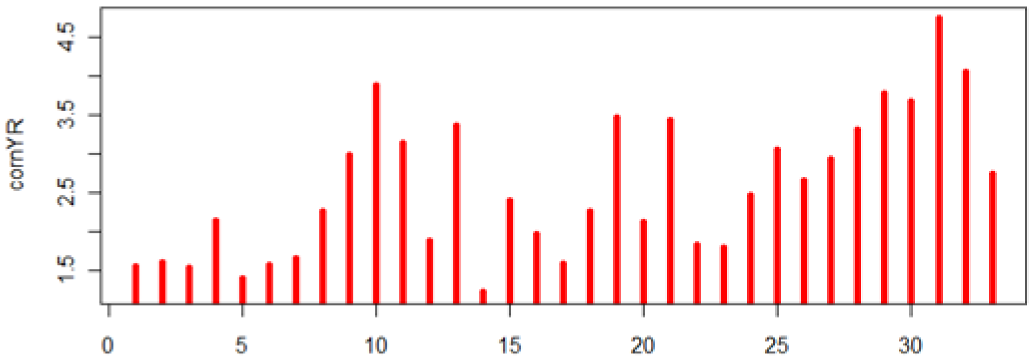


Fig.3 (a) Yearly maxima for the Left Tail

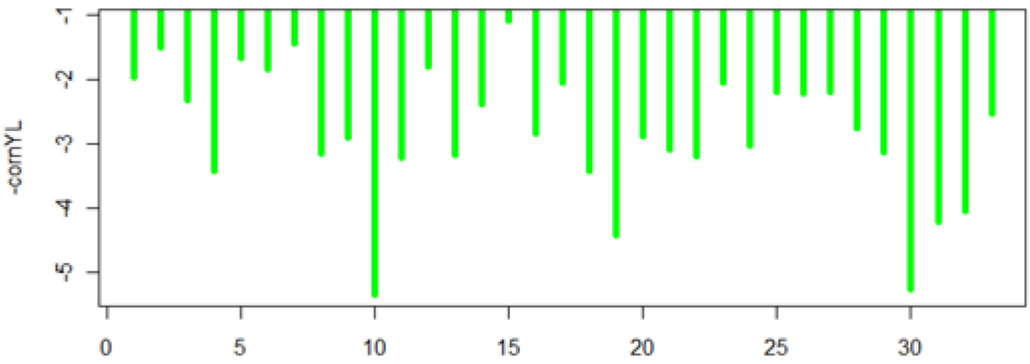


Fig.3 (b) Yearly minima for the Left Tail

The ten year return R^{10} for the minima of U.S. corn is as below figure-4(left) and for the maxima in figure-4(right), the return level is plotted against profile log likelihood in the return level graphs.

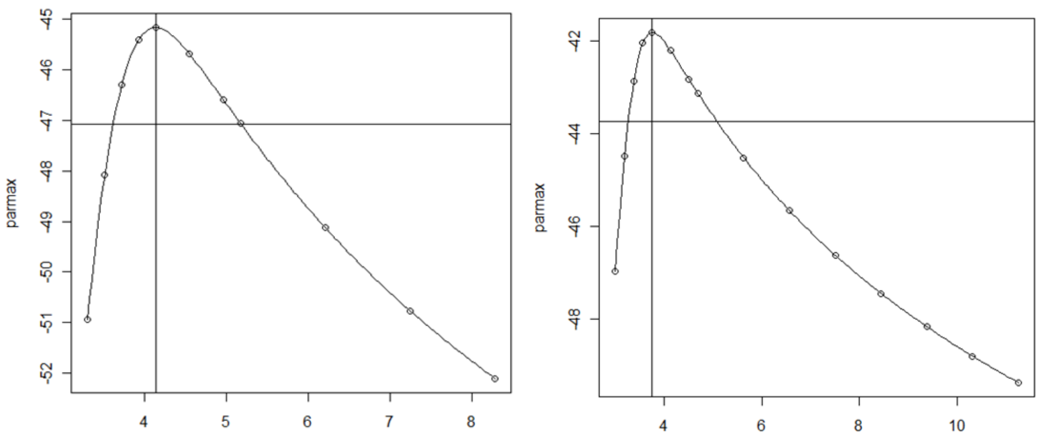


Fig.4 the negative and positive of 10-year return level

Table-2 gives the point and interval estimate (95% confidence intervals) for the parameters of both minima and maxima along with ten year return levels. The point estimate of ξ for the both tails indicate that the distribution of minima and maxima follows Weibull distribution, but under the 95% confidence interval, the sign of ξ is difficult to tell, therefore, it could not judge which distribution it belongs to. The 10-year return level results show that the corn return will exceed a negative return of 4.13 at least in one year of ten years and the positive return is 3.75 in one time of ten years.

Then we turn to analyze the return level and return period, the maxima return level is 4.728 in 2009, we calculate the return period 34.17 years, which means the extremely highest value will be appear in next 34.17 years. Figure 5 illustrates the relationship between return level and return period in the corn market. P356

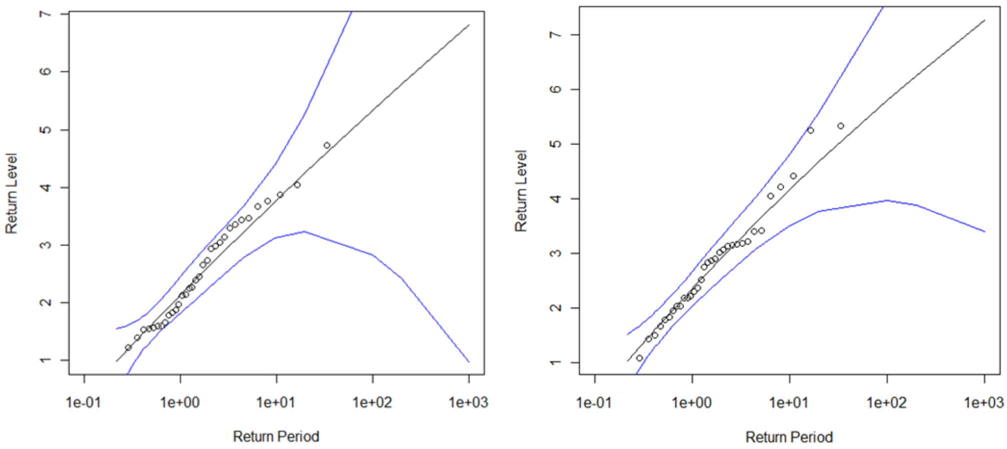


Fig.5 Return Level Plot for the left tails and right tails

4.3 The POT Method

The foremost step in applying the POT method is to select a threshold u. The threshold can be selected by using a **mean excess plot** which is plotted by using GPD mean excess function.

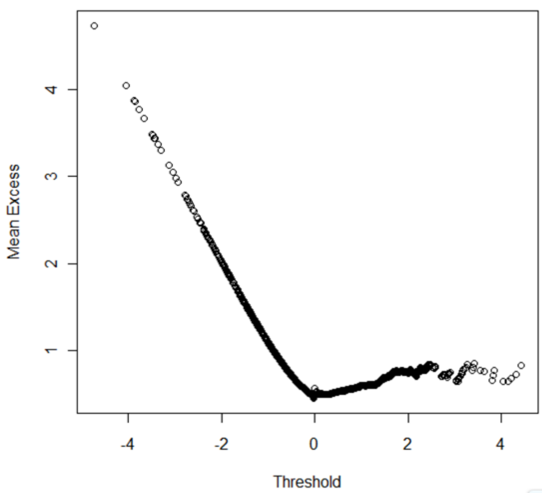


Fig.6 Mean Excess Plot

Table 2: the estimates of GEV parameter and return level

	Left Tail			Right Tail		
	monthly	quarterly	Yearly	Monthly	Quarterly	Yearly
r	0.182 (0.092, 0.271)	0.070 (-0.072, 0.211)	-0.047(-0.311, 0.218)	0.201(0.102, 0.300)	0.087(-0.068, 0.242)	-0.025(-0.457, 0.408)
a	0.517(0.470, 0.563)	0.707(0.603, 0.811)	0.830(0.599, 1.062)	0.449(0.407, 0.491)	0.606(0.515, 0.700)	0.736(0.489, 0.984)
b	0.940(0.881,0.999)	1.404(1.266, 1.543)	2.362(2.041, 2.684)	0.929(0.877, 0.981)	1.346(1.225, 1.466)	2.139(1.823, 2.454)
Return Level (12 month)	2.529(2.329, 2.791)			2.344(2.163, 2.588)		
Return Level(120 month)	4.881(4.111, 6.103)			4.536(3.788, 5.782)		
Return Level(4 quarter)		2.324(2.123, 2.560)			2.143(1.965, 2.350)	
Return Level(40 quarter)		4.366(3.764, 5.515)			3.970(3.422, 5.072)	
Return Level(10 year)			4.137(3.634, 5.181)			3.751(3.291, 5.074)

The first step, i.e. the selection of u is critical, u should be high enough to satisfy the condition of GPD but not too high to decrease the number of observations significantly. Here we use a particular lower quantile of the daily return data as the threshold which can be shown agreeing to the mean excess plot method of selecting u. In Fig.7 u= 1.133 is the 95% quantile of negative log return data of corn U.S and it well lies on the accepted linear regin on the plot. We will model POT using two different thresholds 95% and 90% of –rt for the left tail and same for the right tail. The figure 7 plot the exceedances of corn over the 95% quantile.

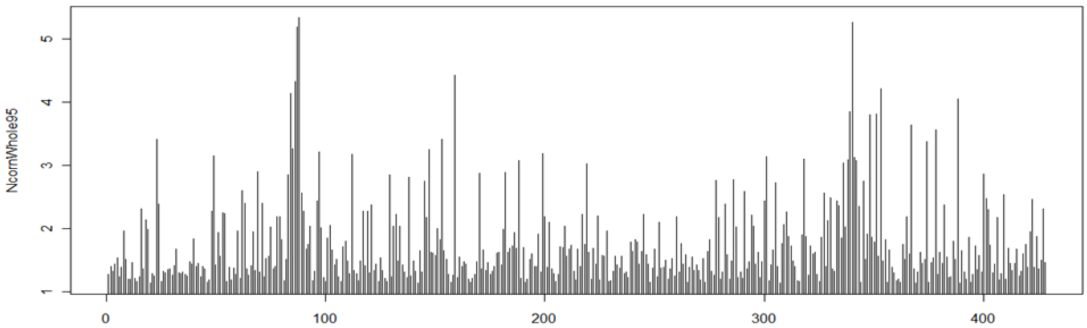


Fig.7 Plot of Excess over the 95% Quantile Threshold

The figure 8 is the GPD fit estimation. The first subplot is excess distribution, the second is tail of underlying Distribution, the third one is scatterplot of reisduals, and the last one is QQ plot of residuals. The QQ plot and excess distribution confirm that the data fits to the GPD distribution. Then we calculate the GPD estimates of parameters and return level.

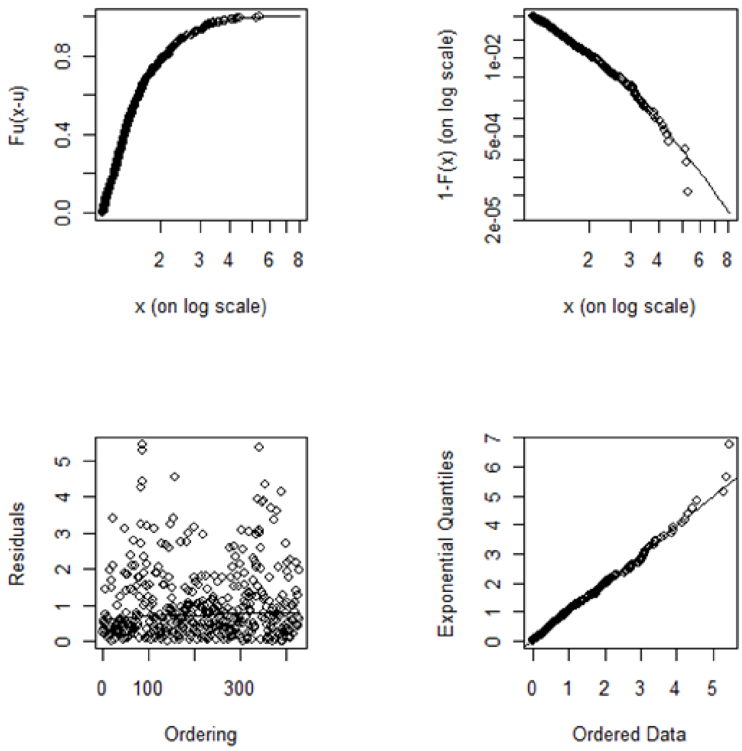


Fig.8 GPD Fit for the corn U.S. Negative Return

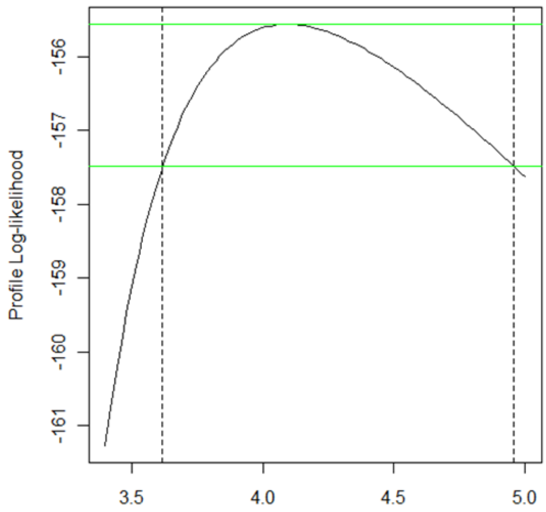


Fig.9 GPD fit return level plot

The point and interval estimates of the parameters of the fitted GPD model for both tails along with 1% VaR and 1% ES values are summerize in table below. The ten year return level is consistent with two different thresholds, but compared with the BMM return level in the last subsection, the results is slightly higher than BMM estimate; the 1% and 5% VaR and ES estimates are quite same in two thresholds. Given threshold equal to 1.132, i.e u=95% in the negative return, with a 5% confidence level we can predic tomorrow’s loss for corn. U.S is 1.133% and if this happens the corresponding expected loss will be 1.743%. the same inference can be drawn in the right tail of the corn return and also for differnet thresholds.

Table 3: the Estimates of Parameters in Declustering Method (Return Level, VaR and ES value)

	Left tails				Right tails			
	threshold: 1.132		threshold: 0.771		threshold: 1.105		threshold: 0.787	
No. of clusters	323	272	596	461	343	272	603	430
Clusters	r=2	r=4	r=2	r=4	r=2	r=4	r=2	r=4
sigma	0.559(0.462, 0.656)	0.603(0.488, 0.717)	0.543(0.477, 0.609)	0.597(0.515, 0.680)	0.548(0.461, 0.634)	0.625(0.517, 0.732)	0.534(0.471, 0.597)	0.599(0.516, 0.682)
r	0.146(0.011, 0.281)	0.129(-0.017, 0.277)	0.120(0.029, 0.212)	0.106(0.002, 0.210)	0.033(-0.084, 0.151)	-0.017(-0.140, 0.108)	0.041(-0.046, 0.127)	0.015(-0.086, 0.117)
Return Level 10	4.803	4.739	4.714	4.671	3.870	3.774	3.897	3.828
VaR(5%)	3.233	3.337	2.73	2.878	2.83	2.929	2.488	2.622
VaR(1%)	4.804	4.927	4.114	4.319	3.832	3.873	3.491	3.644
ES(5%)	4.247	4.358	3.616	3.797	3.457	3.513	3.116	3.259
ES(1%)	6.086	6.183	5.189	5.41	4.493	4.442	4.162	4.297

4.3 Dynamic-EVT VaR

A comparation of the methods, EVT can not only be used in a unconditional approach to predict VaR as seen in the results of previous subsection, it can also be used in a conditional model to predict time varying VaR estimate. Here we use a moving window of the last 1000 days log returns for corn to forecast one day ahead 1% and 5% VaR estimates. The total data period is approximately 3064 observations from 2000/01/03 to 2011/09/29, therefore we will have 2064 days predictions. The results will be compared with the unconditional POT method.

The method uses a two-step approach in which we predict the next day volatility(σ) and mean expected return (μ) using a GARCH(1,1) model in first step and in the second we fit the residuals of the step-1 to GPD to get quantile level as threshold, u to fit the residuals from the GARCH(1,1) model to GPD. The forecasts from this method are compared with the forecasts from normal a GARCH(1,1) where residuals are assumed to belong to normal distribution, student-t distribution.

We use a violation based backtesting method for the forecasted 1% and 5% VaR estimates. We will calculate a two-sided binomial test of the null hyothesis against the alternative that the method has prediction errors and it underestiamtes (too many violations) or overestiamtes (too few violations). On each day $t \in T$ we fit a new GARCH(1,1) model and determine a new GPD tail, then get an prediction $\hat{x}_q^t$. we compare the predictions with x_{t+1} for $q \in \{0.95, 0.99, 0.995\}$. A violation occurs whenever $x_{t+1} > \hat{x}_q^t$.

Figure 11 gives the plot of the real corn U.S return, then we compare this plot with the estiamtes of VaR(1%) by three dynamic models (GARCH-normal, GARCH-t and GARCH-EVT).

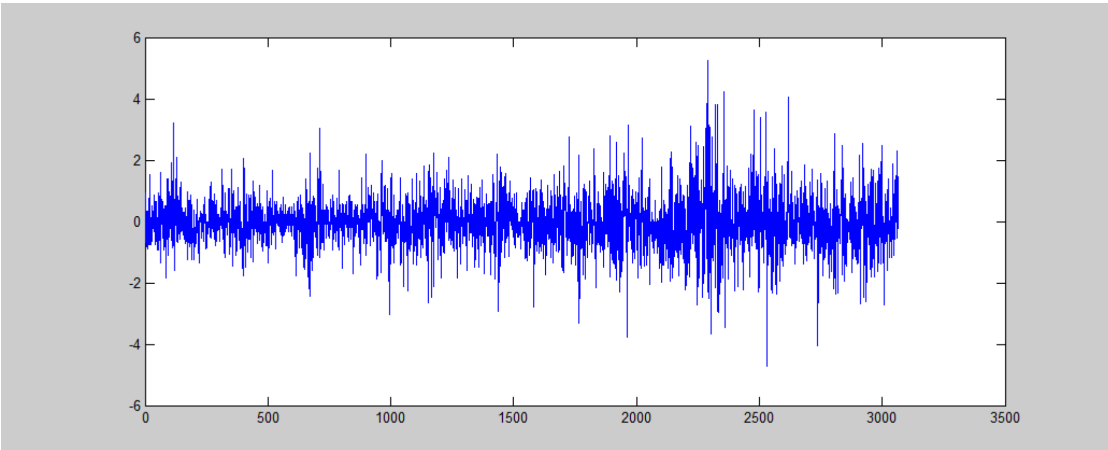


Fig.11 the corn return plot

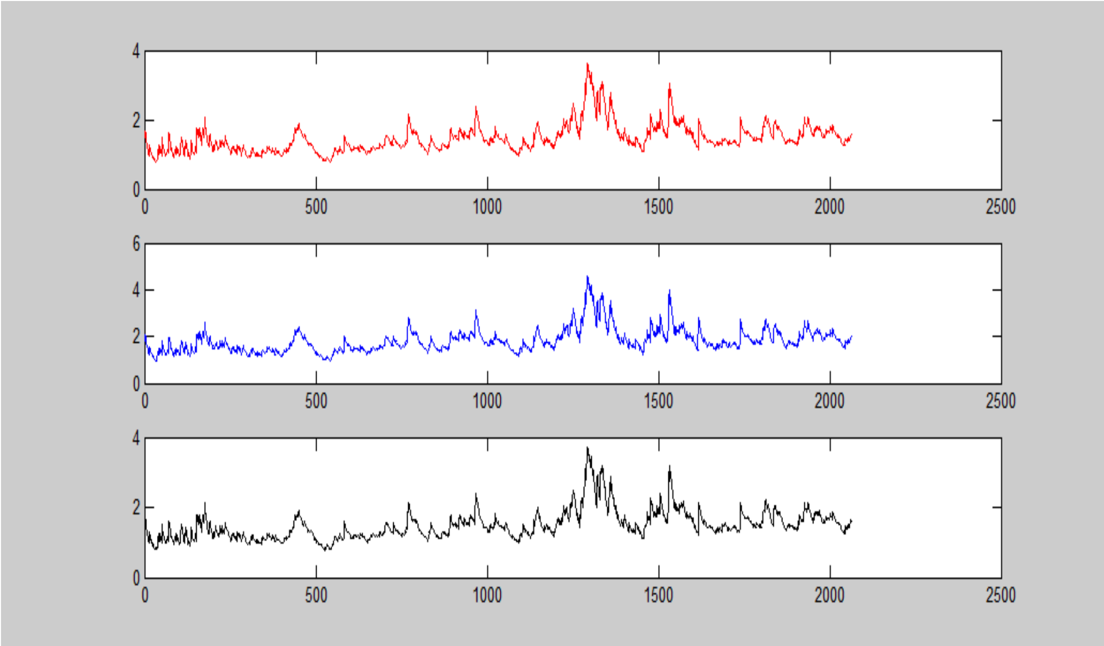


Fig.12 the 1% VaR Estimate of Three Dynamic Models: GARCH-normal, GARCH-t and GARCH-EVT

It is not obvious that the GARCH-EVT can fit the return level better from the graph, but when we turn to the binomal test, the results are clear: GARCH-EVT model performs better than our traditional dynamic models. The violation of conditional EVT is closer to the expected percentage count. The data in the bracket in Table 4 shows the two sided p-value, we can see all the statistics pass the test and hence significant. It is obviously the conditional-EVT method works better than all the other methods, the estimates are changing closely with the changing market dynamics, and hence estimate the extreme risk better in the extreme market conditons.

Table 4: the Three Models with the Binomial Test Results

	0.95 quantile	0.99 quantile	0.995 quantile
Expected	103	20	10
Conditional EVT	99(0.048)	23(0.011)	11(0.005)
Conditional Normal	108(0.052)	41(0.019)	25(0.012)
Conditional t	108(0.052)	37(0.017)	25(0.012)

5. Conclusion and Policy Implication

As the volatility in the corn markets increases, implement the… became a necessity. In this study we focused on the extreme market risk of USA corn return in the period 1979 to 2010. The Return Level, VaR, and ES tools were used to assess extreme tail events and market risk. We hope to give some useful suggestions to the governments , especially t and the low-incoming countries, to protect the interest of both people.

The important findings of this paper is as below: first, in the corn return data produce negative tail indices implying that the limiting extreme value distributions are characterized by a Frechet distribution and hence fat-tailed. Second, the EVT parameters do change through time and with the length of the selection interval. However, the performance of extreme value VaRs is still much better than the normal VaRs.

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บทความที่ 5

Modeling the Volatility of Rubber Price Return using VARMA GARCH Model

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Abstract

Many literatures were written on the volatility of exchange rate which it was affected by trade volume, trade price and investment cost, which the effect of trade volume by volatility of exchange rate does not have final conclusion. On the other hand, the rubber industry is one of the most important economies in Thailand. We apply VARMA-GARCH and VARMA-AGARCH models to determine the relationship between volatility of Thai rubber price return with volatility in different exchange rates. The coefficients of volatility of exchange rates in are Thailand Baht, Chinese Yuan, Euro Dollar and Malaysia Riggit are significant in both two models. The results show that the trade volume is important effect factor for international product price. On the other hand, Thailand government can set up some monetary policies to control it then the rubber price can be affected.

Keywords: Volatility, Rubber price return, Export volume, Exchange rate return, VARMA-GARCH model, VARMA-AGARCH model.

1. Introduction

The exchange rate is very important economic variable in international trade and it was been focused by the government of every countries and many scholars of economics. Before 1973, most of countries performed the fixed exchange rate system by Bretton Woods. After 1973, every country doesn't limit the volatility of exchange rate. The center bank will not control the volatility of exchange rate anymore. The exchange rate of every country was decided by the supply and demand in exchange market. If favorable balance of payments, the foreign exchange supply was increased and exchange rate was depreciated. But if unfavorable balance of payments, the foreign exchange rate demand was increased and exchange rate was imprecated. When most of countries using flexible exchange rate system, the risk of exchange was shifted to exporter. Because the volatility of exchange rate affects the export price, the volume of export product will be affected. The volatility of export price and export volume will impact the Competitiveness of export product in international market. Therefore, when the exporter set up the contracts, beside cost factor, the volatility of exchange rate is very important factor for making maximum profit. If the investment comes from import, the volatility of exchange rate will reflect the cost. The influences of investment in import are more and more. The volatility of exchange rate was normal way in the exchange market. Therefore, many of factors affect the volatility of exchange rate and the risk of investment in exchange rate was increased. Many literatures were written on the volatility of exchange rate which it was affected by trade volume, trade price and investment cost after flexible exchange rate system was be used.

Under the supply and demand model which has one export supply and one import demand, Ethier (1973) and Hopper, et al. (1978) thought that the price of international products become unstable if the volatility of exchange rate increase drastically under the floating exchange rate system. Because of the exchange risk which was made by the volatility of normal exchange rate, the import and export firms of risk aversion will decrease the trade volume whether the exchange rate risk was taken by exporter or importer. Some results of literatures showed that the relationship between volatility of exchange rate and trade volume is not significant. Normally, the firms decrease trade volume because of the real product price is not stable. The reasons of price unstable not only volatility of exchange rate but also the volatility of product price in Home country and abroad. This is also one of the reasons why the effect of trade volume by volatility of exchange rate does not have final conclusion.

Thailand, Malaysia and Indonesia are the major producers and exporters of rubbers in the world. The total rubber output of these three countries is about 94% of the total world market in 2007 which nearly is about 8.32 million tons. The rubber industry is one of the most important economies in Thailand. The area under rubber is 219,933 hectare with an annual output of 3.056 million tons in 2007 and export is about 2.772 million tons (Office of the Rubber Replanting Aid Fund, 2008), which was showed in table 1. The export of rubber is nearly about 90% of total output of rubber in Thailand. Since the Thai baht continued to appreciate and the demands for rubber are increasing, the export price went up to 2.23 U.S. dollar per kilogram in March 2007. Why did the price of rubbers increase in global market at that time? The possible reason is the increasing demands for rubber in American and China causing the price of rubber to rise. On the other hand, the website information from U.S. Department of State showing that the per capital income of Thailand is about only 4,716 US dollars in 2010. As we knew that the Thailand is the most important producer and exporter of rubbers market in the world. Thailand absolutely has advantages on the rubber industry, but unfortunately, it seems that the Thailand's personal income doesn't benefit at all. The key reason is that these farmers don't know how to hedge in the market.

Since the trade of Thailand depends highly on the USA and Japan, the exchange rate becomes a crucial factor. Furthermore, there are some other uncontrollable elements such as tsunamis, floods and political environments and so on also affect the exchange rate directly. There are six countries (including Japan, China, USA, Malaysia, South Korea and Europe) import rubbers from Thailand at present. Therefore, in this research, we will focus on six variables (the relationship of exchange rates between six countries as mentioned above) plus one variable (the export price of rubbers in Thailand) in addition.

[Insert table 1 here]

Since Thailand is the number one in exports of rubber in the world and the agriculture is the most important industry in Thailand, we want to find out the relationships between different exchange rate return and rubber price return. There are two contributions here: (1) we want to find out the relationship between rubber export price and six kinds of exchange rates. (2) We can use the historical information to forecast the export price with different exchange rate helping Thailand government to set up the monetary policy for increasing the price of rubber.

2. Review of the literature

From the viewpoint of literature about exchange rate, many scholars provide profuse proves and basic theories on interrelation analysis. The important point of empirical research about the volatility of exchange rate is how to evaluate the risk of exchange rate. Doroodian(1999) mentioned that the estimation methods of volatility of exchange rate are standard deviation, deviation from trend, difference between forward and current spot rates, Gini mean difference coefficient, coefficient of variation and ARCH or GARCH model. Many of literature used standard deviation to evaluate the volatility of exchange rate. For example, Daly(1998) applied the moving standard deviation to estimate exchange rate. This method is unadvisable if we are not sure the volatility of exchange rate whether stable or not. Baillie, et al. (1989) employed the GARCH model to analyze the volatility of exchange rate. Then Poso(1992), Caporale, et al. (1994), Doroodian(1999) followed GARCH method to estimate.

Hooper, et al. (1978) constructed the static model of the demand of import and supply of export. This study supposed the exporter is risk averter to analyze the effect of volume share and trade price from volatility of exchange rate. The result showed that the uncertainty of exchange rate has negative effect for volume share, but the volatility of exchange rate has positive effect for trade price. Akhtar, et al. (1984) used normal exchange rata to analyze the effect of export and import trade in the manufacturing of America and Germany from exchange rate risk. They found that the significant negative relationship was existed between the export volume and import price of American manufacturing and the import and export trade volume of Germany manufacturing. On the other word, when the exchange rate risk was increased, the international trade could be decreased. Engle and Granger(1987) proved that income and relative price can affect the export volume significantly by applying two-stage estimation, and the volatility of exchange rate can impact the export volume in the short term by using error correction model. In and Sgro(1998) tested the Co-integration relationship between variables, then used error correction model to discuss the affect factor of export volume in South Korea and Singapore. From the error correction model, we can know that the exchange rate is the main source of the export volume variation in Singapore. Thorbecke(2006) discovered that the exchange rate variation will decrease the export from Asia. The appreciation of exchange rate in developed countries can affect the export and import volume between countries, but the export volume cannot guarantee to be increased if US dollar was depreciated. Therefore, the America government should not expect the appreciation of Asia currency will increase the export volume of America. Jarita(2008) tested the export and import price with the volatility of Exchange rate of Malaysia Riggit by using VECM model from January 1999 to December 2006. The results proved that the effects of export and import price from the volatility of exchange rate are significant.

On the other hand, some scholars think there are positive effect in export and import by exchange risk, such as DeGrauwe(1988) denoted that the exchange risk will bring the substitution and income effect, which the substitute effect points that when the volatility of exchange rate increase, the exporter will decrease the risk export trade, then export volume will be decreased and the income effect denotes that when the volatility of exchange rate increase, the exporter will increase the expected return of risk export trade, then the export volume will be increased. When income effect was greater than substitution effect, the positive relationship between volatility of exchange and trade volume could be existed. Giovannini(1988) discovered that when the risk of exchange rate increased, most of the trader of risk neutral will enter to the market quickly and quit to the market slowly, then the number of trader who trade in the market will increase and trade volume will increase either. Bailey, et al.(1988) assumed that the traders can earn the return easily from the volatility of exchange rate who get the knowledge about trade. There is positive relationship between exchange risk and trade volume. Franke(1991) proved that when the volatility of exchange rate increase, the cash flow from export increasing was much more than entry cost and exit cost from the market for the trader who employ bang-bang policy of entry and exit. Broll, et al. (1999) proposed that the real options of export trade will increase when the volatility of exchange rate increase. Higher volatility of exchange rate will raise the potential benefit, which has positive effect for export volume.

Although the conditional correlation is modeled, which can be estimated in practice, it does not allow any interdependencies of volatilities across different markets or assets, and does not accommodate asymmetric behaviour. In order to incorporate interdependencies of volatilities across different markets or assets, Ling, et al. (2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean and the following GARCH specification for the conditional variance:

$$(\mathrm{L})(\mathrm{Y_t} - \mu) = \Psi(\mathrm{L})\varepsilon_t \tag{1}$$

$$\varepsilon_t = D_t \eta_t \tag{2}$$

$$H_t = \omega + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} \beta_l H_{t-l} \tag{3}$$

where $\mathrm{H_t} = (\mathrm{h_{1t}}, \dots, \mathrm{h_{mt}})'$, $\mathrm{D_t} = \mathrm{diag}(\mathrm{h}_{\mathrm{i,t}}^{1/2})$, $\phi(L) = I_m - \phi_1 L - \cdots - \phi_P L^P$, $\Psi(L) = I_m - \Psi_1 L - \cdots - \Psi_q L^q$ are polynomials in L, $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2, \dots, \varepsilon_{mt}^2)'$,and ω $\mathrm{A_k}$ for l=1,…,r and β_l for l=1,…,s are $\mathrm{m} \times \mathrm{m}$ matrices, and represent the ARCH and GARCH effects, respectively. Spillover effects are given in the conditional volatility for each market or asset in the portfolio, specifically where $A_l$and β_l are not diagonal matrix.

As in the univariate GARCH model, VARMA-GARCH model assumes that positive and negative shocks of equal magnitude have identical impacts on the conditional variance. In order to separate the asymmetric impacts of the positive and negative shocks, McAleer et al., (2009) proposed the VARMA-AGARCH specification for the conditional variance:

$$H_t = \omega + \sum_{l=1}^{r} A_k \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I(\eta_{t-l}) \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} \beta_l H_{t-l} \tag{4}$$

Where C_l are $m \times m$ matrices for l=1,…,r and $I_t = diag(I_{1t}, \dots, I_{mt})$, so that

$$I = \begin{cases} 0, \varepsilon_{k,t} > 0 \\ 1, \varepsilon_{k,t} \leq 0 \end{cases} \tag{5}$$

where if m=1, it reduces to the asymmetric univariate GARCH or GJR. If $C_l = 0$ for all l it reduces to VARMA-GARCH. If $C_l = 0$ for all l, with $A_l$and β_l being diagonal metrices for all l and 1, then VARMA-AGARCH reduces to constant conditional correlation (CCC) model.

For the literatures of VARMA-GARCH and VARMA-AGARCH model, C.Nianussornkul et al., (2009) discovered that the VARMA-GARCH and VARMA-AGARCH models show significant volatility spillovers. The volatility spillover effects from the Singapore market to the other markets are statistically significant, which means that hedging or speculation should be considered when the volatility in the Singapore bond market is changing. As in the case of the univariate model, asymmetry in VARMA-AGARCH also exists for Indonesia and Philippines bonds. Thus, the asymmetric model is superior to its symmetric counterpart for Indonesia and Philippines. C.Ninanussornkul, et al., (2009) used four models in Crude Oil and Precious Metals Markets. The results of asymmetric effects are significant in Brent and gold markets as GJR and EGARCH models which mean positive and negative shocks with equal magnitude have the different impact on conditional volatility. Therefore, we can state that asymmetric models are superior to symmetric models for Brent and gold markets whereas silver market is reverse. Rolling windows are used to examine the time-varying of conditional correlations of standardized shocks by using VARMA-GARCH and VARMA-AGRACH models. The rolling windows suggest that the assumption of constant conditional correlations is too restrictive and clearly that the correlations of all pairs of assets are time-varying especially after year 2002. From Chang, C, et al., (2009 and 2010), they used CCC, DCC, VARMA-GARCH and VARMA-AGARCH in different oil markets. The estimates of volatility spillovers and asymmetric effects for negative and positive shocks on conditional variance suggest that VARMA-GARCH is superior to the VARMA-AGARCH model and positive shocks on the conditional variances, which suggested that VARMA-AGARCH was superior to others. In this part, we can know that VARMA-AGARCH is better than VARMA-GARCH model in forecasting the volatilities across different markets or assets.

3. Methodology

3.1 Data variables and selection criteria

There are five levels (from RSS1 to RSS5) of natural rubbers. The highest level is RSS1, but the main kind is RSS3 in spot and future markets in the world. The table 2 shows that there are many countries import rubber from Thailand, which the top 6 of export volume countries or area are China, Malaysia Japan, Europe, U.S.A and South Korea. The export is about 90% in total output of rubber in Thailand. Regarding this part, there are seven variables concern with the rubber price in Thailand and exchange rate in six countries which mentioned above, and each variable involves with 1577 observations. For this study, we want to know the relationship between rubber price in Thailand and exchange rate of export country in rubber from Thailand. The variable names are introduced in Table 2.

[Insert table 2 here]

3.2 Stationary and summary statistics of the variables

The returns of asset i at time t are calculated as following:

$$R_{i,t} = \log(\frac{P_{i,t}}{P_{i,t-1}}) \tag{6}$$

were $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and t-1, separately.

All series data are stationary and tested by using the Augmented Dickey-Fuller (ADF) test, which is given as following:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{P} \emptyset \Delta y_{t-1} + \varepsilon_t \tag{7}$$

The null hypothesis is $\theta = 0$ which, if rejected, than means that the series y_t is stationary, or it is not stationary. The results shows that all series data are stationary in Table 3, which the estimated value of θ and the t-statistics of all the returns are significantly less than zero at the 1% level.

[Insert table 3 here]

Table 4 shows the descriptive statistics of the variables. The standard deviation of rubber price return is higher than all of the volatility of exchange rate in this study. The skewness of PRICE, BAHT and KRW are negative, so that they are significantly skewed to the left. For the excess kurtosis statistics, all of the variables in this study are positive, thereby indicating that the distribution of returns has larger, thicker tails than the normal distribution. Therefore, the assumption of skewed-t is more appropriate in this study.

[Insert table 4 here]

3.3 VARMA-GARCH Model

For this study, we use VARMA-GARCH (Vector ARMA-GARCH) model to analysis data which was proposed by Ling, et al. (2003) and VARMA-AGARCH model which was proposed by McAleer, et al. (2009). The effect of fluctuation cannot be distinguished individually very clearly in the traditional multivariate GARCH model. The VARMA-GARCH model is as following:

$$Y_t = E(Y_t | F_{t-1}) + \varepsilon_t \tag{8}$$

$$\varepsilon_t = D_t \eta_t \tag{9}$$

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{10}$$

And VARMA-AGARCH model is as following:

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{r} C_{ij} I_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{11}$$

Where $H_t = (h_{1t}, h_{2t}, \dots, h_{mt}), \eta_t = (\eta_{1t}, \eta_{2t}, \dots, \eta_{mt}), D_t = \mathrm{diag}(h_{1t}^{1/2}, h_{2t}^{1/2}, \dots, h_{mt}^{1/2})$

For this study, the full model is in following:

$$A_t = \gamma_{A0} + \gamma_{A1} P_{t-1} + \gamma_{A2} B_{t-1} + \gamma_{A3} C_{t-1} + \gamma_{A4} E_{t-1} + \gamma_{A5} J_{t-1} + \gamma_{A6} K_{t-1} + \gamma_{A7} M_{t-1} + \varepsilon_{A,t}$$

(12)

$$\begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{E.t} \end{bmatrix} |\Omega_{t-1} \sim N(0, H_t) \tag{13}$$

Where P is PRICE, B is BAHT, C is CNY, E is EUR, J is JPY, K is KRW, M is MYR and ε is error term.

We use normal distribution and MLE(Maximization Likelihood Estimation) to estimate the parameter of this model.

$$\hat{\theta} = argmin \frac{1}{2} \sum_{t=1}^{n} (log|Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t) \tag{14}$$

Where θ is the vector of parameters to be estimated on the conditional log-likelihood function, and $|Q_t|$ is the determinant of Q_t, the conditional covariance matrix.

4. Empirical Results

For this study, we want to analysis the volatility of rubber price return in AFET from the volatility of exchange rate of six export countries in rubber from Thailand by using VARMA-GARCH and VARMA-AGARCH models because the estimate time-varying volatility can be estimated, and also asymmetric effects of positive and negative shocks of equal magnitude and volatility spillovers can be tested. The results of VARMA-GARCH and VARMA-AGARCH are shown in Tables 5, for which the number of volatility spillovers and asymmetric effects are summarized in Table 6. The result of table 6 shows that the volatility spillovers are not evident in VARMA-AGARCH model. Therefore, we can conclude that VARMA-GARCH is superior to VARMA-AGARCH for the volatility of rubber price return. The table 5 shows that there are four kinds exchange rates return have spillovers to the volatility of rubber price return not only in VARMA-GARCH model but also in VARMA-AGARCH model, which are Thailand Baht, Chinese Yuan, Euro Dollar and Malaysia Riggit.

[Insert table 5 and 6 here]

We use rolling windows to examine time-varying conditional correlations using the VARMA-GARCH and VARMA-AGARCH models. The rolling window size is set at 1,000 for exchange rate of six export countries in rubber from Thailand, and the results are shown in Figures 2 and 3, separately. For the VARMA-GARCH model, the correlations of six variables are not constant over time, so that the assumption of constant conditional correlations may be too restrictive. However, the changes in the estimated correlations are small. The correlation between the volatility of rubber price return and all of the volatility of exchange rates return are small (not more than 0.1). The result of VARMA-AGARCH model is similar than VARMA-GARCH model.

[Insert figure 1 and 2 here]

5. Concluding Remarks

This paper estimated conditional volatility, covariance and correlations volatility of rubber price return by using multivariate volatility models. The VARMA-GARCH model showed that volatility spillovers were evident between volatility of rubber price return and volatility of four exchange rates return, which are Thailand Baht, Chinese Yuan, Euro Dollar and Malaysia Riggit in the model. The VARMA-GARCH model showed the same results with VARM-AGARCH. The volatility of rubber price return will be affected by those four kinds of volatility of exchange rates in both of two models. The coefficients of volatility of exchange rates in are Thailand Baht, Chinese Yuan, Euro Dollar and Malaysia Riggit are significant in both two models, so the exchange rate of Thailand Baht, Chinese Yuan, Euro Dollar and Malaysia Riggit are very important factors in volatility of rubber price return. From table 1, we can know that China, Malaysia and Euro are the top 3 of export countries or area in rubber, so it is reasonable that the Chinese Yuan, Euro Dollar and Malaysia Riggit can affect the rubber price. The rolling window shows that correlation between the volatility of rubber price return and all kinds of the volatility of exchange rates return are small (not more than 0.1). The result of VARMA-AGARCH model is similar than VARMA-GARCH model. For the mean results of this study, firstly, we can see that the exchange rate of Thailand Baht return can affect the rubber price return. The agriculture is the basic industry in Thailand. Since the farmers are the mainstay of the Thailand's economy and the number of people was large, so Thailand government should take care of them. On the other hand, Thailand absolutely has advantages on the rubber industry, but unfortunately, Thailand’s personal income doesn’t benefit at all. Therefore, I suggest that Thailand government can set up some monetary policies to control it then the rubber price can be affected. On the other hand, we can know that the first one of rubber export country of Thailand is China and the second on Malaysia from table 1. Therefore, we can get second mean result that the volatility of rubber price will be affected by the volatility of exchange rate in most important export country. This also means that the trade volume is important effect factor for international product price either.

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Table1. The export and output in Thailand

unit: ton

	Export								Total output
	Japan	China	U.S.A.	Malaysia	South Korea	Europe	Other	total	
2001	505,233	417,638	329,504	243,708	136,387	231,178	302,505	2,166,153	2,319,549
2002	435,453	368,114	302,174	296,989	139,295	233,390	266,664	2,042,079	2,615,104
2003	498,854	436,637	382,317	363,651	138,756	266,392	321,809	2,354,416	2,876,005
2004	542,837	650,898	278,693	365,486	165,832	294,239	275,465	2,573,450	2,984,293
2005	525,654	619,800	249,196	383,695	171,668	291,670	395,413	2,637,096	2,937,158
2006	540,485	573,385	237,858	403,506	185,308	281,090	410,766	2,632,398	3,136,993
2007	492,740	747,168	210,784	442,664	173,477	261,882	442,958	2,771,673	3,056,005
2008	405,599	827,369	213,080	413,049	151,824	262,182	430,659	2,703,762	3,089,751
2009	394,742	824,833	219,986	398,043	154,340	249,509	433,830	2,675,283	3,164,379
2010	346,302	1,128,553	177,859	443,000	171,530	268,693	330,510	2,866,447	3,252,135

Table 2. Introduce of Variable Names

Variables	Names
PRICE	Rubber price
BAHT	Exchange rate of Thailand Baht
CNY	Exchange rate of Chinese Yuan
EUR	Exchange rate of Euro Dollar
JPY	Exchange rate of Japanese Yen
KRW	Exchange rate of Korea Won
MYR	Exchange rate of Malaysia Riggit

Table 3: ADF Test of Unit Roots in Returns

Returns	Coefficient	t-statistic
PRICE	-0.5165	-11.1036
BAHT	-1.0347	-24.7531
CNY	-1.0040	-23.9896
EUR	-1.0676	-25.5970
JPY	-1.0232	-24.4772
KRW	-1.1833	-28.7615
MYR	-1.0503	-25.1073

Table 4: Summary statistics

	PRICE	BAHT	CNY	EUR	JPY	KRW	MYR
Mean	0.0003	-0.0002	0.0000	-0.0001	0.0000	0.0002	0.0000
SD	0.0107	0.0032	0.0067	0.0090	0.0098	0.0107	0.0072
Skewness	-0.4902	-0.3293	0.3519	0.0463	0.0019	-0.1363	0.2140
Kurtosis	8.7482	7.1771	121.4066	34.492	30.5565	34.6872	88.4493
Max	0.0463	0.0163	0.1194	0.1085	0.1191	0.1167	0.1171
Min	-0.0529	-0.0188	-0.1104	-0.1113	-0.1062	-0.1154	-0.1083
JB	816.0708	429.1715	920686.50000	65126.9600	49864.6900	65939.1600	479482.40000

Table 5: Estimates of VARMA-GARCH(1,1) and VARMA-AGARCH(1,1)

Returns of rubber price	ω	α_{PRICE}	α_{BAHT}	α_{CNY}	α_{EUR}	α_{JPY}
VARMA-GARCH	0.0000^{***}	0.19727^{***}	2.72806^{**}	-1.98220^{**}	-0.1345^{***}	0.0150
	48.0720	4.45952	2.48305	-2.24116	-2.6031	0.2880
VARMA-AGARCH	0.0000^{***}	0.16816^{**}	2.84640^{**}	-2.09856^{**}	-0.5700^{***}	0.0053
	53.2316	2.42505	2.34941	-2.07233	-3.2040	0.1022

Table 5. (Continued 1)

Returns of rubber price	α_{KRW}	α_{MYR}	Γ	β_{PRICE}	β_{BAHT}
VARMA-GARCH	0.0108	-0.4402^{**}		0.6268^{***}	-1.6354^{***}
	0.4377	-1.9663		26.1728	-3.3775
VARMA-AGARCH	0.0051	-0.1026^{*}	0.0930	0.6115^{***}	-1.5487^{***}
	0.2135	-1.8380	0.9247	24.8285	-2.7376

Table 5. (Continued 2)

Returns of rubber price	β_{CNY}	β_{EUR}	β_{JPY}	β_{KRW}	β_{MYR}
VARMA-GARCH	1.1463***	-0.3188***	0.0427	0.0515	0.5397***
	2.9576	-3.2276	0.5478	-1.6415	2.9496
VARMA-AGARCH	1.1115**	-0.3893***	0.1066	0.0524*	0.4809***
	2.3247	-3.4762	1.2550	1.6535	2.7582

Notes: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge(1992) robust t-ratios.

(2) * indicates statistical significance at the 10% level;

** indicates statistical significance at the 5% level;

*** indicates statistical significance at the 1% level.

Table 6: Summary of Volatility Spillovers and Asymmetric Effects

Returns	Number of volatility spillovers		Asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
Rubber Prices	5	5	NO

Figure 1: Dynamic Path of Conditional Correlations in VARMA-GARCH model

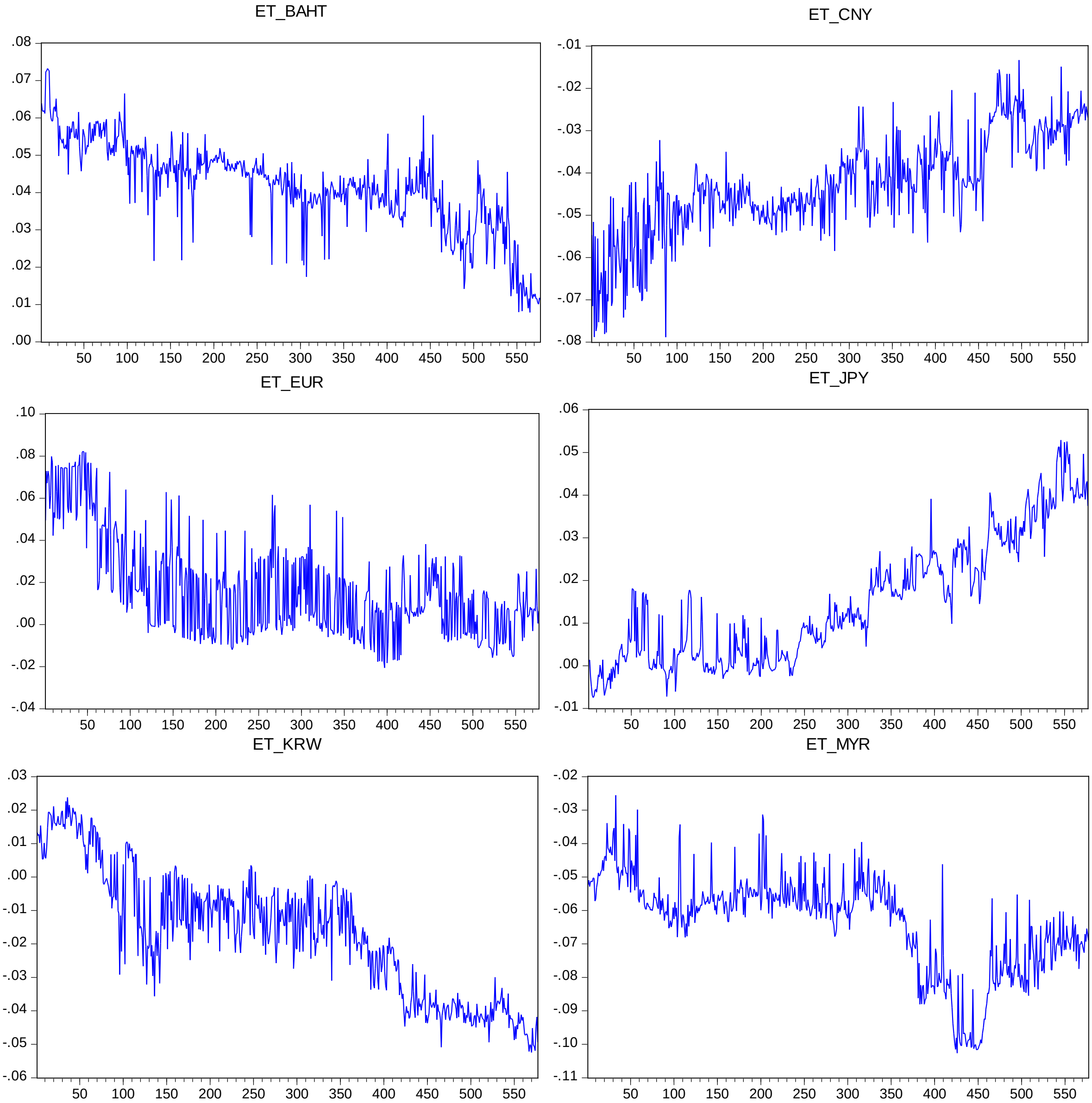
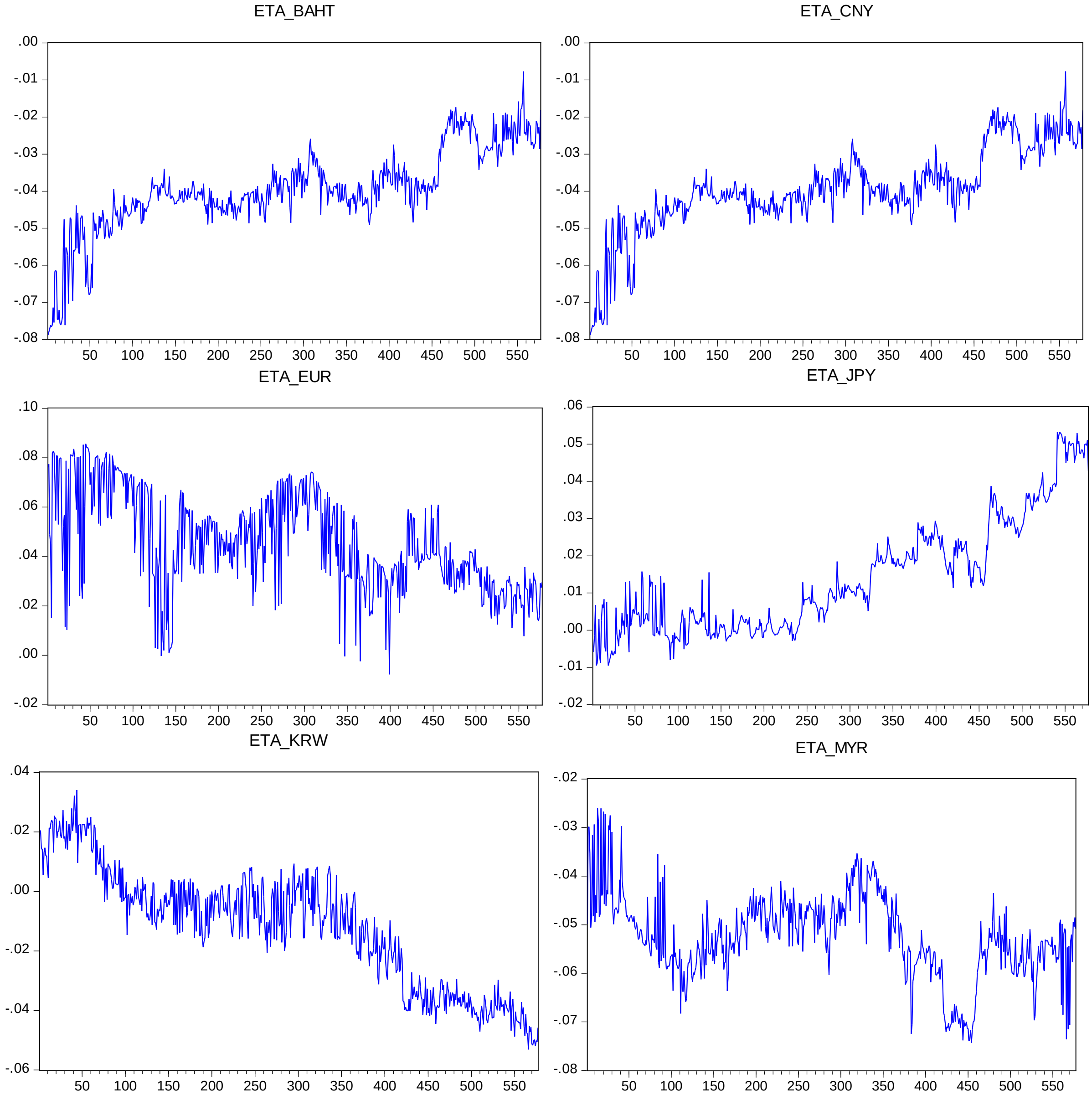


Figure 2: Dynamic Path of Conditional Correlations in VARMA-AGARCH model



บทความที่ 6

Modeling Volatility and Dependency of Agricultural Price and Production Indices of Thailand: Static versus Dynamic Copulas

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Abstract

This paper aims to estimate the dependency between the percentage changes of the agricultural price and agricultural production indices of Thailand and also their conditional volatilities using copula-based GARCH models. The motivation of this paper is twofold. First, the strategic department of agriculture of Thailand would like to have reliable empirical models for the dependency and volatilities for them to use for policy strategy. Second, this paper provides less restrictive models for dependency and the conditional volatility GARCH. The copula-based multivariate analysis nested the traditional multivariate as a special case by Tae-Hwy-Lee and Xiangdong Long [13]. Static as well as time varying copulas were estimated. The empirical results were found that the time varying copula i.e., the time varying rotate Joe copula (270) was the choice for the policy makers to follow.

Keywords: Volatility; Dependency; Static and Dynamic Copulas; Agricultural price index; Agricultural production index; Thailand

1. Introduction

Thailand is one of the major export countries of agricultural products and food in the world. The agricultural sector is an important sector contributing 8.6% of GDP at 1988 constant price [1] and employs 16.95 million people which are 43.25 percent of Thailand labor force in December 2011 [10]. Even though the relative contribution to GDP has been decreasing it is still an important sector of the Thai economy. Because of more severe world climate change, the agricultural sector is more volatile in terms of production of the Thai economy e.g., the severe flood that Thailand faced in late 2011 damaged the agricultural output of Thailand causing the agricultural production decrease substantially, especially the rice production [2]. However, the world has faced severe and extreme weather (see US National Climate Data Center in ADB March 2011 Report for details) resulting in extremely heavy flooding in many major crop production areas [11], agricultural and food prices had increased severely and suffered people severely in the world. Thailand is not exceptional. In September 2008, the inflation from food and beverage in Thailand had increased of 18.79% (figures 1 and 2) annually [3] which were seriously high and suffered people in a large extent especially the lower income people. Figure 1 shows the annual (year on year) inflation of food and beverage price of Thailand. The impact of food price increases on poverty for 25 developing Asian countries is shown in appendix 1 of the Asian Development Bank report on Global Food price Inflation and Developing Asia (March 2011). The increase in food prices by 10, 20 and 30 percent would cause the increase in the percentage of the poor people by 1.9, 3.9 and 5.8 percent or 64.41, 128.83 and 193.24 million people respectively [4]. The Asian Development bank [11] reported that contradictory to the believes and expectations of most of the experts that the commodity price would rise gradually over the next decade(2011-2020), the high commodity prices have been reemerging, even though the crude oil prices remain below the recorded high in July,2008. The agricultural commodity prices surpassed the 2008 recorded peak (figures 3 and 4). The report pointed out causes of the crisis of food prices during 2007-2008. Those causes included the severe falling in the stocks of major grains, the increase of world population, the strong growth rate of the big emerging economies which brought up the increase of meat and processed food consumption. The causes were also from the competition between the crop productions for food versus oil crops. It could be seen that the agricultural price and production are related. It is very much interesting for policy makers to investigate the behavior of agricultural price and production behaviors and their relationship in order to make policy formulation and management.

From these figures, it is seen that the rates of changes of the price and production indices are correlated and more volatile than before. Those rates of changes look heavy tail and not symmetric. Univariate analysis of each index without taking the correlated index into consideration is less informative resulting in biased and inconsistent estimates. Studying the behavior of those indices by traditional analysis is seen inappropriate. This paper aims to model volatilities of agricultural price inflation and the growth rate agricultural production as well as the correlation between these two variables.

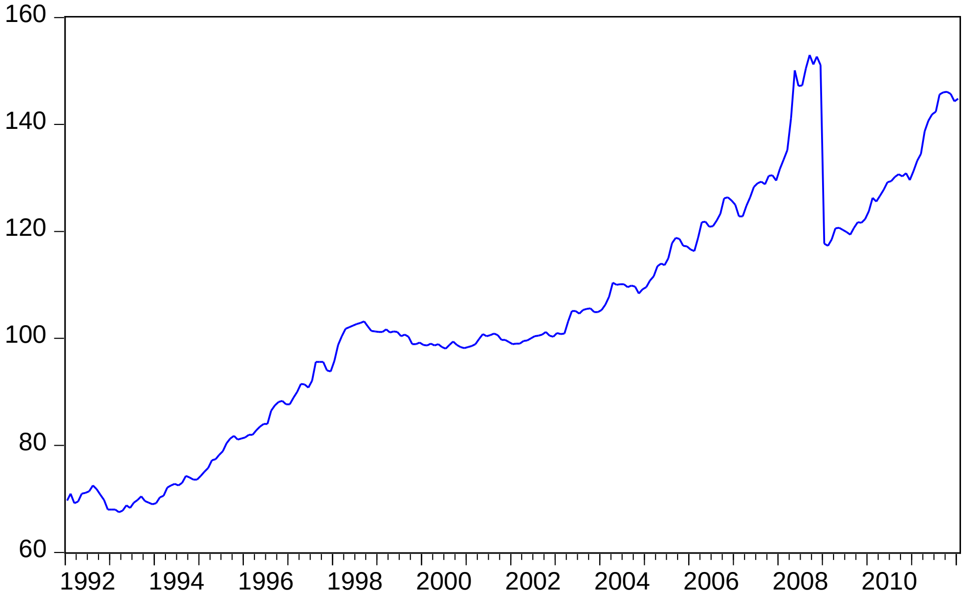

Fig.1. Food and beverage price index of Thailand

Source: Bank of Thailand

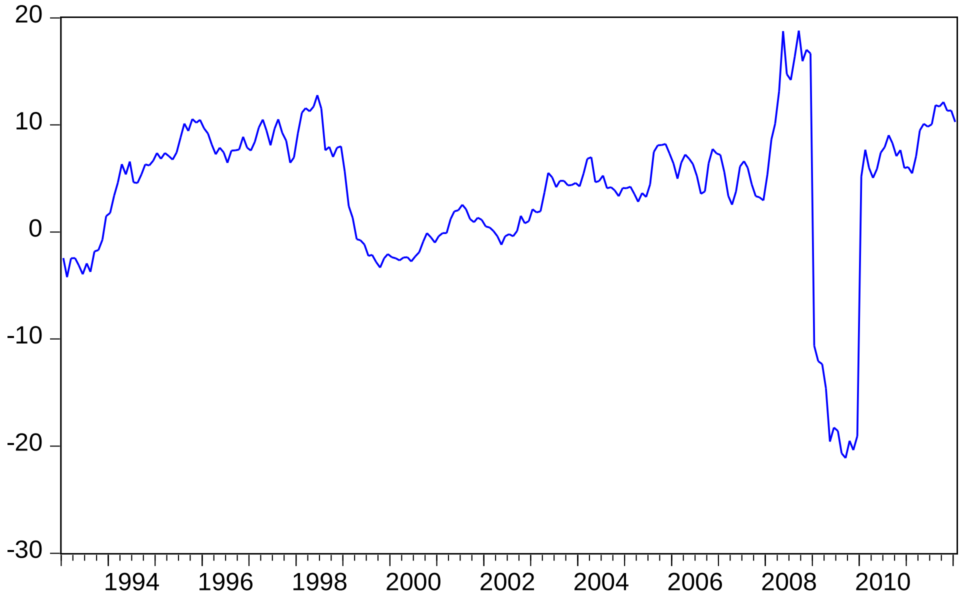

Fig.2. Growth rate of food and beverage price index of Thailand

Source: Computation from Bank of Thailand

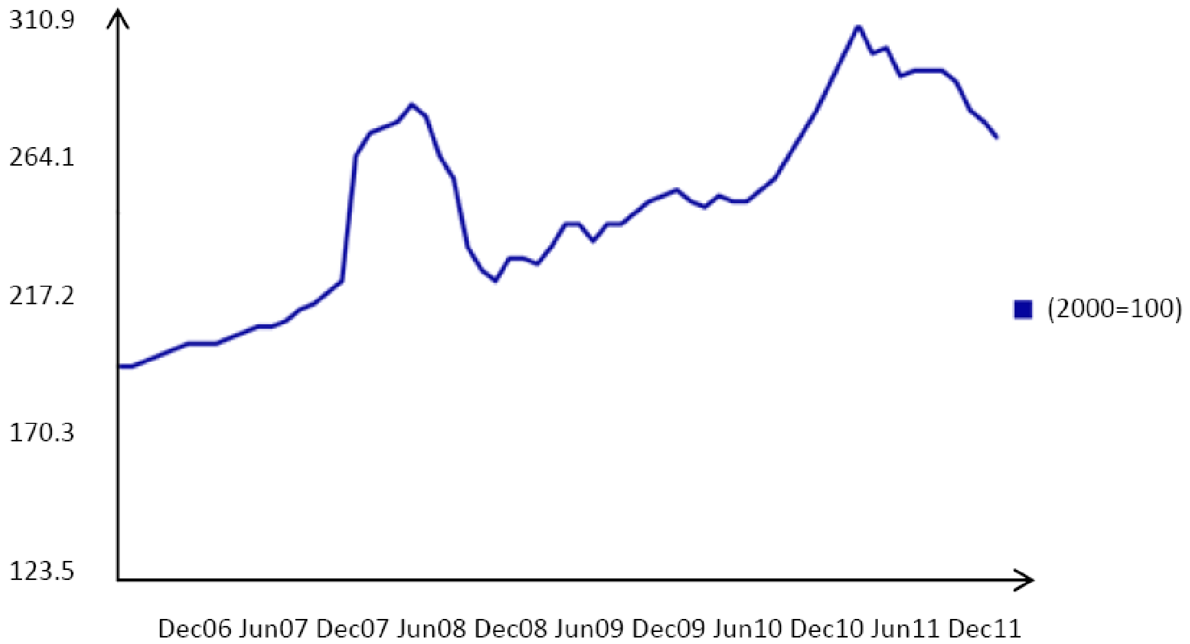

Fig. 3. Agriculture Index Price

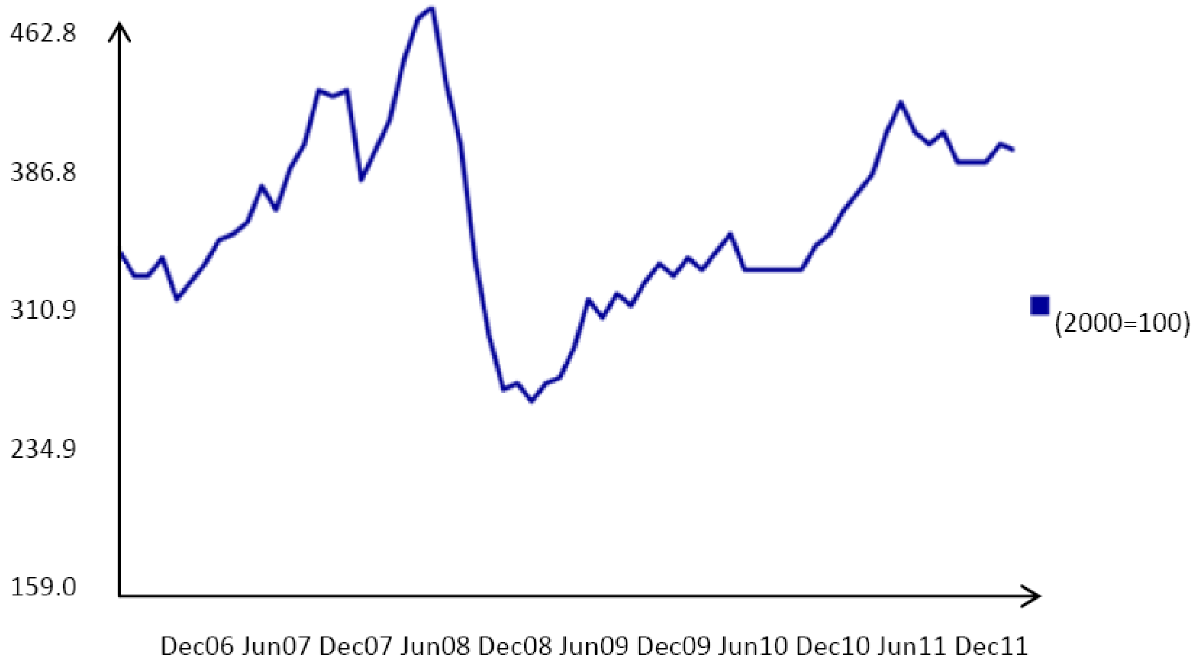

Fig.4. Energy Index Price Index Price

2. Literature review

To find the relationship between random variables in recent years several models were used such as GMM model was used, e.g. Yousefi and Wirjanto(2004). Akram(2004) found a non-linear relationship. The multivariate CCC-GARCH-M model was employed by Cifarellli and Paladinr(2010). Modeling time-varying volatility, sometimes, multivariate GARCH models e.g. Bekiros and Diks(2008) which were based on strong assumptions to have a well-behaved matrix of covariance(Wu,2011) were used. Vector Error Correction Models e.g. Krichene (2005),Chaiwat (2009), Kunsuda (2009) were implemented to analyze the multivariate relationship. Generalized impulse response function and generalized variance forecast error variance decomposition e.g. Sari et al (2009) (in Wu et al (2011)) was used as a tool to find the relationship of the random variables.

Also, multivariate analysis of volatility using multivariate GARCH together with VAR model with assumptions that the multivariate model followed symmetric multivariate normal or student-t distribution and, of course, usually with Pearson correlation(based on linear correlation). These assumptions may be considered as strong assumptions in empirical studies. In many data sets, it was found that the data were skewed (asymmetric), heavy tail and leptokurtic with different marginal distribution. And also if the distributions have degrees of freedom, the degrees of freedom need not to be the same for each marginal distribution.

The relationship between random variables might be nonlinear and/or asymmetric. Some studies, e.g. Chang et al. (2011), and Bekiros and Diks(2008) investigated time varying dependence of the random variables in the model by employing multivariate GARCH models. However, this model was set up with some strong assumptions in order to have a desirable variance-covariance matrix (Wu, 2011). And again for each equation of the random variable in the multivariate analysis, the VAR-GARCH or VAMA—GARCH it was assumed to have linear relationship with multivariate student-t or normal distribution (Wu, 2011). These assumptions, in many cases, are not conformable to data.

These drawbacks could possibly be handled by Copula-based GARCH model because it provides better flexibility to estimate the joint distributions and also the transformation invariant correlations which are not necessary to assume linear correlation.

The contributions from this paper using the Copula-based GARCH models are : 1) the model could capture the skewness and leptokurtosis of the data; 2) restrictive assumptions of the distribution are relaxed from traditional methods i.e., normality or student t distribution, which normally are assumed to be the same for each random variable; 3) this approach in this paper could find the dependency and hence the correlation without assuming the linear correlation, as a result we could obtain the transformation invariant correlations, especially when variances do not exist (for some heavy tail distributions); 4) since agricultural price and production indices are correlated by their natures, the revenue distribution could not be found by the product of price and production indices. This paper would pave the way to obtain the revenue index distribution; 5) this paper could find the marginal effects of the random variable in correlation with other random variables without imposing the conventional strong assumption of some distributions of the random variables through the conditional density function.

This paper, after this introduction section , was organiz

for volatility and dependency were introduced in section 2. Data were discussed in section 3. Section 4 presented the empirical results. Conclusion was drawn in section 5.

3. Econometric model

This section was organized as follows (3.1) static copulas (3.2) time varying copulas (3.3) marginal density (3.3.1) two tests for satisfying i.i.d (3.3.2) specification for marginal distribution (3.4) CML method of estimation (3.5) goodness of fit tests.

3.1 static copulas

This study employed a variety of parametric copulas. The candidates includes, Gaussian copula, t copula, frank copula, (rotate) Clayton copula, (rotate) Gumbel copula, (rotate) Joe copula, (rotate) BB1, (rotate) BB6, (rotate BB7) and (rotate) BB8 copula.

(1) Gaussian copula. We follow Patton (2006)'s Gaussian copula notations and formula as follows.

$$C_{\mathrm{Ga}}(u,v;\rho)=\int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)}\frac{1}{2\pi\sqrt{1-\rho^2}}\exp\left(-\frac{x_1^2-2\rho x_1x_2+x_2^2}{2\left(1-\rho^2\right)}\right)\mathrm{d}\,x_1\,\mathrm{d}\,x_2$$
$$=\Phi_\rho\left(\Phi^{-1}(u),\Phi^{-1}(v);\rho\right) \tag{1}$$

where the u and v are CDFs or ECDFs of standardized residuals, and they are subject to uniform distribution between 0 and 1. The correlation coefficient ρ affects linear correlation (Embrechts et al., 1999), in addition, Gaussian copula cannot capture tail dependence, which are the critical flaws for it anyway.

(2) T copula. The formulas of T copula are followed from Jondeau and Rockinger(2006).

$$C(u,v)=\int_{-\infty}^{T_v^{-1}(u)}dx\int_{-\infty}^{T_v^{-1}(v)}dy\frac{1}{2\pi\sqrt{1-\rho^2}}\left(1+\frac{x^2-2\rho xy+y^2}{v(1-\rho^2)}\right)^{-(v+2)/2} \tag{2}$$

$$T_v(x)=\int_{-\infty}^{x}\frac{\Gamma((v+1)/2)}{\sqrt{\pi v}\,\Gamma(v/2)}(1+\frac{z^2}{v})^{-(v+1)/2}dz \qquad (3)$$

T is student-t distribution with degree of freedom v and correlation ρ which is still linear. Compare with Gaussian copula, the biggest advantage of t copula is that it can capture tail dependence, although they are symmetric structure. It is well known that there are strong skewness in financial field, thus, it is a crucial reason why Archimedean copulas come out.

Both Gaussian and Student-t copulas belong to the elliptical-copula family. In the following, this study introduces non-elliptical copula, which consider upper tail or lower tail dependence or both. The formulas and notations of Gumbel, Clayton and Frank copula, we refer to Tae-Hwy Lee (2009)'s research.

(3) Gumbel Copula

$$C_{\mathrm{Gum}}(u,v;\theta)=\exp\left(-\left((-\ln u)^{1/\theta}+(-\ln v)^{1/\theta}\right)^{\theta}\right) \qquad (4)$$

where $1 \leqq \theta < +\infty$, it is easy to find $\theta = 1$ is independent and $\theta = +\infty$ is more dependent. kendall.tau equals $1-1/\theta$, meanwhile, it can capture upper tail dependency, $\lambda_{up}=2-2^{1/\theta}$, the lower tail dependence $\lambda_{low}=0$.

(4)Clayton Copula

$$C_{\mathrm{Cl}}(u,v;\theta)=(u^{\theta}+v^{\theta}-1)^{-1/\theta} \qquad (5)$$

In the contrary, Clayton copula can catch lower tail dependence ($\lambda_{low}=2^{-1/\theta}$), and the parameter $\theta \longrightarrow 0$ implies they are independent and $\theta = +\infty$ is perfectly correlated. kendall.tau equals $\theta/(\theta+2)$.

(5)Frank Copula

$$C_{\mathrm{Fr}}(u,v;\theta)=-\frac{1}{\theta}\ln\left(1+\frac{(\exp(-\theta u)-1)(\exp(-\theta v)-1)}{\exp(-\theta)-1}\right) \qquad (6)$$

Similarly, $\theta \in (-\infty, +\infty)\backslash\{0\}$, frank copula describes symmetric heavy tail: $\theta > 0$ for positive dependence structure; $\theta \longrightarrow 0$ for independence; $\theta < 0$ for negative dependence structure.

(6) Joe copula

The Joe copula (Joe, 1993) is defined as follows:

$$C_{Joe}^{\theta}(u,v)=1-[(1-u)^{\theta}+(1-v)^{\theta}-(1-u)^{\theta}(1-v)^{\theta}]^{1/\theta} \qquad (7)$$

Where $\theta \geq 1$, this copula can help us capture the upper tail dependence, $\lambda_{up}=2-2^{1/\theta}$.

(7)BBX copulas

BBX copulas are put forward by Joe and Hu (1996). BB1 and BB7 copula reflect different tail dependence between upper tail and lower tail. On the contrast, BB6 and BB8 can capture the upper tail dependence structure.

$$C_{BB1}^{\theta,\delta}(u,v) = (1+[(u^{-\theta}-1)^{\delta}+(v^{-\theta}-1)^{\delta}]^{1/\delta})^{-1/\theta} \tag{8}$$

Where $\theta \in (0, +\infty)$ and $\delta \in [1, +\infty)$, $\lambda_{up}=2-2^{1/\delta}$, $\lambda_{low}=2^{-1/(\delta\theta)}$.

$$C_{BB6}^{\theta,\delta}(u,v) = 1-(\exp(-[(-\log(1-(1-u)^{\theta}))^{\delta}+(-\log(1-(1-v)^{\theta}))^{\delta}]^{1/\delta})^{1/\theta}) \tag{9}$$

Where $\theta \in [1, +\infty)$ and $\delta \in [1, +\infty)$, $\lambda_{up}=2^{-1/(\delta\theta)}$.

$$C_{BB7}^{\theta,\delta}(u,v) = 1-(1-[1-(1-u)^{\theta})^{-\delta}+(1-[1-(1-v)^{\theta})^{-\delta}-1]^{-1/\delta})^{1/\theta} \tag{10}$$

Where $\theta \in [1, +\infty)$ and $\delta \in (0, +\infty)$, $\lambda_{up}=2-2^{1/\theta}$, $\lambda_{low}=2^{-1/\delta}$.

$$C_{BB8}^{\theta,\delta}(u,v) = \frac{1}{\delta}(1-\{1-(1-\delta)^{\theta}\}^{-1}\cdot\{1-(1-\delta u)^{\theta}\}\{1-(1-\delta v)^{\theta}\}]^{1/\theta}) \tag{11}$$

Where $\theta \in [1, +\infty)$ and $\delta \in [0, 1]$, $\lambda_{up}=2-2(1-\delta)^{\theta-1}$

(8) Rotate copulas

There are many copulas that cannot display negative tail dependence such as Gumbel, Clayton and BBX copula etc. Once the bivariate random variable is negative dependence, these copulas would not be fitted. These copulas may be rotated, thus, they can be applied again. A thorough review of rotated copulas may be found in Christian Cech(2006) and Jiying Luo (2010). The rotate copula can be derived from copula as follows:

For rotate 180°Copula, Christian Cech(2006) defined $\overline{u}=1-u$ and $\overline{v}=1-v$,proposed the copula of $\overline{u}$ and $\overline{v}$ as

$$C^{--}(u,v) = u+v-1+C(1\text{-}u,1\text{-}v) \tag{12}$$

where $c^{--}(u,v) = c(1\text{-}u,1\text{-}v)$. Christian Cech(2006) called C^{--} as survival copula.

For rotate 90°Copula, Christian Cech(2006) proposed

$$C^{-+}(u,v) = u-C(1\text{-}u,v) \tag{13}$$

where $c^{-+}(u,v) = c(1\text{-}u,v)$ is the density of copula C^{-+} .

Regarding rotate 270°Copula, Christian Cech(2006) came up with

$$C^{+-}(u,v) = u-C(u,1-v) \tag{14}$$

of which its density was $c^{+-}(u,v) = c(u,1-v)$.

As a result of the symmetry of $C(u,v)$, we have

$$C(u,v) = C^{--}(u,v) \text{ and } C^{-+}(u,v) = C^{+-}(u,v). \tag{15}$$

3.2 time varying copulas

Since the nature of copulas might be static or time varying, we then allow several candidates of time varying copulas to be included in our analysis. Time varying copulas might be considered as the dynamic characteristics of Pearson correlation or kentall.tau, but it is still difficult to find forcing variable for explaining the dynamic characteristics (Patton, 2006 and Hans Manner, 2012). Therefore, it is often in practice assumed that they follow ARMA (p, q) process. The following are some time varying copulas candidates.

(1) Time varying Gaussian copula

$$\rho_t = \tilde{\Lambda}(\omega_N + \beta_{N1} \cdot \rho_{t-1} + \cdots + \beta_{Np} \cdot \rho_{t-p} + \alpha_N \cdot \frac{1}{q}\sum_{j=1}^{q} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})) \tag{16}$$

(see Patton(2006a))

$\tilde{\Lambda}$ is a logistic transformation which is defined as follows: $\tilde{\Lambda} = (1\text{-e}^{-x})(1\text{+e}^{-x})^{-1}$. The purpose of using this logistic transformation is for keeping the correlation coefficient ρ belongs to (-1, 1).

(2) Time varying T copula

$$\rho_t = \tilde{\Lambda}(\omega_T + \beta_{T1} \cdot \rho_{t-1} + \cdots + \beta_{Tp} \cdot \rho_{t-p} + \alpha_T \cdot \frac{1}{q}\sum_{j=1}^{q} \Phi^{-1}(u_{t-j}; v) \cdot \Phi^{-1}(v_{t-j}; v)) \tag{17}$$

(see Patton(2006b))

(3) Time varying (rotate) Gumbel copula

$$\tau_t = \Lambda(\omega_G + \beta_{G1} \cdot \tau_{t-1} + \cdots + \beta_{Gp} \cdot \tau_{t-p} + \alpha_G \cdot \frac{1}{q}\sum_{j=1}^{q} \left|u_{t-j} - v_{t-j}\right|) \tag{18}$$

(see S.G.J. Verheggen (2009))

where $\Lambda = (1\text{+e}^{-x})^{-1}$, it can make sure that the kentall.tau will between -1 and 1.

(4) Time varying (rotate) Clayton copula

$$\tau_t = \Lambda(\omega_C + \beta_{C1} \cdot \tau_{t-1} + \cdots + \beta_{Cp} \cdot \tau_{t-p} + \alpha_{C1} \cdot \left|u_{t-1} - v_{t-1}\right| + \cdots + \alpha_{Cq} \cdot \left|u_{t-q} - v_{t-q}\right|) \tag{19}$$

(seeVogiatzoglou (2010))

(5) DCC copulas

The DCC model was proposed by Engle (2002), which can be used to research dynamic conditional correlations in Gaussian and T distribution. the standardized residuals of each series is assumed that they obey to Gaussian or T distribution, and we estimate GARCH model for getting the parameters of each series, and then estimating the parameters driving the correlation dynamics. This specification can easily be adapted to model the dynamics of copula parameters (Hans Manner, 2012). The DCC model specifies the correlation matrix R_t as:

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \tag{20}$$

where Q_t follows

$$Q_t = \bar{Q}_t (1 - \alpha - \beta) + \alpha Y_{t-1} Y'_{t-1} + \beta Q_{t-1} \tag{21}$$

with scalar parameters α and β and parameter matrix $\bar{Q}_t$. Y_t is the inverse standard normal and t distribution (given degree of freedom) of u and v.

3.3. Marginal density

3.3.1. Two tests for satisfying i.i.d

Several candidates of marginal densities were chosen to this study, such as normal distribution, student t distribution, skewed t distribution etc. However, each selected marginal must be tested if it is conformable to the data e.g., the distribution function must be uniformly distributed. K-S (Kolmogorov-Smirnov) test was used to test if CDF or ECDF is the uniform distribution. Also the data must satisfy the assumption of i.i.d., and the test statistic K is expressed as follows (Jianxu liu and Songsak Sriboonchitta, 2012) test the uniform distribution together with Box-Ljung test to test the autocorrelation.

$$K = \max \left| A_i - O_i \right| \tag{22}$$

A_i is the cumulative relative frequency for the theory distribution with each category; O_i is the corresponding value of the sample frequency. When K is greater than K(n, p) that denotes the sample size is n and confidence level is p, we reject the null hypothesis that the sample from population is some specific distribution.

The second condition of independence of the data must also be tested as mentioned above was the autocorrelation of the data i.e., the first, second, third and fourth moments by using Box-Ljung test. If the condition was violated it is essential to correct the data to satisfy the condition of no autocorrelation.

3.3.2. Specification for marginal distribution

Both growth rate of production and price in agriculture have the characteristic of heteroscedasticity, volatility and skewness etc. Therefore, we proposed that ARMA-GARCH model and standardized residuals of satisfying skewed-t distribution are used in this study. Following Shiqing Ling(2007), the ARMA(p, q)-GARCH(k, l) model can be formed as:

$$r_t = c + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \varepsilon_t \tag{23}$$

$$\varepsilon_t = h_t \cdot \eta_t \tag{24}$$

$$h_t^2 = \omega + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{l} \beta_i h_{t-i}^2 \tag{25}$$

Where $\sum_{i=1}^{p} \phi_i < 1$, $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\sum_{i=1}^{k} \alpha_i + \sum_{i=1}^{l} \beta_i < 1$. η_t is the standardized residual, which can be assumed any distribution. Normally, we assumed that it is Gaussian, student t or skewed-t distribution. Specially, skewed-t distribution can capture characteristics of heavy tail and asymmetry anyway, and symmetric heavy tail for t distribution.

The formula of Skewed-t distribution (Carmen Fernandez, 1998) is shown in the followings.

$$P(x_i \mid v, \gamma) = \frac{2}{\gamma + \frac{1}{\gamma}} \left\{ f_v\left(\frac{x_i}{\gamma}\right) I_{[0,\infty)}(x_i) + f_v(\gamma x_i) I_{(-\infty,0)}(x_i) \right\} \tag{26}$$

where fv(.) is unimodal and symmetric around zero, and γ is the skewness parameter that is defined from 0 to ∞; I denotes the indicator function and v is degree of freedom. Arnold and Groeneveld (1995) introduced detailed information about skewness measure as follows:

$$SM(x \mid \gamma) = \frac{\gamma^2 - 1}{\gamma^2 + 1} \tag{27}$$

It is easy to find that $\lim_{\gamma \to 0} SM(x \mid \gamma) = -1$ would be extreme left skewness, $\lim_{\gamma \to \infty} SM(x \mid \gamma) = 1$ would be extreme right skewness and γ=1 is no skewness.

3.4. CML method of estimation

We will use maximum likelihood method to estimate the parameters in GARCH model, after that, the Canonical Maximum Likelihood will be applied for estimating the parameters of copula function.

In FML and IFM estimations, assumptions of marginal distributions must be mde in order to estimate the parameter θ of Copula. The difference in CML is that it uses directly empirical distribution, and does not need to make assumptions about the marginal distribution.

Step 1 : Make use of the empirical distribution of x_t and y_t to transform them into the new series of $\hat{u}_t$ and $\hat{v}_t$.

$$\hat{u}_t = \hat{F}_X(x_t) = \frac{1}{T+1} \sum_{t=1}^{T} 1_{(X_t \leq x)} \tag{28}$$

$$\hat{v}_t = \hat{F}_Y(y_t) = \frac{1}{T+1}\sum_{t=1}^{T} 1_{(Y_t \le y)} \tag{29}$$

Step 2 θ.Then, the ML function can be u

$$\hat{\theta} = \arg\max \sum_{t=1}^{T} \ln c(\hat{u}, \hat{v}; \theta) \tag{30}$$

3.5. goodness-of-fit tests

(1) AIC and BIC

After we calculate the parameters of every copula, we still have to choose which copula is the best one. The selection of copula may use Akaike and Bayesian Information Criteria, respectively. The formulas of AIC and BIC follow (Brechmann, E. C. ,2010) as:

$$AIC := -2\sum_{i=1}^{N} \ln[c(u, v|\theta)] + 2k \tag{31}$$

where k = 1 for one parameter copulas and k = 2 for the two parameter copulas such as t and BBX copulas etc. Similarly, the BIC is given by

$$BIC := -2\sum_{i=1}^{N} \ln[c(u, v|\theta)] + \ln(N)k \tag{32}$$

(2) Two tests based on Kendall's transform

Genest and Rivest (1993), Wang and Wells (2000), Genest and Quessy(2006) investigated copula goodness of fit test using Cramer-von Mises and Kolmogorov Smirnov statistics as well as the according p-values using bootstrapping. The formulas of empirical kendall process follows Jiying Luo(2010) as:

$$\kappa_n(t) = \sqrt{n}(K_n(t) - K_{\theta n}(t)) \tag{33}$$

The null hypothesis was defined as follows:

$$H_0 : K \in \mathrm{K}_0 = \{K_\theta : \theta \in o\} \tag{34}$$

Where K_θ is kendall distribution of copula function C_θ and K_n denotes the empirical kendall distribution functions.

The Cramer-von Mises and Kolmogorov Smirnov test statistics for this GOF test are given by

$$S_n = \int_0^1 |\kappa_n(t)|^2 dK_{\theta n}(t) \tag{35}$$

$$T_n = \sup|\kappa_n(t)| \tag{36}$$

On the one hand, the AIC and BIC may be used to measure the goodness of fit and the copula with the lowest values of AIC and/or BIC would be selected as the best model; on the other hand, after computing the AIC and BIC, the application of Cramer-von Mises and Kolmogorov Smirnov tests would be used to ensure the accuracy of fitted copula.

4. Data and descriptive statistics

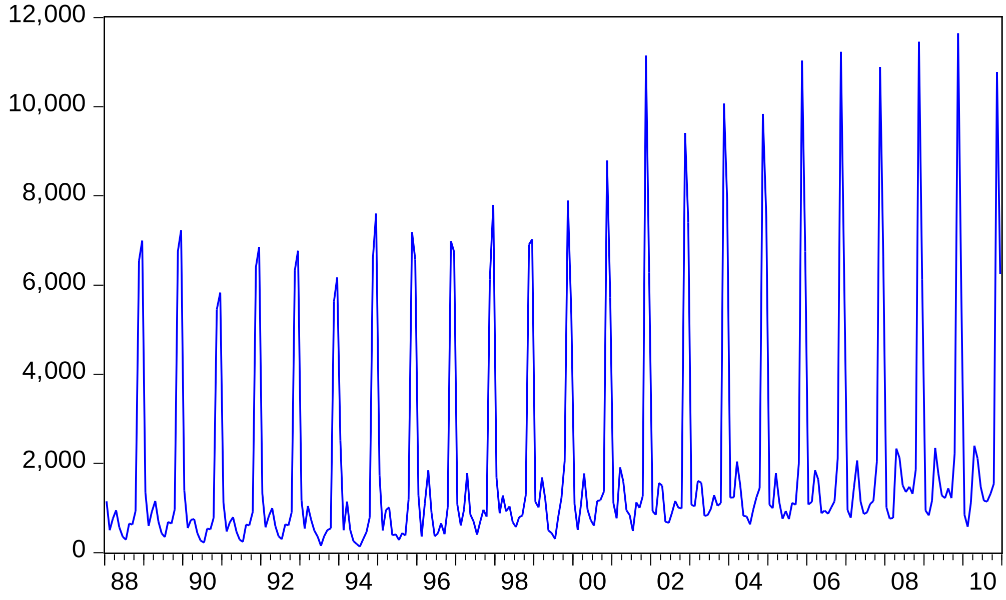

Fig.5. agricultural production index of Thailand

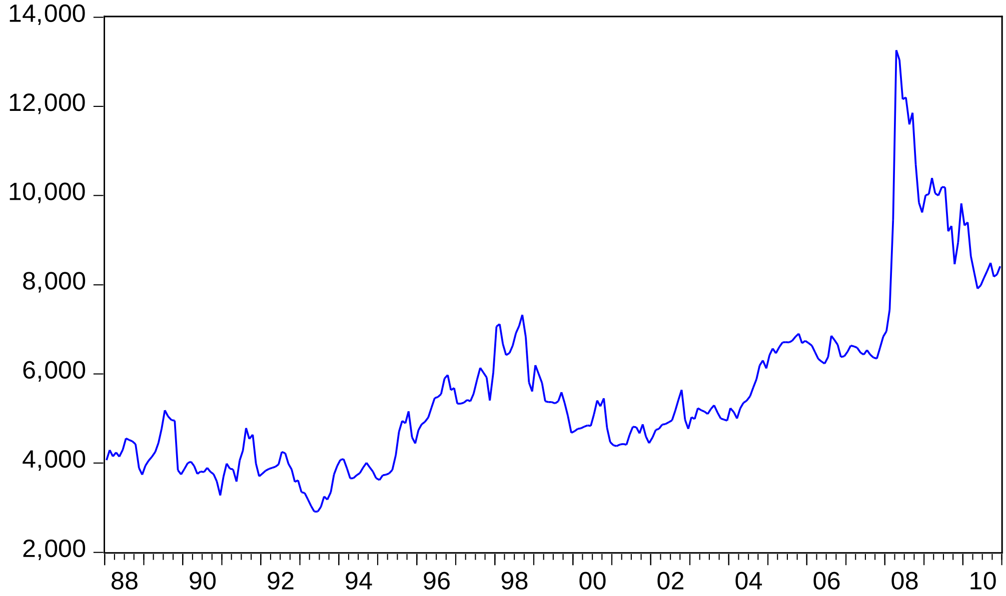

Fig.6. agricultural price index of Thailand

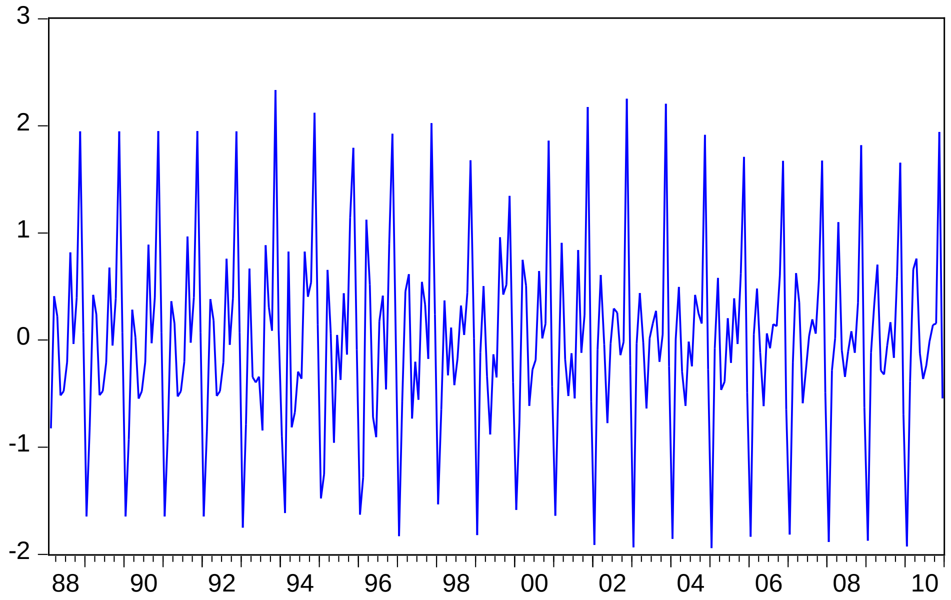

Fig.7. growth rate of agricultural production index of Thailand

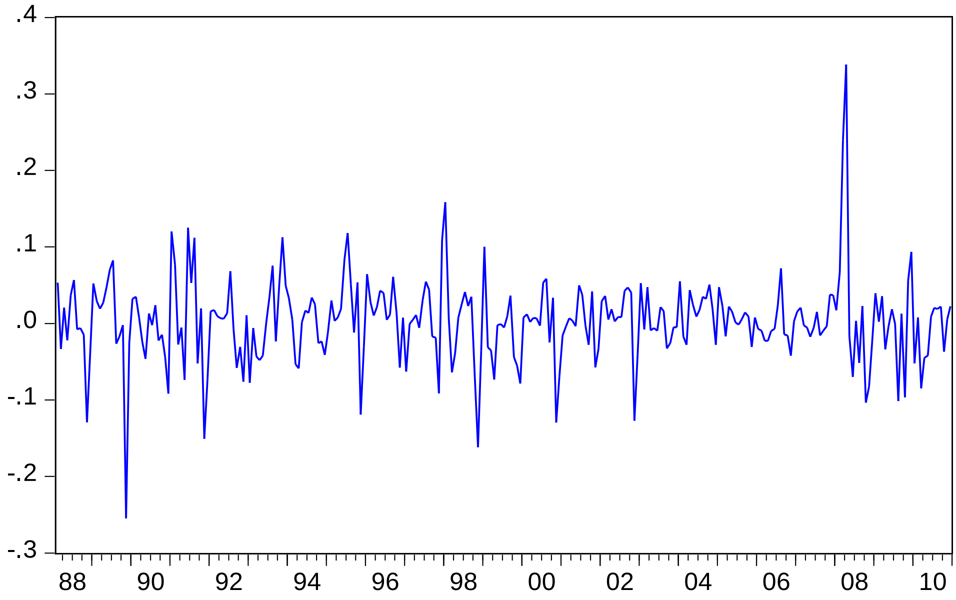

Fig.8. growth rate of agricultural price index of Thailand

Table1. Data description and statistics

	Growth rate of production	Growth rate of price
Mean	0.006153	0.002644
Median	-0.029566	0.004982
Maximum	2.333880	0.338327
Minimum	-1.942147	-0.254712
Std. Dev.	0.866698	0.055136
Skewness	0.232136	0.529312
Kurtosis	3.717323	10.28370
Jarque-Bera	8.365736	620.7316
Probability	0.015255	0.000000
Sum	1.692133	0.726974
Sum Sq. Dev.	205.8193	0.832959
Observations	275	275

From the table 1, descriptive data, etc was formed that the data of the growth rate of production and price were not normal from the rejection of Jarque-Bera test at 5% level of significance. The distribution of the data of the growth rate had positive skewness. Therefore, our first guess for these two marginal distributions were the skewed-t distributions.

Table 2 ADF test for growth rate of production and price

Null Hypothesis: Growth rate of production has a unit root			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.82940	0.0000
Test critical values	1% level	-2.573784	
	5% level	-1.942035	
	10% level	-1.615894	
Null Hypothesis: Growth rate of price has a unit root			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.68982	0.0000
Test critical values	1% level	-2.573429	
	5% level	-1.941986	
	10% level	-1.615926	

Source: computation

Table 3 Phillips-Perron test for growth rate of production and price

Null Hypothesis: Growth rate of production has a unit root			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-24.00733	0.0000
Test critical values	1% level	-2.573784	
	5% level	-1.942035	
	10% level	-1.615894	
Null Hypothesis: Growth rate of price has a unit root			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.26067	0.0000
Test critical values	1% level	-2.573429	
	5% level	-1.941986	
	10% level	-1.615926	

Source: computation

However, the unit root test of the data, the growth rates of production and price must be carried out, ADF and PP test statistics showed that the data had not unit roots in both kinds of data.

5. Empirical results

This section was organized in the following manners. Subsection 5.1 would discuss the estimation of the marginal distributions of both the growth rates of production and price. The assumptions of i.i.d were tested in subsection 5.2. Subsection 5.3 presented the estimate of one parameter models. Subsection 5.4 illustrated the estimation of the copula models of two parameters. Goodness of fit of candidate static Copulas was tested in subsection 5.5. Subsection 5.6 aimed to discuss the estimated results of candidate time varying copulas.

Table 4 Estimates of parameters of the skew t marginal distribution for growth rate of production in ARMA(4,12)-GARCH(1,1) Skew t

	Estimate	Std. Error	t value	Pr(>|t|)
ar1	1.808	0.10907	0.06034	0.070669
ar2	-0.90708	0.05001	-18.137	< 2e-16 ***
ar3	-0.02169	0.05246	-0.413	0.679246
ar4	-0.55061	0.08764	-6.283	3.33e-10 ***
ma1	-0.11504	0.04416	-2.605	0.009190 **
ma2	0.29625	0.05552	5.336	9.48e-08 ***
ma3	-0.25063	0.09780	-2.563	0.010390 *
ma4	0.20454	0.07915	2.584	0.009761 **
ma5	-0.36871	0.06669	-5.529	3.22e-08 ***
ma6	-0.50328	0.07475	-6.733	1.67e-11 ***
ma7	-0.07138	0.05550	-1.286	0.198411
ma8	-0.18692	0.07603	-2.458	0.013953 *
ma9	0.16213	0.03953	4.102	4.10e-05 ***
ma10	-0.18842	0.05449	-3.458	0.000544 ***
ma11	0.23905	0.06308	3.790	0.000151 ***
ma12	0.57510	0.06958	8.265	2.22e-16 ***
ω	0.09417	0.66365	0.142	0.887159
α	1.00000	2.80707	0.356	0.721658
β	0.95057	0.02438	38.984	< 2e-16 ***
λ	1.20697	0.10658	11.325	< 2e-16 ***
DoF	2.02271	0.01801	112.297	< 2e-16 ***

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

Log Likelihood: -133.6345

Source: computation

Table 5 Estimates of parameters of the skew t marginal distribution for growth rate of price in ARMA(0,1)-GARCH(1,1) Skew t

	Estimate	Std. Error	t value	Pr(>|t|)
ma1	0.3230183	0.0587836	5.495	3.91e-08 ***
ω	0.0012248	0.0004672	2.622	0.00875 **
α	0.7074998	0.3104872	2.279	0.02269 *
β	0.1855050	0.1002525	1.850	0.06426
λ	0.8442494	0.0515531	16.376	< 2e-16 ***
DoF	3.2409564	0.7939274	4.082	4.46e-05 ***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

Log Likelihood: -220.6853

Source: computation

5.1

For marginal density of the growth rate of production, it was found that ARMA (4, 12) – GARCH (1, 1) skew t distribution is appropriate because it satisfied the i.i.d assumptions. However, for the growth rate of price, the suitable margin became ARMA (0, 1)-GARCH (1, 1) skew t satisfying the i.i.d assumptions. The estimated GARCH from both margins also satisfied the assumption convergence. The skewness, λ, and the degree of freedom were significant implying that the skew t distribution is appropriate for this data set.

5.2

Table 6 showed that the margins of growth rates of production and price had the uniform distribution (from KS test). Also Box-Ljung test for autocorrelation of both margins showed no autocorrelation from the first to the fourth moments.

Table6 KS Test for Uniform and Box-Ljung Test for Autocorrelation

KS Test of Both Margins for Uniform	statistic	P value	Hypothesis
Margins of Growth rate of production	0.0218	0.9994	0 (acceptance)
Margins of Growth rate of price	0.0018	1	0 (acceptance)

Box-Ljung Test of Both Margins for Autocorrelation		X-squared	P-value
Margins of Growth rate of production	First moment	3.2084	0.6679
	Second moment	8.2886	0.141
	Third moment	3.9253	0.5602
	Fourth moment	6.5063	0.26
Margins of Growth rate of price	First moment	4.114	0.5331
	Second moment	1.3753	0.927
	Third moment	4.3758	0.4967
	Fourth moment	0.6177	0.9872

Source: computation

5.3

For the estimation of static copulas with one parameter, the results showed that all the copula parameters are statistically significant at 5% level as shown in table 7. However, from AIC and BIC perspective the rotate Joe copula (270°) was the best among one parameter static copula.

Table 7 the results for copula model of one parameter

	Parameter	Stand error	T statistics	P value	AIC	BIC
Gaussian	-0.2142	0.0565	-3.7916	9.208e-05	-10.8016	-7.1849
Rotate Clayton Copula (90°)	-0.3731	0.0901	-4.1417	2.298e-05	-22.1635	-18.5467
Rotate Gumbel Copula (90°)	-1.1078	0.0477	-23.2346	4.98e-67	-5.4570	-1.8402
Rotate Joe Copula(90°)	-1.0731	0.0582	-18.4125	3.95e-50	-0.7859	2.8309
Rotate Clayton Copula (270°)	-0.1309	0.0781	-1.6755	0.0474	-1.4707	2.1460
Rotate Gumbel Copula (270°)	-1.1858	0.0491	-24.1161	0	-22.3600	-18.7432
Rotate Joe Copula(270°)	-1.2967	0.0761	-17.0471	3.21e-45	-25.4471	-21.8303
Frank	-1.1823	0.3739	-3.1620	0.0009	-7.9837	-4.3669

Source: computation

5.4

Table 8 illustrated the estimates of the two parameters' static copulas. The best copula model in this two parameter static copula is the rotate BB8 (270°). However, it was still inferior to the rotate Joe copula (270°).

Table8 the results for copula model of two parameters

		Parameter	Stand error	T statistics	P value	AIC	BIC
t copula	θ	-0.2031	0.0646	-3.1410	0.0009	-15.059	-7.8255
	DoF	5.5362	2.3605	2.3453	0.0091		
Rotate BB1(90°)	δ	-1.001	0.1436	-6.9691	1.18e-11	19.6450	26.8785
	θ	-1.0006	0.0319	-31.3604	8.64e-93		
Rotate BB6(90°)	δ	-1.001	0.22443	-4.4601	5.98e-06	-3.4196	3.8139
	θ	-1.1071	0.1660	-6.6694	7.10e-11		
Rotate BB7(90°)	δ	-1.0155	0.0349	-29.0634	5.51e-86	-20.4286	-13.1951
	θ	-0.3650	0.0915	-3.9850	4.33e-05		
Rotate BB8(90°)	δ	-6	6.1641	-0.9734	0.16561	-5.1365	2.0971
	θ	-0.1887	0.1940	-0.9726	0.16580		
Rotate BB1(270°)	δ	-1.001	0.1404	-7.1269	4.58e-12	86.8018	94.0353
	θ	-1.0006	0.0219	-45.7021	0		
Rotate BB6(270°)	δ	-1.2949	0.2609	-4.9629	6.11e-07	-23.4389	-16.2054
	θ	-1.001	0.1474	-6.7901	3.48e-11		
Rotate BB7(270°)	δ	-1.2955	0.0786	-16.4857	3.74e-43	-23.4503	-16.2168
	θ	-0.0036	0.0632	-0.0564	0.4775		
Rotate BB8(270°)	δ	-1.3014	0.0772	-16.8423	1.94e-44	-23.4570	-16.2234
	θ	-0.9992	0.0005	-1852.74	0		

Source: computation

5.5

Table 9 showed the results of goodness of fit by providing the probabilities values of CvM and KS. There were five copulas i.e., the rotate gumbel(90), rotate clayton(270), rotate BB6(90), rotate BB8(90) and rotate Joe(90) which did not fit our data. However, the result also showed that the rotate Joe (270) was accepted and consistent with the best choice among the one parameter static copula. For the two parameter static copula CvM and KS tests again showed consistent result with the best choice in the two parameter copula. Namely, we could not reject the null hypothesis that the rotate BB8 (270) copula is true and the rotate BB8 (270) was the best among the two parameter copulas.

Table 9 Goodness of fit of Crame-von Mises and KS test

copula	P value of CvM	P value of KS	copula	P value of CvM	P value of KS
Gaussian copula	0.95	0.94	Rotate BB6(90)	0	0
T copula	0.83	0.69	Rotate BB7(90)	0.43	0.64
Rotate clayton(90)	0.44	0.67	Rotate BB8(90)	0	0
Rotate gumbel(90)	0	0	Rotate Joe(90)	0	0
Rotate BB1(90)	0.46	0.57	Rotate gumbel(270)	0.26	0.33
Rotate clayton(270)	0	0	Rotate Joe(270)	0.31	0.30
Rotate BB1(270)	0.19	0.32	Rotate BB6(270)	0.79	0.67
Rotate BB7(270)	0.80	0.75	Rotate BB8(270)	0.83	0.78
Frank copula	0.94	0.97			

Source: computation

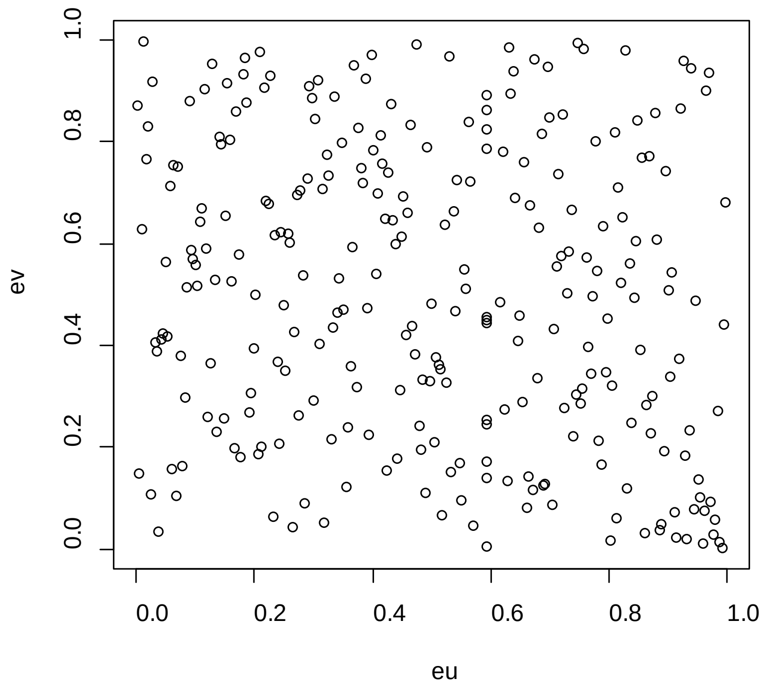

Fig.9. Scatter Plot of Empirical Copula

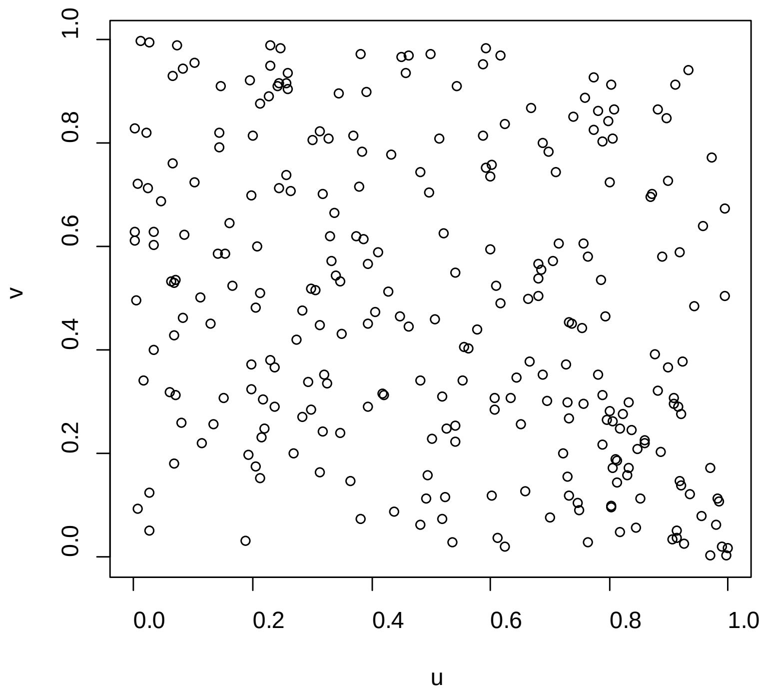

Fig.10. Scatter Plot of rotate Joe Copula (270)

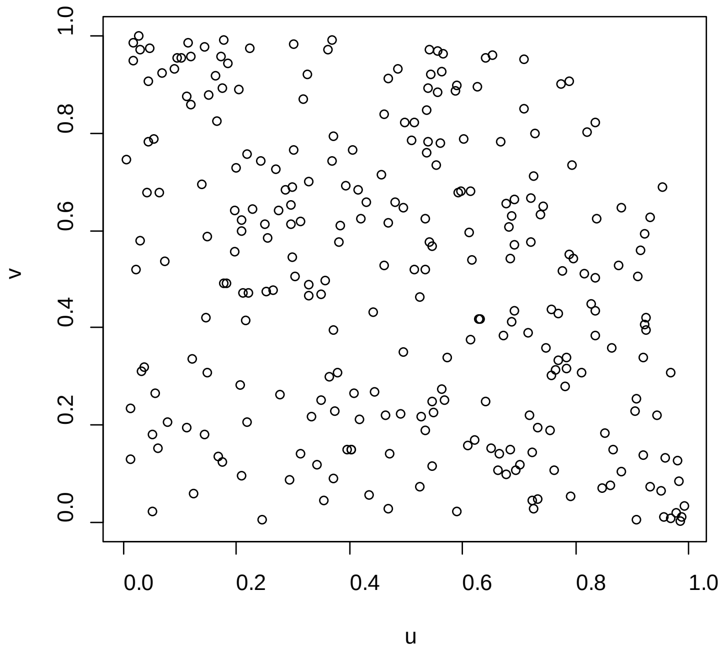

Fig.11. Scatter Plot of rotate Clayton Copula (90)

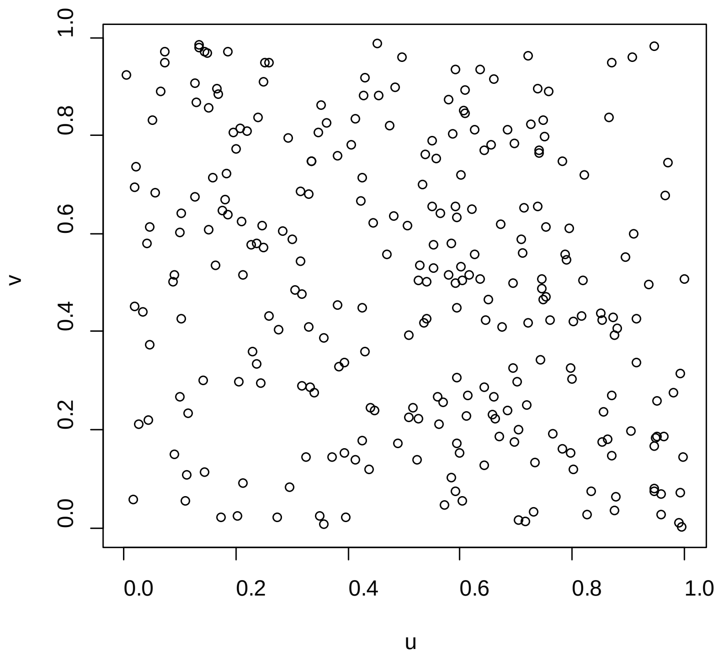

Fig.12. Scatter Plot of rotate Gumbel Copula (270)

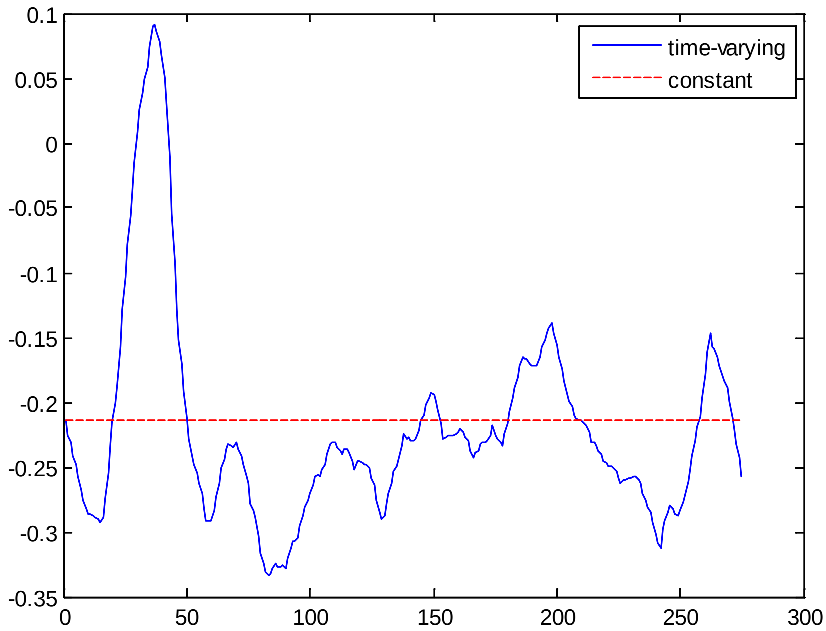

Fig.13. Pearson correlation (ρ)from Normal copula

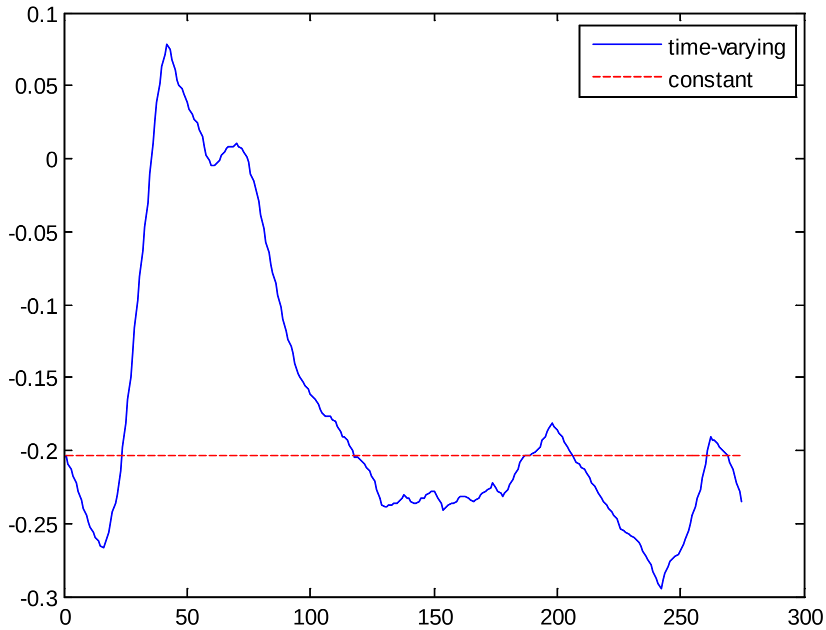

Fig.14. Pearson correlation (ρ) from T copula

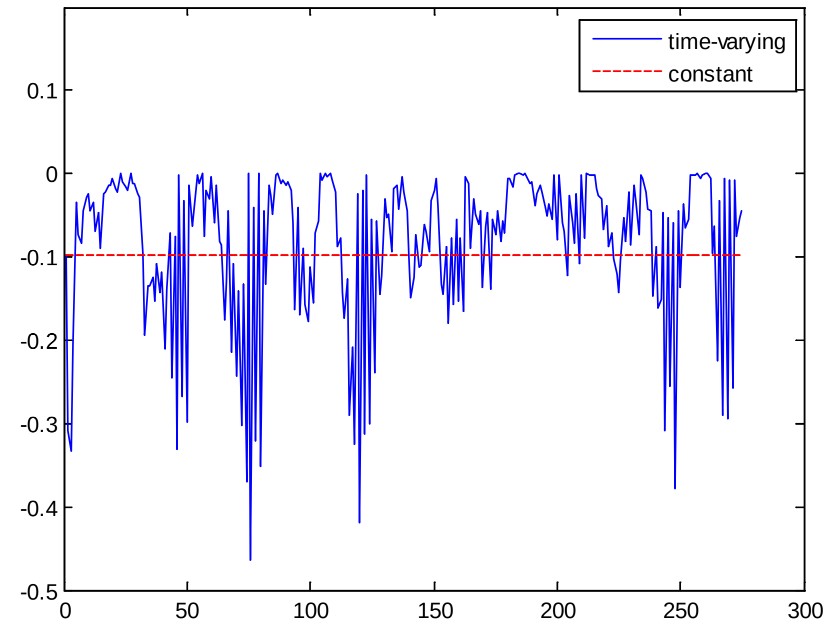

Fig.15. Kendall's tau (τ) from Rotate Gumbel copula(90°)

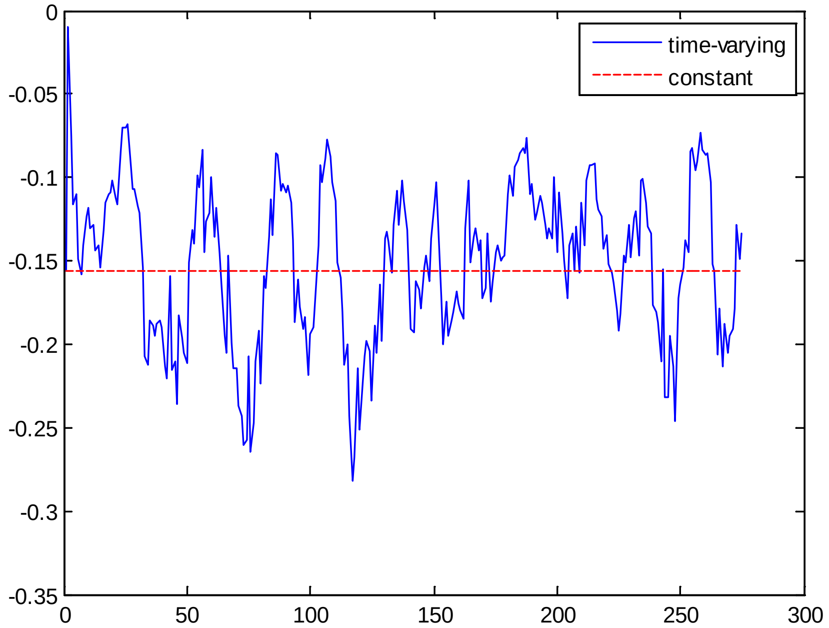

Fig.16. Kendall's tau (τ) from Rotate Gumbel copula(270°)

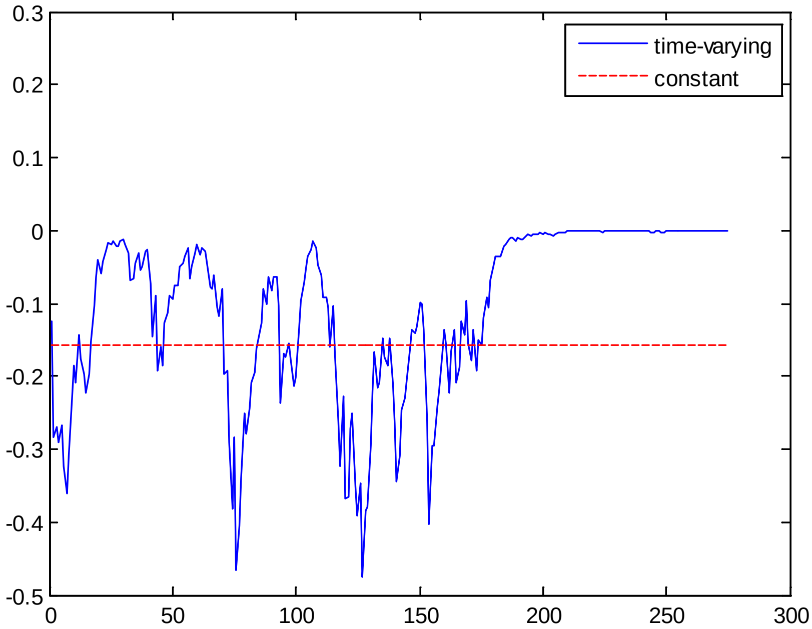

Fig.17. Kendall's tau (τ) from Rotate Clayton copula(90°)

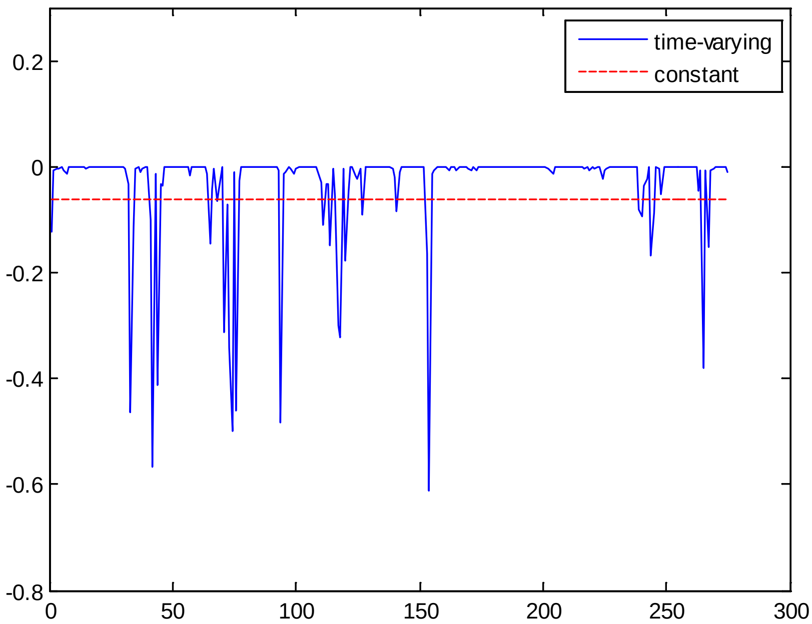

Fig.18. Kendall's tau (τ) from Rotate Clayton copula(270°)

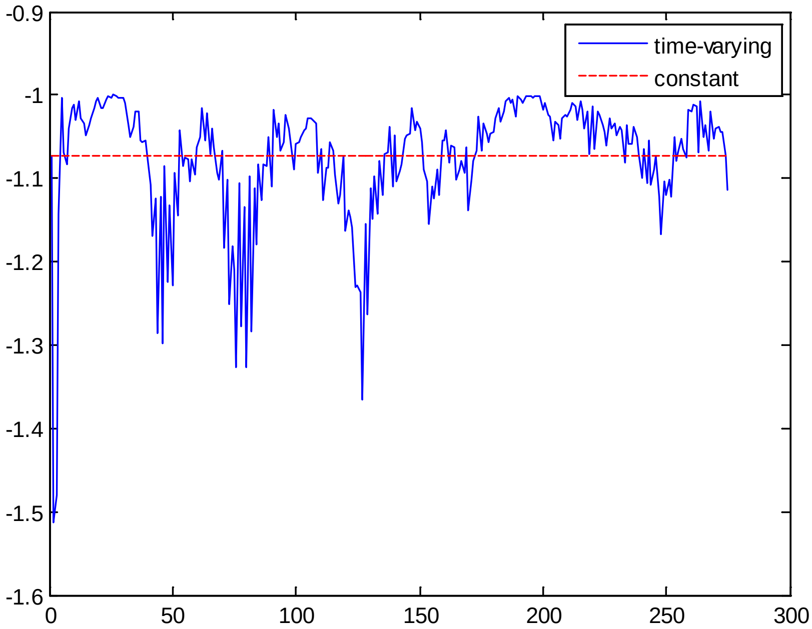

Fig.19. parameter (θ) from Rotate Joe copula(90°)

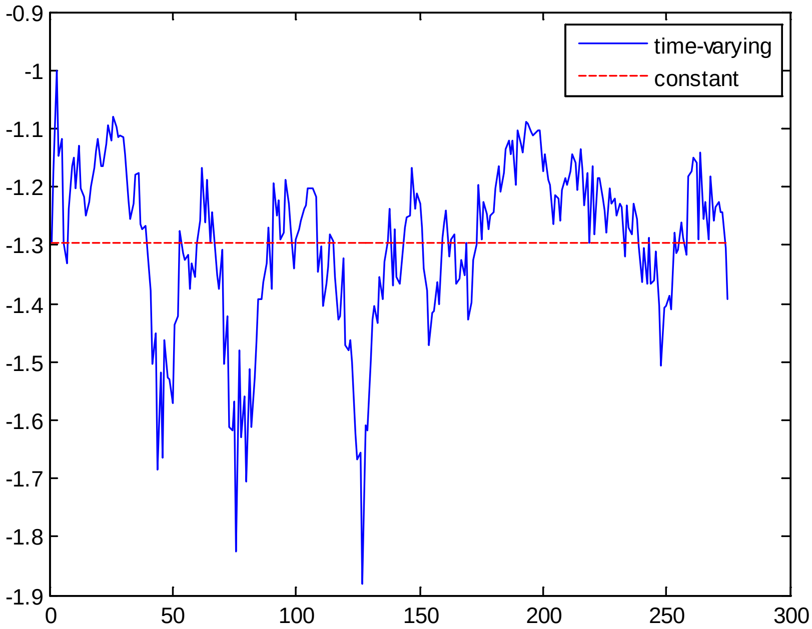

Fig.20. parameter (θ) from Rotate Joe copula(270°)

5.6

For time varying copula, relevant copulas in equation (16)-(19) were employed. From this empirical study, it was found that the copula parameter followed ARMA (1, 20) process very well. It looked more natural as expected because it had the negative correlation always, and it did not hit the upper bound at zero and some part of the correlation were not constant contradictory to the best model rotate Clayton copula (90) of which it provided the minimum AIC which was a slightly lower than the time varying rotate Gumbel copula (270). However, if BIC was considered to be the criterion for model selection, the time varying rotate Gumbel copula (270) was substantially lower than the time varying rotate Clayton copla (90).

In this study, therefore, the time varying rotate Gumbel copula (270) was selected for policy implication.

Table 10 Time varying copula

	ω	α	β	AIC	BIC
Time varying Gaussian Copula	-0.0691 (0.0079) ***	-0.1200 (0.0100) ***	1.8535 (0.0257) ***	-14.1254	-10.5087
Time varying T Copula	-0.0089 (0.0005) ***	-0.0289 (0.0007) ***	2.0505 (0.0027) ***	-20.5395	-13.3059
Time varying rotate Gumbel Copula(90)	-1.1000 (0.0345) ***	1.5405 (0.0272) ***	-2.7748 (0.0487) ***	-8.1658	-4.5490
Time varying rotate Gumbel Copula(270)	-0.3466 (0.0427) ***	0.25 (0.0416) ***	-1.2555 (0.0666) ***	-24.0336	-20.4168
Time varying rotate Clayton Copula(90)	0.5727 (0.023) ***	-1.8421 (0.059) ***	-0.9989 (0.003) ***	-25.8737	-15.0234
Time varying rotate Clayton Copula(270)	4.9819 (0.404) ***	-10 (0.0001) ***	-0.7017 (0.050) ***	-1.6994	9.1509
Time varying rotate Joe Copula(90)	-0.1349 (0.0742) *	0.9269 (0.0507) ***	-3.7623 (0.1100) ***	-1.5525	2.0642
Time varying rotate Joe Copula(270)	0.1716 (0.0454) ***	0.3001 (0.0335) ***	-3.7402 (0.1425) ***	-28.7401	-25.1234
DCC Gaussian and T Copula					
DCC Gaussian	---------	0.00001 (0.000086)	0.5351 (4.597)	-8.8009	-1.5674
DCC T	5.7908 (2.660) *	0.000007 (0.000064)	0.7484 (0.7067)	-12.8909	-2.0406

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05. The standard errors are in parenthesis.

Note: the ρ of DCC Gaussian and T would be constant, which equal -0.2142 and 0.2031 respectively. The first parameter in DCC T copula is degree of freedom.

Source: computation

6. Policy Implication

The negative correlation between the growth rates of agricultural production and agricultural price was found as expected. The correlation was time varying. This time varying correlation could be used to make the forecast of the next period correlation. This time varying correlation would make the policy makers to be aware of what is going to happen in the future e.g., when the correlation was forecasted as high as -0.25 and if it is known from the forecast of the growth rate of production is going to drop at a certain rate, the inflation has to rise at a substantial rate. The policy makers would prepare to e.g., import some relevant agricultural products to increase the supply. Then the inflation would calm down. It would relieve the suffer of the people especially the lower income group which would help to prevent the political unrest.

This paper could provide the forecast of the growth rate of agricultural price and hence the price level conditional on the growth rate of the agricultural production. The conditional density of the growth rate of agricultural price could be obtain from

$$p|q = \frac{c(u,v)\cdot f_p \cdot f_q}{f_q} = c(u,v)\cdot f_p \qquad (37)$$

Where $c(u,v)$ is the copula density; f_p =the marginal density of the growth rate of agricultural price; f_q = the marginal density of the growth rate of agricultural production. In this paper, it was recommended to use the copula density of time varying rotate Joe copula (270) with parameters specified in table 10. Of course, the marginal density of growth rate of agriculture price was the skewed t distribution with the estimates of parameters of the mean MA (1) and conditional volatility GARCH (1, 1), skewness and degrees of freedom as shown in table 5. This approach enables us to include the spillover effects of the other variables on the random variable on consideration. This point forecast could be obtained by taking the expectation to equation (37). The interval estimate could be achieved by using simulation of equation (37).

This study also showed the behaviors of conditional volatilities of the growth rates of agricultural price and production. These estimated conditional volatilities allow policy makers understand the behaviors of volatilities and hence could do some hedging to prevent undesirable effects due to the price and production change.

7. Conclusions

For modeling volatility and dependency of agricultural price and production indices of Thailand, we found that the appropriate marginal density for the growth rates of agricultural production and price indices were the skewed t distribution with the means, volatilities, skewness and degree of freedom shown in table 4-5. The time varying rotate Joe Copula was the best one among several copula candidates. The behavior of the growth rate of agricultural price could be explained very well by equation (37) with the selected marginal skewed t distribution, conditional volatility. Using the selected models for the growth rates of agricultural price and production indices allowed us to obtain the point forecast of the growth rate of the price by taking the expectation and also the interval forecast by simulation. When the production growth rate was forecasted, we could forecast the inflation rate of the agricultural sector. The policy makers could prepare some measures to manage the inflation.

Acknowledgements

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บทความที่ 7

Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH model

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Abstract

This paper tries to use the Copula-based GARCH model to find out the relationships between the volatility of rubber futures returns in AFET and four other variables. The results show that the Student-t dependence structure exhibits better explanatory ability than the Gassusian dependence structure in determining the volatility of rubber futures in AFET and two rubber futures in SICOM and TOCOM. However, the Gassusian dependence shows better explanatory ability in the volatility of rubber futures in AFET and two kinds of oil futures in TOCOM. For the multivariate Copula model, all the parameters between AFET and other variables are significant.

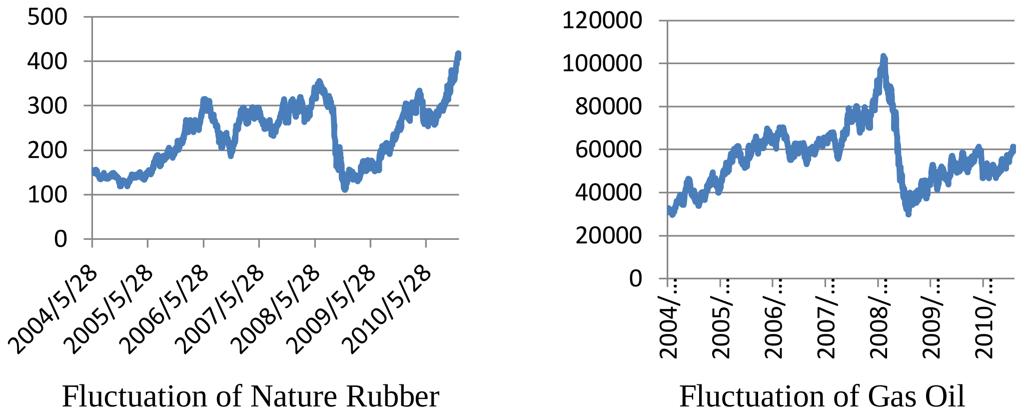
Keywords: Volatility, Rubber futures return, crude oil futures return, gas oil futures return, *Copula-based GARCH* model.

1. Introduction

Thailand, Malaysia, and Indonesia are the major producers and exporters of rubber in the world. The total rubber output of these three countries was about 8.32 million tons in 2007, representing almost 94% of the total world market. The rubber industry is one of the most important sectors of the Thai economy. The area planted with rubber is 219,933 hectares, with an annual output of 3.056 million tons in 2007 (Office of the Rubber Replanting Aid Fund, 2008). Online information from the United States Department of State shows that the per capita income of Thailand is only about US$ 4,716. As the most important producer and exporter of rubber market in the world, Thailand has some absolute advantages in the industry. However, the income of its citizens does not reflect the benefits gained from rubber production. The key reason is that farmers do not know how to hedge their position in the market.

Rubber has two kinds. The first is natural rubber, which is taken from the rubber tree. Rubber trees grow for about six or seven years and has a life span of around 30 years. The second kind is synthetic rubber, which is produced using oil. Synthetic rubber is a substitute for natural rubber, and its price is affected by the price of oil. Fluctuations in the prices of natural rubber and gas oil in the Tokyo Commodity Exchange (TOCOM) are shown in Figure 1.

Figure1. The Fluctuation of Nature Rubber and Gas Oil in TOCOM



This paper will use daily data via the Copula model to give a positive analysis on rubber futures and the oil index. A strict basic analysis and model enactment are employed to obtain expected results, which are positive relationships between each variable in those three areas and the price of rubber in Thailand. If the covariance between each series is an unsettled type (i.e., the coefficient of the condition between the error items of two series will change over time), then it will be more rational and can provide another positive analysis to be used as a reference in future research. It can also provide investors and the Thai government some useful information in strategic decision making.

Thailand is the world's number one exporter of rubber, and agriculture is its most important industry. Thus, this paper hopes to determine the relationships between each variable and the futures price of rubber in Thailand. This paper has two objectives. First, it will investigate the relationships between rubber futures and oil futures. Second, it will use historical information to forecast the futures price return in the rubber and oil markets to help farmers hedge their market position and assist investors in their decision making.

For this paper, we try to use bivariate and multivariate Copula model to forecasting the volatility of futures return in rubber. There are just few literature discuss about finance market by using bivariate Copula model, especially in multivariate Copula model. One the other hand, the oil's price is also the important factor for rubber and we choose the optimal one to characterize the dependence structures of the different futures markets. Therefore, this paper focuses on the forecasting the futures price of rubber in Thailand two different rubber futures market and two kinds of oil futures product in TOCOM using Copula-based GARCH models.

2. Literature review

Numerous finance papers have provided profound analyses and basic theories of interrelation between different markets. Eun and Shim (1989) proved that the US stock market is the main source of international transmission and that its variation affects the foreign stock market; however, the variation of the foreign stock market does not explain the reasons for the variation in the US stock market. Theodossiou and Lee (1993) pointed out that the US stock market has a positive transmission to the stock markets of the United Kingdom (UK), Germany, and Canada, and a significant transmission to the stock markets of the UK, Germany, Canada, and Japan. Kearney (2000) also argued that the variation of most stock markets in the world is derived from the variation of the stock market in the US and Japan, then transferred to Europe. Kasih (2001) discovered that, whether long or short term, the stock markets of the US, UK, and Japan are the leaders in the world because they account for 75% of the capital in the global market.

With respect to volatility in the futures market, Scholes (1981) pointed out that the differences between spread trade and hedge trade depend on investor demand in the spot market. He also stated that spread traders have speculative demand, indicating that they trade for short-term profits, and the hedge traders buy or sell futures to avoid risks. In addition, Scholes also noted that traditional spread trading has been applied to different products to decrease risk and to increase liquidity in the market simultaneously. Peterson (1997) analyzed the advantages of spread trade, which include providing the arbitrage to test the efficiency of pricing in the futures market and setting up the risk transfer to spread risk by increasing the scope of investment. Therefore, speculative traders entering the futures market can increase the liquidity between products and benefit from price volatility. Bernstein (2007) proved that increasing the complexity of spread trade can increase the investment benefit. When the portfolio becomes complex, the investor cannot have real-time information to calculate the price change. Therefore, information asymmetry from the volatility might increase the benefit from the market. If futures price shocks exist, the pricing will deviate because of different expectations. Butterworth et al. (2002) studied the spread trade using the cost of carry model; the variables of their study were the Financial Times Stock Exchange (FTSE) 100 index and the FTSE Mid 250 index. Their study assumed that those two markets comprise more than 90% of the UK stock market, which receives all kinds of information from the market. Their result showed that if the transaction costs are not considered, the benefit can be obtained by spread trade. However, if the fees and Bid-Ask Spread are taken into account, traders will not enter the market because the benefit cannot cover the fee of every deal. Dunis et al. (2006) also studied the spread trade from the West Texas Intermediate (WTI) and Brent blend (a benchmark crude oil from the North Sea), and used the time-series model to estimate the correlations among products. Daigler (2007) discussed the relationships among the cross spread, calendar spread, and trade volume of exchange futures from four kinds of traders in the Chicago Mercantile Exchange (CME), which are individual traders, corporate traders, dealers and hedge traders.

A range of literature on Copula methods is also available. Roncalli (2001) built one portfolio that includes five financial assets in the London Metal Exchange (LME), then used Gaussian Copula and Student's Copula to analyze the correlations between financial instruments. His results showed a significant difference in the correlation coefficient. Hu (2002) used the Copula model to discuss the correlation between the stock market and bond market. The main references of his paper were the Standard & Poor's (S&P) 500 index and the J. P. Morgan Government Bond Index. The results of his study stated that the correlation between the stock market and bond market in a bearish market is better than that in a bullish one. Bartram, Taylor, and Wang (2004) put the Gaussian Copula function to the GJR-GARCH-t model to discuss the correction effect of the lead in EURO viewing point from the stock market of 17 countries in Europe. They proved that the correlation is increased only in large-scale capital markets after lead in common customs (e.g., the stock markets of France, Germany, Italy, Netherlands, and Spain). Patton (2006) used the Copula function to build a bivariate Copula model between the exchange rate of the German mark and Japanese yen, and to compare with the BEKK model. His result showed that the Copula model is better than the BEKK model in explaining the correction between financial markets. When the exchange rates of the German mark and the Japanese yen depreciate, the correction is higher than when the exchange rates appreciate. Meng, Si, and Gong presented a paper in 2004 that studied the relationships of the soybean futures markets in Dalian, the US, and Japan based on the dollar/yen exchange rate. The results suggested a highly strong dependence between different futures markets. Their paper studied four representative future contracts: January soybean contract of Dalian Commodity Exchange (DCE), January soybean contract of Chicago Board of Trade (CBOT), National Soybean Index (NSI) contract of Minneapolis Grain Exchange Inc. (MGEX), Index and Option Market (IOM) soybean contract of the Tokyo Grain Exchange, and the dollar/yen foreign exchange rate (denoted by US/J). The samples were divided into four groups: DCE and CBOT, DCE and NSI, DCE and IOM, DCE and US/J.

Hence, the current paper will study the bivariate dependence structure of each group separately. After obtaining the estimation of τ for each group, it will estimate the parameter of Copulas and choose the optimal one to characterize the dependence structures of the different futures markets.

3. Methodology

3.1 Data, variables and selection criteria

Natural rubber is classified into five levels. The highest level is RSS1, but the main kind is RSS3 in spot and future markets around the world. Compared with the Agricultural Futures Exchange of Thailand (AFET), both the TOCOM and Singapore Commodity Exchange Limited (SICOM) possess higher volumes in the world. The volatility of oil price can affect the price of natural rubber as well as the price of synthetic rubber, which is the substitute of natural rubber. In Asia, two kinds of oil are traded in the futures market. TOCOM only trades crude oil and gas oil. Regarding this, five variables are concerned with futures products from the three futures markets mentioned above. For each variable, 1,609 observations are required from May 28, 2004 (the first trading day of AFET) to December 31, 2010. This paper aims to identify the relationships between the futures prices of rubber and oil. The variable names are introduced in Table 1.

Table 1 Introduce of Variable Names

Variables	Names
AFET	Rubber Futures in AFET
SICOM	Rubber Futures in SICOM
TOCOM	Rubber Futures in TOCOM
Crude	Crude Oil Futures in TOCOM
Gas	Gas Oil Futures in TOCOM

3.2 Stationarity and summary statistics of the variables

The returns of asset i at time t are calculated as following:

$$R_{i,t} = \log(\frac{P_{i,t}}{P_{i,t-1}}) \quad (1)$$

Where: $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and t-1, separately.

All series data are stationary and tested by using the Augmented Dickey-Fuller (ADF) test, which is given as following:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{P} \emptyset \Delta y_{t-1} + \varepsilon_t \quad (2)$$

The null hypothesis is $\theta = 0$ which, if rejected then means that the series y_t is stationary.

3.3 Econometric models

3.3.1 GARCH model

Bollerslev (1986) proposed the Generalized ARCH(GARCH) model which put conditional variance of lags to ARCH model and make it generally.

GARCH model

$$R_t = \mu_{t-1} + \varepsilon_t \tag{3}$$

$$\varepsilon_t|\Omega_{t-1} \sim N(0, h_t) \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5}$$

When $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$, the GARCH model is stable.

GARCH(p,q) model

$$R_t = \mu_{t-1} + \varepsilon_t \tag{6}$$

$$\varepsilon_t|\Omega_{t-1} \sim N(0, h_t) \tag{7}$$

$$H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-1} \tag{8}$$

Where: i=1,2,…,q, J=1,2,…,p, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$.

In this model, μ_{t-1} is the conditional mean of R_t at time t, h_t is the conditional variance at time t and Ω_{t-1} is the all useful information set at time t-1.

The GARCH(1,1) model can be written as following:

$$r_{i,t} = c_0 + c_1 r_{i,t-1} + e_{i,t}, e_{i,t}|\Psi_{t-1} = h_{i,t}, z_{i,t}, z_{i,t} \sim skewed-t(z_i|\eta_i, \lambda_i) \tag{9}$$

$$e_{i,t} \sim N(0, h_{i,t}^2) \tag{10}$$

$$h_{i,t}^2 = \omega_{i,t} + \alpha e_{i,t-1}^2 + \beta h_{i,t-1} \tag{11}$$

Where: $\omega_{i,t}$>0 , $\alpha, \beta \geq 0$ and , $\alpha + \beta < 1$.

The error term $e_{i,t}$ is assumed to be skewed-t distribution which can be used to describe the possibly asymmetric and heavy tail characteristics of each variable. Following Hansen(1994), the density function is

$$skewed-t(z|\eta,\lambda) = \begin{cases} BC\left(1+\frac{1}{\eta-2}\left(\frac{Bz+A}{1-\lambda}\right)^2\right)^{-(\eta+1)/2} & ,z < -\frac{A}{B} \\ BC\left(1+\frac{1}{\eta-2}\left(\frac{Bz+A}{1-\lambda}\right)^2\right)^{-(\eta+1)/2} & ,z \geq -\frac{A}{B} \end{cases} \tag{12}$$

The value of A, B and C are defined as following:

$$A \equiv 4\lambda C\frac{\eta-2}{\eta-1}, B \equiv 1 + 2\lambda^2 - A^2 \text{ and } C \equiv \frac{\Gamma(\eta+1/2)}{\sqrt{\pi(\eta-2)\Gamma(\eta/2)}} \tag{13}$$

Where: λ and η are the asymmetry and kurtosis parameters, separately. Those are restricted to be -1< λ <1 and 2< η<∞. When $\lambda = 0$, it will turn to the Student –t distribution. If $\lambda = 0$ and η diverge to infinite, it will be the normal distribution.

3.3.2 Elliptical copulas

Because the Copula function is always used in discussing the problems between many variables, it called dependence function (Deheuvels, 1978). Sklar (1959), proposed Copula theory who pointed that one unit distribution can be analyzed to n marginal distribution and one Copula function. In general, since the number of parameters can be large, two step methods are usually employed. On the other hand, two stage estimators provide computational tractability in the expense of loss of full efficiency. At the first step, the marginal parameters are estimated by optimizing the marginal log likelihoods, independently of each other. The Copula parameters are estimate by optimizing the corresponding copula log likelihood at the second step.

The marginal log likelihood function:

$$m\mathcal{L}(\theta; x) = \sum_{i=1}^{P} \sum_{j=1}^{T} \log(F_i(x_{1,t}; \emptyset_i)) \quad (14)$$

The Copula log-likelihood function:

$$c\mathcal{L}(\theta; u, \emptyset) = \log(c(F_1(x_{1,t}), \ldots, F_p(x_{p,t}); \theta) \quad (15)$$

Where contains the marginal parameters are $\emptyset = (\emptyset_i, \ldots, \emptyset_p)$ and the copula parameters are θ.

Therefore, the log likelihoods of two elliptical copula, the Guassian and Student-t Copula are given by:

$$\mathcal{L}_G(R; u_t) = -\frac{1}{2}\sum_{t=1}^{T}(log|R| + \epsilon_t'(R^{-1} - I)\epsilon^t) \quad (16)$$

$$\mathcal{L}_{St}(R, d, u_t) = -T\log\frac{\Gamma(\frac{d+p}{2})}{\Gamma(\frac{d}{2})} - pTlog\frac{\Gamma(\frac{d+1}{2})}{\Gamma(\frac{d}{2})} - \frac{d+p}{2}\sum_{t=1}^{T}\log\left(1 + \frac{\epsilon_t'R^{-1}\epsilon^t}{d}\right) - \sum_{t=1}^{T}\log|R| + \frac{d+1}{2}\sum_{t=1}^{P}\sum_{t=1}^{T}\log(1 + \frac{\epsilon_{it}^2}{d}) \quad (17)$$

Where: the vector ϵ_t is the vector of the transformed standardized residuals which depend on the copula specification. For the Gaussian Copula, the vector $\in_t$ is defined as: $\epsilon_t = (\phi^{-1}(u_{1,t}), \ldots, \phi^{-1}(u_{p,t}))$, which ϕ^{-1} is the inverse univariate standard normal distribution. For the Student-t Copula, it defined analogously as: $\epsilon_t = (t_d^{-1}(u_{1,t}), \ldots, t_d^{-1}(u_{p,t}))$, which t_d^{-1} is the inverse student's t distribution with d degrees of freedom. Both likelihood R denotes the correlation matrix of $\in_t$.

The DCC(1.1) model of Engle(2002)was defined that the degree of freedom parameter is static for the Student-t Copula and the correlation R_t evolves through time.

$$Q_t = (1 - \alpha - \beta) \cdot \bar{Q} + \alpha\epsilon_{t-1} \cdot \epsilon_{t-1}' + \beta \cdot Q_{t-1} \quad (18)$$

$$R_t = \tilde{Q}_t^{-1} Q_t \tilde{Q}_t^{-1} \quad (19)$$

Where: $\overline{\mathrm{Q}}$ is sample covariance of $\in_t$, $\widetilde{\mathrm{Q}}_t$ is a square p×p matrix with zeros as off-diagonal elements and diagonal element the square root of those of Q_t. The parameter constraints for the DCC are the same as for the univariate GARCH (1,1) models.

$$\alpha + \beta < 1, \alpha, \beta \in (0,1) \tag{20}$$

3.3.3 Archimedean copula

In general, the Copulas of Gumbel and Clayton are commonly employed in the financial studies. Because the Gumbel copula is limited to the description of a positive dependence structure, this paper will use the Clayton copula, which possesses similar properties with the Gumbel copula, but it does not have a positive dependence restriction. The log likelihood of Clayton Copula is given by:

$$\mathcal{L}_{Clayton}(d; u_t) = \sum_{t=1}^{T} \log((1+d)(u_{1t} \cdot u_{2t})^{-1-d}(u_{1t}^{-t} + u_{2t}^{-t} - 1)^{-2-\frac{1}{d}}) \tag{21}$$

With $\mathrm{d} = \frac{2\mathcal{T}}{1-\mathcal{T}}$, where $\mathcal{T}$ is the Kendall's tau and $\mathrm{u}_t = (\mathrm{u}_{1t} \cdot \mathrm{u}_{2t})$.

The equation for the Clayton Copula in Patton (2006) defined the evolution of dependency parameter as following:

$$\mathcal{T}_t = \Lambda(w + \beta\mathcal{T}_{t-1} + \alpha \cdot |u_{1,t-i} - u_{2,t-i}|) \tag{22}$$

Where: Λ denotees the logistic transformation: $\Lambda(\mathrm{x}) = (1 + \mathrm{e}^{-\mathrm{x}})^{-1}$ in order to keep the parameters of Clayton copula in (0,1).

For the multivariate Copula model, it should be defined the model that when it is be fitted to a multivariate (p>2) data set that consist of iid uniform U(0,1) margins. Therefore, a filtration of the data set often through a GARCH model will extract the iid residuals from the raw data and transform them to uniform. The multivariate Copula is the decomposition to a product of bivariate Copula in a form of a nested set of p-1 trees. The first tree consists of p-1 bivariate Copula and the second tree consists of p-2 Copula and so on. The corresponding multivariate Copula log likelihood is the sum of these (p(P-1))/2 bivariate log likelihoods. This paper wi follow the suggestion from Aas et al., (2009) that one should estimate the copula parameters with the multi step method first and then use these estimates as starting values for the one step method. The multivariate Copula tree is written as following:

$C(F(X_1),\ldots, F(X_5))=$

$C_{12} \cdot C_{13} \cdot C_{14} \cdot C_{15}$ Tree1

$C_{23|1} \cdot C_{24|1} \cdot C_{25|1}$ Tree2

$C_{35|12} \cdot C_{34|12}$ Tree3

$C_{45|123}$ Tree4

(23)

For parameter estimation method, it uses the inference functions for margins (IFM) or calls two-stage estimation method to estimate parameter of copula-based GARCH modes. Joe (1997) showed that this estimator was closed to the maximum likelihood estimator and asymptotic efficiency to it. Therefore, the IFM will employ to compute the estimator efficiently without losing the realist information.

Let Θ_{p} be the parameter of marginal distribution of price, Θ_{v} be the parameters of marginal distributions of four variables, which are Oil, Dollar, TempD and Rain, separately, and Θ_{c} be the parameters be the parameters in the Copula function C_{t} .

The likelihood function of $\Theta = (\Theta_{\mathrm{p}}\ , \Theta_{\mathrm{v}}, \Theta_{\mathrm{v}})$ is as following:

$$L_{p,v}(\Theta) = L_p\left(\Theta_p\ \right) + L_v(\Theta_v) + L_c(\Theta_c) \quad (24)$$

For the first stage, it will estimate the parameter of marginal distributions by the maximum likelihood method, separately,

$$\widehat{\Theta}_p \equiv \arg\max \textstyle\sum_{t=1}^{T} log g_{p,t}(r_{p,t}|\Psi_{t-1}; \Theta_p\ ) \quad (25)$$

$$\widehat{\Theta}_v \equiv \arg\max \textstyle\sum_{t=1}^{T} log g_{v,t}(r_{v,t}|\Psi_{t-1}; \Theta_v\ ) \quad (26)$$

For the second stage, given the marginal estimates obtained above, the dependence parameters are estimated by

$$\widehat{\Theta}_c \equiv \arg\max \textstyle\sum_{t=1}^{T} log C_t(u_{p,t}, u_{v,t}, \widehat{\Theta}_p, \widehat{\Theta}_v; \Theta_c) \quad (27)$$

Where: $u_{p,t} = (r_{p,t}|\Psi_{t-1}, \widehat{\Theta}_p)$ and $u_{v,t} = (r_{v,t}|\Psi_{t-1}, \widehat{\Theta}_v)$.

4. Empirical Results

For the ADF test, the results show that all series data are stationary in Table 2, which the estimated value of θ and the t-statistics of all returns are significantly at the 1% level.

Table 2 ADF Test of Unit Roots in Returns

Returns	Coefficient	t-statistic
AFET	-0.9039	-22.3211
SICOM	-0.8337	-20.7700
TOCOM	-1.1827	-29.5608
Crude	-0.9836	-24.1767
Gas	-1.0711	-26.4310

The Table 3 shows the descriptive statistics of variables of this paper. The standard deviation of AFET is higher than SICOOM, TOCOM, CRUDE and GAS. The skewness of SICOM, TOCOM, CRUDE and GAS are negative, so that they significantly skewed to the left. For the excess kurtosis statistics, all of variables in this paper are positive, thereby indicating that the distributions of returns have larger, thicker tails than the normal distribution. Similarly, therefore, the assumption of skewed-t is more appropriate in this paper.

Table 3 Summary statistics

	AFET	SICOM	TOCOM	CRUDE	GAS
Mean	0.0007	0.0008	0.0006	0.0003	0.0004
SD	0.0743	0.0163	0.0280	0.0247	0.0236
Skewness	0.2060	-0.5837	-0.6337	-0.1467	-0.0645
Kurtosis	679.9909	9.2110	8.2884	4.6793	4.8328
Max	2.0265	0.0990	0.1439	0.1153	0.1067
Min	-2.0143	-0.0163	-0.1877	-0.1272	-0.1211
JB	30707227.0000	2675.9610	1981.4350	194.7152	226.1842

As mentioned, this paper hopes to analyze the volatility of rubber futures returns in AFET from two different rubber futures market and two kinds of oil futures product in TOCOM using Copula-based GARCH models. Table 4 presents the estimated results for Copula-based GARCH models with feedback trading activities. Panel A shows the parameter estimates of marginal distributions with the GARCH model. The parameters in the mean equation are autocorrelations of returns. The constant components of the autocorrelation ω, are significant for AFET and TOCOM, and non-significant for SICOM, CRUDE, and GAS. In addition, the parameter β is statistically positive and statistically significant for all variables. The asymmetry parameters λ are significant and negative for TOCOM, but non-significant for AFET, SICOM, CRUDE, and GAS, revealing the skew of TOCOM to the left. Panels B and C report the parameter estimates for different Copula functions, namely, Gaussian Copula and Student-t Copula. In terms of the values of AIC and BIC, the Student-t dependence structure has better explanatory ability than the Gaussian dependence structure between AFET and two variables, SICOM and TOCOM, but the Gaussian dependence has better explanatory ability between AFET and the other variables. The result shows that the autoregressive parameter β is significantly positive between AFET and all variables in this paper, implying persistence with regard to the dependence structure between rubber futures returns in AFET and four variables in the paper. β is positive; thus, if the returns in SICOM, TOCOM, CRUDE, or GAS are positive, then the return of AFET will also be positive. On the other hand, β is less than 0.5 between AFET and Gas and higher than 0.9 between AFET and the others. For the multivariate Copula model, all parameters between AFET and other variables are significant, as presented in Table 5.

Table 4 Estimation result of Copula based GARCH models

	AFET	SICOM	TOCOM	GAS	CRUDE
Panel A: Estimation of marginal					
C_0	0.0006*	0.0010***	0.0009	0.0008	0.0007
	(1.7012)	(3.5563)	(1.4709)	(1.6193)	(1.1665)
C_1	0.0044	0.1218***	-0.1814***	-0.0441	-0.0185
	(0.2398)	(4.7667)	(-7.2297)	(-1.4796)	(-0.6478)
ω	0.0000**	0.0000*	0.0000**	0.0000	0.0000*
	(2.1473)	(1.8480)	(2.3198)	(1.5947)	(1.7927)
α	0.3267***	0.1161***	0.0629***	0.0429***	0.0497***
	(8.9666)	(7.3630)	(4.3210)	(3.4918)	(4.2073)
β	0.6733***	0.8839***	0.9137***	0.9469***	0.9387***
	(17.5159)	(53.8789)	(42.7052)	(57.8226)	(57.1815)
υ	5.2562***	4.8990***	6.3875***	10.9274***	11.9330***
	(4.2369)	(8.1505)	(6.5227)	(4.0208)	(3.6536)
λ	-0.0311	-0.0385	-0.1193***	-0.0097	-0.0513*
	(-1.4901)	(-1.6209)	(-3.8965)	(-0.5336)	(-1.7480)
Panel B: Estimation of Gaussian dependence structure for AFET					
α		0.0517**	0.0483	0.0451*	0.0092*
		(2.0182)	(1.5480)	(1.7362)	(1.9521)
β		0.3773	0.9311***	0.4495***	0.9810***
		(0.7122)	(17.9143)	(2.6075)	(93.3557)
ln(L)		608.566	165.645	50.038	63.530
AIC		-1213.1327	-327.2891	-96.0761	-123.0607
BIC		-1202.3672	-316.5236	-85.3106	-112.2953
Panel C: Estimation of student-t dependence structure					
υ		15.5083***	16.0426***	155.4639	196.5094**
		(5.0382)	(3.3401)	(1.3597)	(2.3069)
α		0.0297***	0.0510*	0.0454*	0.0093*
		(2.7793)	(1.6972)	(1.7540)	(1.7275)
β		0.9370***	0.9327***	0.4505***	0.9809***
		(45.5626)	(20.2403)	(2.5750)	(87.3008)
ln(L)		643.316	171.078	50.108	63.329
AIC		- 1280.6328	-336.1566	-94.2170	-120.6583
BIC		-1264.4846	-320.0083	-78.0688	-104.5100
Panel D: Estimation of Clayton dependence structure					
ω		0.4587***	0.2085**	-1.3972**	-2.1924
		(2.8738)	(2.4405)	(-2.1465)	(-0.2894)
α		-0.8867	-1.6588**	-1.0479	-1.0299
		(-1.5052)	(-2.5314)	(-1.2427)	(-0.3321)
β		-0.2362	0.8483***	0.0436	-0.4690
		(-1.0799)	(15.0932)	(0.1174)	(-0.1190)
ln(L)		494.402	129.631	34.481	40.300

AIC	-982.8048	-253.2611	-62.9620	-74.6008
BIC	-966.6565	-237.1128	-46.3138	-58.4525

Notes: * indicates statistical significance at the 10% level; ** indicates statistical significance at the 5% level; *** indicates statistical significance at the 1% level.

Table 5 Estimation result of multivariate Copula based GARCH models

Multivariate Copula model(Claton)	
C_{12}	0.4210***
	(22.7427)
C_{13}	0.1800***
	(9.3480)
C_{14}	0.0644***
	(4.0488)
C_{15}	0.0752***
	(4.5182)
$C_{23\|1}$	0.0735***
	(4.7362)
$C_{24\|1}$	0.0285***
	(2.6734)
$C_{25\|1}$	0.0382***
	(3.0658)
$C_{34\|12}$	0.0655***
	(4.9096)
$C_{35\|12}$	0.0401***
	(2.9831)
$C_{45\|123}$	0.3337***
	(19.7358)
ln(L)	1000.582
AIC	-1981.1640
BIC	-1927.3365

Notes: * indicates statistical significance at the 10% level;
** indicates statistical significance at the 5% level;
*** indicates statistical significance at the 1% level.

5. Concluding Remarks

This paper estimated the conditional volatility, covariance, and correlations volatility of rubber futures using the Copula-based GARCH model. Empirical results showed that the Gaussian dependence has better explanatory ability than the Student-t dependence structure and the persistence pertaining to the dependence structure between rubber futures returns in AFET and rubber futures returns in others (i.e., SICOM and TOCOM). The Student-t dependence has better explanatory ability than the Gaussian dependence structure and the persistence pertaining to the dependence structure between rubber futures returns in AFET and oil futures returns in the others (i.e., crude oil futures returns and gas oil futures returns in TOCOM). The results also imply that the rubber futures returns in AFET will follow the rubber futures returns in

TOCOM, the rubber futures returns in SICOM, the crude oil futures returns in TOCOM, or the gas oil futures returns in TOCOM in the same manner. Higher relationships are observed between AFET and the two other rubber futures markets because they are trading the same product. The price volatility of synthetic rubber is close to the price of crude oil, indicating higher relationships between AFET and CRUDE. The multivariate Copula model demonstrates that all variables discussed in this paper can affect the rubber futures returns in AFET. For the Coefficients not only in the multivariate Copula, but also in the Gaussian dependence and student-t dependence structure in bivariate Copula are positive. It means that the volatility of futures return in AFET follows those four kinds of futures return in SICOM and TOCOM. Because AFET is a new futures market comparing with SICOM and TOCOM, the volatility of futures price in AFET will follow those two futures market.

Agriculture is Thailand's most important sector. Farmers have an essential role in the Thai economy, and they represent a large sector of the population. Thus, the national government should take care of them. Given their low income, farmers may not have enough money to invest in commodity futures markets. After examining the relationship between rubber futures returns and four variables, this paper proposes that the Thai government should contribute to the hedge mutual funds that are invested in rubber futures in AFET following the volatility of rubber futures of TOCOM, the rubber futures of SICOM, the crude oil futures of TOCOM, and the gas oil futures of TOCOM. By doing so, the government can gather the funds from farmers to invest in each commodities futures market. Sufficient funds will enable Thai farmers to better hedge their bets in the futures market.

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บทความที่ 8

Modeling volatility and interdependencies of Thai rubber spot price return with climatic factors, exchange rate and crude oil markets

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Abstract

Thailand is a leading producer and exporter of rubber in the world market. The interdependencies and volatility of Thai rubber price return with climatic factors (precipitation and temperature), exchange rate, and crude oil market returns are determined in this paper. Vector autoregressive moving average process with generalized autoregressive conditional heteroscedasticity (VARMA-GARCH), VARMA with generalized autoregressive conditional heteroscedasticity (VARMA-AGARCH), and copula-based GARCH models were employed for the analyses. The results demonstrated the interdependencies of Thai rubber price return with dollar and crude oil returns as well as with crude oil return and climatic factors in the VARMA-AGARCH and the *copula-based GARCH models,* respectively*. We conclude that the volatility of Thai rubber price return is linked with volatility in the exchange rate and crude oil markets as well as climatic factors. Thus, stakeholders in the rubber industry should consider movements in those markets when forecasting Thai rubber price returns. Using a set of robust approaches is also recommended to obtain a complete picture of the volatilities and interdependencies of the asset markets.*

Keywords: Thai rubber spot price return, climatic factors, crude oil index return, dollar index return, VARMA-GARCH, VARMA-AGARCH model, Copula-based GARCH model.

1. Introduction

The rubber industry is one of the most important industries in Thailand. The total area occupied by the industry devoted to rubber is 219,933 hectares; in 2007, the industry also recorded an annual output of 3.056 million tons in 2007 (Office of the Rubber Replanting Aid Fund, 2008). Apart from Thailand, Malaysia and Indonesia are also considered major producers and exporters of rubber. The total rubber output of these three countries reached 8.32 million tons in 2007, accounting for 94% of the total world market (Office of the Rubber Replanting Aid Fund, 2008).

Rubber trees thrive in tropical climates with high temperature (e.g., 26 °C to 32 °C) and rainfall with average precipitation of 2000 mm or more. In the Southeast Asian region, rubber output varies according to the season: (a) output reduction is highest during the high dry period (February to April); (b) highest output is achievable during the monsoon period (May to June), (c) output is reduced to some extent during the mild dry period (August to October), and (d) an increase in output occurs during the high monsoon period (November to January).

Recently, crude rubber output has increased due to the assistance program launched by the Thai government, which aimed to provide better options and varieties to farmers. Heavy monsoon in Thailand normally causes an annual increase in rubber output during the third and the fourth quarters, particularly in the southern regions that comprise the largest area of domestic rubber production. During the same period, rubber prices tend to decline due to the increase in supply.

In December 2008, the domestic price of rubber fell rapidly to only 43 baht per kg in 20 days. Originally, the purchase price of fresh rubber and the production cost were 70 baht and about 27 baht per kg, respectively. Thus, the total production cost of each kilogram of processed rubber should have been almost 97 baht. These figures indicated that farmers suffered a maximum loss of about 54 baht per kg of processed rubber.

Meanwhile, due to the economic recession in the USA, the Cooperative of the Thailand Rubber Farmers urged exporters to focus on China as a potential market for exporting rubber. The Thai Ministry of Agriculture also intervened by extending the repayment duration of rubber loans. When rubber prices fall, most farmers abandon rubber planting and begin planting other crops. Thus, the Rubber Association of Thailand stopped rubber production for six months to allow rubber prices to rise again. The boom in synthetic rubber likewise caused an increasing number of rubber gardens in Thailand to disappear over the past decade.

Given the aforementioned scenario, accurately forecasting the future prices of Thai rubber can safeguard farmers and maintain the competitiveness of Thailand's important export item. Given that rubber is an important industrial product, price fluctuations may be attributable to fluctuations in its production as well as in price fluctuations in this era of globalization. Specifically, industrial commodities traded in the world market are not immune from other important market indices, particularly exchange market and crude oil market returns. Furthermore, climatic conditions in the producing country may play an important role in rubber price fluctuations. Such fluctuations cannot take place in isolation.

With this background, the current study used three robust methods to examine the relationships of Thai rubber price volatility with climatic factors (e.g., precipitation and temperature), the US dollar exchange market, and the crude oil market. The models applied included the copula-Based generalized autoregressive conditional heteroscedasticity (GARCH), vector autoregressive moving average with GARCH (VARMA-GARCH), and VARMA with asymmetric AGARCH (VARMA-AGARCH) models.

The paper is organized as follows. Section 2 reviews relevant literature on modeling volatility in markets. Section 3 presents the methodology and the data. Section 4 presents the estimated results. Section 5 presents the conclusion.

2. Review of the literature

Measuring volatility is most common in the financial market, where researchers examine interrelationships among different stock markets, because movements in prices in these markets are not immune from each other due to the globalized nature of trading. For example, Eun and Shim (1989) report that the stock market in the USA is the main source of international transmission of volatility that can, in turn, affect foreign stock markets. However, foreign stock market variations cannot explain variations within the US stock market, implying a unidirectional effect. Theodossiou and Lee (1993) prove that the US stock market has positive transmission effects on stock markets in the UK, Germany, Canada, and Japan. Kearney (2000) also notes that the variation in most stock markets in the world is derived from stock market variations in the USA and Japan, which are then transferred to Europe. Kasih (2001) argues that whether long-term or short-term, the stock markets in the USA, UK, and Japan are the leaders in the world, accounting for 75% of the total global capital traded.

With respect to volatility in the exchange rate market, Hooper and Kohangen (1978) note that changes in the margin of the exchange rate changes give way to changes in the relative price of the international product. DeGrauwe (1988), meanwhile, notes that the exchange rate risk produces substitution and income effects on the product markets, that is, exports tend to increase if the margin of exchange rate change is volatile. Doroodian (1999) concludes that fluctuation in exchange rates exert overall negative effects in international trade for developing countries.

Few studies also illustrate the importance of adaptation to climatic factors (e.g., Kaiser et al., 1993; Mendelsohn et al., 1994) to explain volatility in product markets. For example, Kaiser et al. (1993) simulate the effect of climatic factors on product market. However, their model is based on selecting an individual representative farm and simulating its returns without considering aggregation or the market-level impact of adaptation to climate change. Mendelsohn et al. (1994) examine changes in land values as well as farmers' revenues using county-level data that incorporate adaptations to climate, as reflected in current production practices. Although their study demonstrates the nature of adaptations to climatic variables, the results do not address potential changes in prices.

The aforementioned studies used simple regression frameworks to examine volatilities in the markets and/or climate change. However, they did not analyze the interdependencies of volatilities across different markets or assets nor accommodate the asymmetric behavior of these markets.

In order to incorporate interdependencies of volatilities across different markets or assets, Ling and McAleer (2003) proposed a VARMA specification of the conditional mean and the following GARCH specification for the conditional variance:

$$\phi(\mathrm{L})(\mathrm{Y_t} - \mu) = \Psi(\mathrm{L})\varepsilon_\mathrm{t} \tag{1}$$

$$\varepsilon_t = D_t \eta_t \tag{2}$$

$$H_t = \omega + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} \beta_l H_{t-l} \tag{3}$$

where $\mathrm{H_t} = (\mathrm{h_{1t}}, \dots, \mathrm{h_{mt}})'$, $\mathrm{D_t} = \mathrm{diag}(\mathrm{h_{i,t}^{1/2}})$, $\phi(L) = I_m - \phi_1 L - \cdots - \phi_P L^P$, $\Psi(L) = I_m - \Psi_1 L - \cdots - \Psi_q L^q$ are polynomials in L, $\eta_\mathrm{t} = (\eta_{1\mathrm{t}}, \dots, \eta_{\mathrm{mt}})'$, $\vec{\varepsilon}_\mathrm{t} = (\varepsilon_{1\mathrm{t}}^2, \dots, \varepsilon_{\mathrm{mt}}^2)'$,and ω $\mathrm{A_k}$ for l=1,…,r and β_l for l=1,…,s are $\mathrm{m} \times \mathrm{m}$ matrices, and represent the ARCH and GARCH effects, respectively. Spillover effects are given in the conditional volatility for each market or asset in the portfolio, specifically where $A_l$and β_l are not diagonal matrix.

As in the univariate GARCH model, VARMA-GARCH model assumes that positive and negative shocks of equal magnitude have identical impacts on the conditional variance. In order to separate the asymmetric impacts of the positive and negative shocks, McAleer et al., (2009) proposed the VARMA-AGARCH specification for the conditional variance:

$$H_t = \omega + \sum_{l=1}^{r} A_k \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I(\eta_{t-l}) \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} \beta_l H_{t-l} \tag{4}$$

Where C_l are $m \times m$ matrices for l=1,…,r and $I_t = diag(I_{1t}, \dots, I_{mt})$, so that

$$I = \begin{cases} 0, \varepsilon_{k,t} > 0 \\ 1, \varepsilon_{k,t} \le 0 \end{cases} \tag{5}$$

where if m=1, it reduces to the asymmetric univariate GARCH or GJR. If $C_l = 0$ for all l it reduces to VARMA-GARCH. If $C_l = 0$ for all l, with $A_l$and β_l being diagonal metrices for all l and 1, then VARMA-AGARCH reduces to constant conditional correlation (CCC) model.

Nianussornkul et al. (2009a) note that the application of the VARMA-GARCH and VARMA-AGARCH models shows significant volatility spillovers from one market to another. They showed significant volatility spillover effects from the Singapore market to other markets, and demonstrated that hedging or speculation in other markets should be considered when the volatility in the Singapore bond market is changing. They also showed that as in the case of the univariate model, asymmetry in the VARMA-AGARCH model also exists for the Indonesian and Philippine bonds; thus, the asymmetric model estimation is superior to its symmetric counterpart for these two countries. Similarly, Ninanussornkul et al. (2009b) use four models to examine volatilities in the crude oil and precious metals markets (i.e., gold and silver). The results of asymmetric effects are significant in Brent and gold markets in the GJR and EGARCH (exponential GARCH) models, indicating that positive and negative shocks with equal magnitude have different impacts on conditional volatility. also use rolling windows to examine the time-varying conditional correlations of standardized shocks using VARMA-GARCH and VARMA-AGRACH models. Their results suggested that the assumption of constant conditional correlations is too restrictive and that the correlations of all pairs of assets are clearly time-varying, especially after 2002 (Ninanussornkul et al., 2009b).

Chang et al. (2009 and 2010) use constant conditional correlation (CCC), dynamic conditional correlation (DCC), VARMA-GARCH, and VARMA-AGARCH in different oil markets. Their estimates of volatility spillovers and asymmetric effects for negative and positive shocks on conditional variance suggested that VARMA-GARCH is superior to the VARMA-AGARCH model, and that VARMA-AGARCH is more suitable for examining only positive shocks on the conditional variances.

From the above literature review we can see that VARMA-AGARCH performs better than VARMA-GARCH models in forecasting volatilities across different markets or assets.

Finally, various studies apply copula methods to analyze correlations across markets and financial assets. Roncalli (2001) proposes a portfolio, which includes five financial assets in the London Metal Exchange. He used Gaussian copula and Student's copula to analyze the correlation between financial assets demonstrating significant difference in correlation coefficients. Hu (2002) uses the copula model to analyze the correlation between stock market and bond market, noting that the correlation is better in a bear market than in a bull market. Bartram et al. (2004) applies the Gaussian copula function to the GJR-GARCH-t model to estimate the correction effect of lead in Euro currency among the stock markets of 17 European countries. They proved that the correlation increased only in large-scale capital markets, namely, those of France, Germany, Italy, the Netherlands and Spain, after a change in common customs tariff. Patton (2006), meanwhile, uses the copula function to build a bivariate copula model between the exchange rate of German mark and Japanese yen, then compared it with the Baba-Engle-Kraft-Kroner (BEKK) model. The result shows that the copula model can better explain the correlation between financial markets than the BEKK. They concluded that when the exchange rate of German mark and Japanese yen depreciates, the correlation becomes higher than when exchange rates appreciate.

Meng et al. (2004) examine the relationships of the futures markets, such as the soybean futures market in Dalian, USA and Japan, using the dollar/yen exchange rate as an example. Their results suggest that there is a strong dependence between different futures markets.

The aforementioned studies make it clear that the volatility of a specific asset in a market, in relation to other markets, must be examined because there is always evidence of dependencies in the movement of different markets affecting each other either positively or negatively. Hence, our modeling framework for the current study attempts to incorporate the interdependencies of Thai rubber price returns with other important markets (i.e., US dollar exchange rate and crude oil market) as well as climatic factors (i.e., precipitation and temperature).

3. Methodology

3.1 Data variables and selection criteria

Natural rubbers are classified into five levels (from RSS1 to RSS5). Although the highest level is RSS1, the main one is RSS3, which is traded in the spot and futures markets in the world. Thai natural rubber has been traded in the Agricultural Futures Exchange of Thailand (AFET) since May 28, 2004.

Given that Thailand trade depends highly on the USA and Japan, the exchange rate of Thai baht is a crucial factor. Other uncontrollable elements, such as tsunamis, floods and political environments, also have a direct effect on the exchange. Therefore, the US dollar/Thai baht index was chosen as the first variable.

The second variable chosen was the crude oil price. Two kinds of crude oil are traded in the futures market in Asia; these are traded exclusively by the Tokyo Commodity Exchange (TOCOM).

This study used daily data from May 28, 2004 to Dec 31, 2010, i.e., a total of 1,581 observations to match the first trading day of AFET for Thai rubber. This study aims to determine the relationships among exchange rate, crude oil, and Thai rubber. Therefore, crude oil traded in TOCOM was selected.

Finally, the growth in rubber output is closely related to seasonality. Due to the fact that temperature and precipitation are important factors in natural rubber output (as mentioned in the introduction), the variables representing the production environment of rubber were included. Thus, climatic data from 25 locations with high rubber outputs were chosen.

The complete set of variables assumed to be related to volatility in Thai rubber prices used in the study is presented in Table 1.

Table 1. Variables used in the study

Variables	Unit	Names
Rubber price	Baht	Export Price of Thai natural rubber
US dollar	Index number	US dollar index at close – Trade weighted
Crude oil	Index number	Crude oil index in TOCOM
TempD	Celcius	Difference between todays temperature from yesterday, 1581 observations, which is made up of average temperatures by top 25 rubber producing areas in Thailand. These are: Burirum, Chanthaburi, Chon buri, Chumphon, Krabi, Nakhon Thammarat, Narathiwat, Nong Khai, Pattani, Phangnga, Phattaluang, Phetchabun, Phitsanulok, Ranong, Rayong, Sakon Nakhon, Satun, Si Sa Ket, Songkhla, Surat Thani, Trad, Trang, Udon Ratchathuni, Udon Thani and Yalain.
Rainfall	mm	Average precipitation per day, 1581 observations, where the average precipitation is from the top 25 rubber producing areas named above.

3.2 Stationarity and summary statistics of the variables

The returns of asset i, which are price, dollar and oil at time t are calculated as follows:

$$R_{i,t} = \log(\frac{P_{i,t}}{P_{i,t-1}}) \tag{6}$$

were $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and t-1, separately.

The stationarity of all data series are tested by using the Augmented Dickey-Fuller (ADF) test, which is given by:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{P} \emptyset \Delta y_{t-1} + \varepsilon_t \tag{7}$$

For temperature, we used the difference of average temperature in this study, which is given by:

TempD= Temp – Temp(-1) (8)

The null hypothesis is $\theta = 0$ which, if not rejected, means that the series y_t is not stationary. The results shows that all series data are stationary in Table 2, as the estimated value of θ of all the returns are significantly less than zero at the 1% level.

Table 2: ADF Test of Unit Roots

Variables	Coefficient	t-statistic
Rubber price	-0.6285	-16.2503
US dollar	-1.0700	-25.7667
Crude Oil	-1.0224	-24.5450
TempD	-1.0109	-24.2884
Rainfall	-0.4068	-8.6020

Table 3 shows the descriptive statistics of the variables. The standard deviation of rubber price return is higher than those of the oil index and dollar index returns. The skewness of Price, Dollar, Oil, and TempD are negative, so they are significantly skewed to the left. For the excess kurtosis statistics, all of the variables in this study are positive, indicating that the distribution of returns has larger, thicker tails than the normal distribution. Therefore, the assumption of skewed-t is more appropriate in this study.

Table 3: Summary statistics of the volatility of the data

	Rubber price	US dollar	Crude oil	TempD	Rainfall
Mean	0.0006	-7.02E-05	0.0003	-0.0033	5.9165
SD	0.0133	0.0057	0.0251	0.6099	6.1759
Skewness	-1.0245	-0.0815	-0.1803	-0.1234	2.7080
Kurtosis	22.4839	5.1712	4.8619	7.3715	21.0084
Max	0.1238	0.0252	0.1153	3.3212	72.4000
Min	-0.1414	-0.0306	-0.1272	-2.7960	0.0000
JB	25284.2300	312.3000	236.9238	464.0900	23310.3400

Note: For Rubber price, US dollar, and Crude oil, the data type is the volatility data. It measures the differences in the indices between today and yesterday. The values for each observation could be either +ve or –ve. Overall, the mean of these variables are close to 0. The data of TempD is close to 0 because it is the difference between today's average temperature from yesterday.

3.3 Econometric models

3.3.1 VARMA-GARCH model

We apply VARMA-GARCH model to analyze the data proposed by Ling and McAleer (2003) and VARMA-AGARCH model proposed by McAleer et al., (2009). The effect of fluctuation cannot be distinguished individually very clearly in the traditional multivariate GARCH model.

The VARMA-GARCH model is expressed as:

$$Y_t = E(Y_t|F_{t-1}) + \varepsilon_t \tag{9}$$

$$\varepsilon_t = D_t \eta_t \tag{10}$$

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{11}$$

And VARMA-AGARCH model is in following:

$$H_t = \omega \quad + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j} + \sum_{j=1}^{r} C_{ij} I_{ij} \varepsilon_{i,t-j} + \sum_{j=1}^{s} \beta_{ij} H_{i,t-j} \tag{12}$$

Where $H_t = (h_{1t}, h_{2t}, \dots, h_{mt})$, $\eta_t = (\eta_{1t}, \eta_{2t}, \dots, \eta_{mt})$, $D_t = \mathrm{diag}\left(h_{1t}^{1/2}, h_{2t}^{1/2}, \dots, h_{mt}^{1/2}\right)$

For this study, the full model is in following:

$$A_t = \gamma_{A0} + \gamma_{A1} A_{t-1} + \gamma_{A2} B_{t-1} + \gamma_{A3} C_{t-1} + \gamma_{A4} D_{t-1} + \gamma_{A5} E_{t-1} + \varepsilon_{A,t} \tag{13}$$

$$\begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{E.t} \end{bmatrix} |\Omega_{t-1} \sim N(0, H_t) \quad (14)$$

Where A is the export price of natural rubber in Thailand, B is the futures price of crude oil in TOCOM, C is the dollar index, D is the difference of average temperature with yesterday, E is the average precipitation and ε is error term.

We use normal distribution and MLE (Maximization Likelihood Estimation) procedure to estimate the parameters of this model.

$$\hat{\theta} = argmin \frac{1}{2} \sum_{t=1}^{n} (log|Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t) \quad (15)$$

Where θ is the vector of parameters to be estimated on the conditional log-likelihood function, and $|Q_t|$ is the determinant of Q_t, the conditional covariance matrix.

3.3.2 GARCH model

Bollerslev (1986) proposed the GARCH model which put conditional variance of lags in to ARCH model and make it general. The GARCH model is given by:

$$R_t = \mu_{t-1} + \varepsilon_t \quad (16)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \quad (17)$$

$$H_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (18)$$

When $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$, the GARCH model is stable. GARCH (p,q) model can be describes as follows:

$$R_t = \mu_{t-1} + \varepsilon_t \quad (19)$$

$$E_t | \Omega_{t-1} \sim N(0, h_t) \quad (20)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-1} \quad (21)$$

Where i=1,2,…,q, J=1,2,…,p, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$.

In this model, μ_{t-1} is the conditional mean of R_t at time t, ht is the conditional variance and Ω_{t-1} is the all useful information set at time t-1.

The GARCH (1,1) model can be described as follows:

$$r_{i,t} = c_0 + c_1 r_{i,t-1} + e_{i,t}, e_{i,t} | \Psi_{t-1} = h_{i,t}, z_{i,t}, z_{i,t} \sim skewed - t(z_i | \eta_i, \lambda_i) \quad (22)$$

$$e_{i,t} \sim N(0, h_{i,t}^2) \quad (23)$$

$$h_{i,t}^2 = \omega_{i,t} + \alpha e_{i,t-1}^2 + \beta h_{i,t-1} \quad (24)$$

Where $\omega_{i,t}$>0 , $\alpha, \beta \geq 0$ and , $\alpha + \beta < 1$.

The error term $e_{i,t}$ is assumed to be skewed-t distribution which can be used to describe the possibly asymmetric and heavy tail characteristics of each variable.

Following Hansen (1994), the density function is

$$skewed - t(z | \eta, \lambda) = \begin{cases} BC\left(1 + \frac{1}{\eta - 2}\left(\frac{Bz + A}{1 - \lambda}\right)^2\right)^{-(\eta+1)/2} & , z < -\frac{A}{B} \\ BC\left(1 + \frac{1}{\eta - 2}\left(\frac{Bz + A}{1 - \lambda}\right)^2\right)^{-(\eta+1)/2} & , z \geq -\frac{A}{B} \end{cases} \quad (25)$$

The value of A, B and C are defined in following:

$$\mathrm{A} \equiv 4\lambda C\frac{\eta-2}{\eta-1}\text{ , } B \equiv 1+2\lambda^2-A^2 \text{ and } C \equiv \frac{\Gamma(\eta+1/2)}{\sqrt{\pi(\eta-2)\Gamma(\eta/2)}} \tag{26}$$

Where λ and η are the asymmetry and kurtosis parameters, separately. Those are restricted to be -1< λ <1 and 2< η<∞. When $\lambda = 0$, it will turn to the Student –t distribution. If $\lambda = 0$ and η diverge to infinite, it will be the normal distribution.

3.3.3 Elliptical Copula

The copula function is used in discussing problems between many variables, and is also called the dependence function (Deheuvels, 1978). Sklar (1959) advances the copula theory, pointing out that one unit distribution can be analyzed to *n* marginal distribution and one copula function. Given that the number of parameters can be large, two-step methods are generally employed. Thus, in this paper, the marginal parameters were first estimated by optimizing the marginal log likelihoods independently of each other. Second, the copula parameters were estimated by optimizing the corresponding copula log likelihood at the second step.

The marginal log likelihoods function:

$$m\mathcal{L}(\theta; x) = \sum_{i=1}^{P}\sum_{j=1}^{T}\log(F_i(x_{1,t};\emptyset_i)) \tag{27}$$

The copula log-likelihood function:

$$c\mathcal{L}(\theta; u, \emptyset) = \log(c(F_1(x_{1,t}),\dots,F_p(x_{p,t});\theta) \tag{28}$$

Therefore, the log likelihoods of two elliptical copula, the Gaussian and Student-t copula are given by:

$$\mathcal{L}_G(R;u_t) = -\frac{1}{2}\sum_{t=1}^{T}(log|R| + \epsilon_t'(R^{-1}-I)\epsilon^t) \tag{29}$$

$$\mathcal{L}_{St}(R,d,u_t) =$$

$$-T\log\frac{\Gamma(\frac{d+p}{2})}{\Gamma(\frac{d}{2})} - pTlog\frac{\Gamma(\frac{d+1}{2})}{\Gamma(\frac{d}{2})} - \frac{\mathrm{d+p}}{2}\sum_{\mathrm{t=1}}^{\mathrm{T}}\log\left(1+\frac{\epsilon_\mathrm{t}'\mathrm{R}^{-1}\epsilon^\mathrm{t}}{\mathrm{d}}\right) - \sum_{\mathrm{t=1}}^{\mathrm{T}}\log|\mathrm{R}| +$$

$$\frac{\mathrm{d+1}}{2}\sum_{\mathrm{t=1}}^{\mathrm{P}}\sum_{\mathrm{t=1}}^{\mathrm{T}}\log(1+\frac{\epsilon_{\mathrm{it}}^2}{\mathrm{d}}) \tag{30}$$

where the vector ϵ_t is the vector of the transformed standardized residuals which depends on the copula specification. For the Gaussian copula, the vector $\in_t$ is defined as: $\epsilon_t = (\phi^{-1}(u_{1,t}),\dots,\phi^{-1}(u_{p,t})$), which ϕ^{-1} is the inverse univariate standard normal distribution. For the Student-t copula, it defined analogously as: $\epsilon_t = (t_d^{-1}(u_{1,t}),\dots,t_d^{-1}(u_{p,t}))$, which t_d^{-1} is the inverse student's t distribution with d degrees of freedom. In both of likelihoods R denotes the correlation matrix of $\in_t$.

The DCC (1.1) model of Engle (2002) defined that the degree of freedom parameter is static for the Student-t copula and the correlation R^t evolves through time.

$$Q_t = (1-\alpha-\beta)\cdot\bar{Q} + \alpha\epsilon_{t-1}\cdot\epsilon_{t-1}' + \beta\cdot Q_{t-1} \tag{31}$$

$$R_t = \tilde{Q}_t^{-1}Q_t\tilde{Q}_t^{-1} \tag{32}$$

Where $\overline{\mathrm{Q}}$ is sample covariance of $\in_t$, $\widetilde{\mathrm{Q}}_t$ is a square p×p matrix with zeros as off-diagonal elements and diagonal element the square root of those of Q_t. The parameter constraints for the DCC are the same as for the univariate GARCH (1,1) models.

$$\alpha + \beta < 1, \alpha, \beta \in (0,1) \quad (33)$$

4. Empirical results

The analysis of the volatility of rubber price return in relation to the volatility of oil index and dollar index returns, as well as average temperature and average precipitation, was undertaken using the VARMA-GARCH and VARMA-AGARCH models. Time-varying volatility was estimated and the asymmetric effects of positive and negative shocks of equal magnitude and volatility spillovers were tested using these models. The results of the VARMA-GARCH and VARMA-AGARCH are presented in Table 4, and the number of volatility spillovers and asymmetric effects are summarized in Table 5. Table 4 shows that three variables have spillovers to the volatility of rubber price return in the VARMA-GARCH model, including volatility of oil index return and volatility of dollar index return. For the VARMA-AGARCH model, only the volatility of dollar return has spillover effects on the volatility of rubber price. Table 5 shows that the volatility spillovers are not evident in the VARMA-AGARCH model. Therefore, we can conclude that VARMA-GARCH is superior to VARMA-AGARCH in examining the volatility of rubber price return.

Table 4: Estimates of VARMA-GARCH(1,1) and VARMA-AGARCH(1,1)

Returns of rubber price	ω	α_{price}	α_{oil}	α_{dollar}	α_{tempD}	α_{rain}	Γ
VARMA-	0.0000***	0.1076***	0.0100**	-0.1699***	-0.0000***	0.0000	
GARCH	14.1663	4.3565	2.6135	-3.0683	-96.8093	1.1277	
VARMA-	0.0000***	0.1847***	0.0099***	-0.1090**	-0.0000***	-0.0000	-0.1031
AGARCH	6.0904	3.2536	3.1778	-2.3871	-16.9753	-0.0917	1.2004

Table 4. (Continued)

Returns of rubber price	β_{price}	β_{oil}	β_{dollar}	β_{tempD}	β_{rain}
VARMA-	0.8570***	-0.0055	0.4064***	6.88E-07	-0.0000
GARCH	39.5998	-0.7693	3.1504	0.3306	-0.0923
VARMA-	0.8610***	-0.0122**	0.2412**	2.59E-06	-0.0000
AGARCH	40.2522	-2.1605	2.3945	1.6428	-0.1999

Notes: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge (1992) robust t-ratios.

(2) * indicates statistical significance at the 10% level; ** indicates statistical significance at the 5% level *** indicates statistical significance at the 1% level.

Table 5: Summary of Volatility Spillovers and Asymmetric Effects

Returns	Number of volatility spillovers		Asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
Rubber price	1	2	NO

Rolling windows are also used to examine time-varying conditional correlations using the VARMA-GARCH and VARMA-AGARCH models. The rolling window size was set at 1,000 for the dollar index and oil index as shown in Figures 1 and 2, respectively. For the VARMA-GARCH model, the correlations of dollar index and oil index are not constant over time, so the assumption of constant conditional correlations may be too restrictive. However, the changes in the estimated correlations are small. Specifically, the correlation between the volatility of rubber price return and volatility of oil index return is smaller (at around 0.1) than that between volatility of rubber price return and the other three variables. The VARMA-AGARCH model shows similar results to VARMA-GARCH in that the correlations vary over time.

Figure 1: Dynamic Path of Conditional Correlations in VARMA-GARCH model

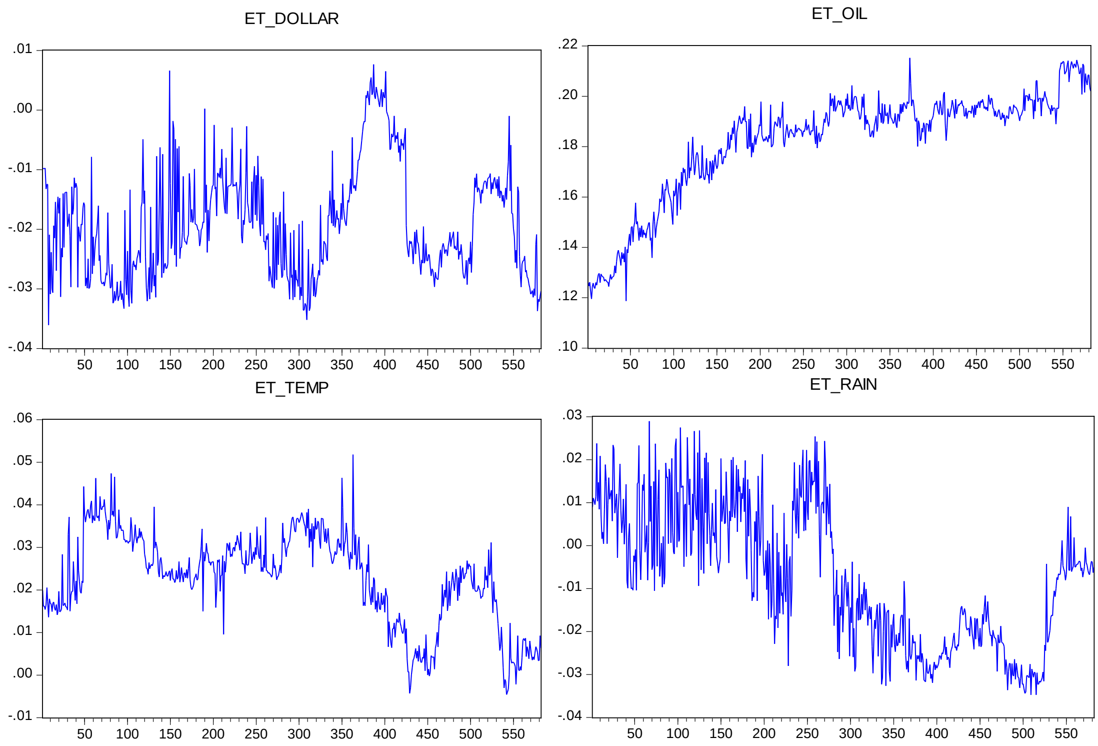

Figure 2: Dynamic Path of Conditional Correlations in VARMA-AGARCH model

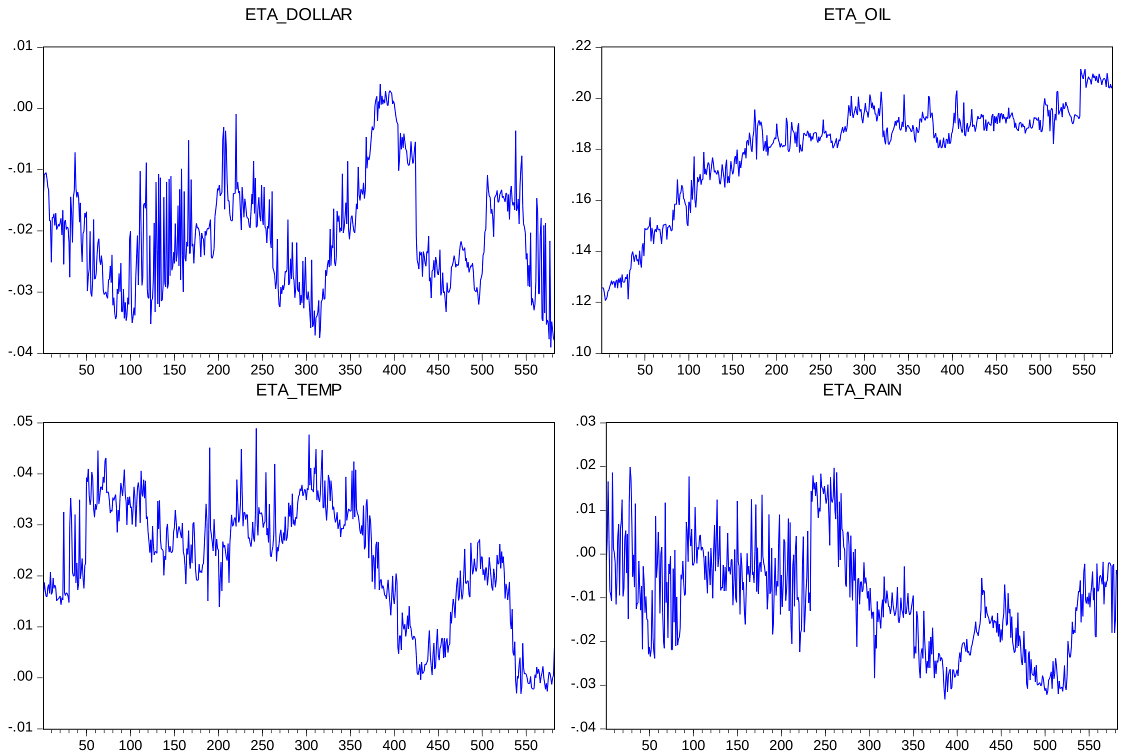

Table 6 presents the estimated result for copula-based GARCH models with feedback trading activities. Panel A shows the parameter estimates of marginal distributions with the GARCH model. The parameters of greatest interest in the mean equation are the autocorrelation of returns. The constant components of the autocorrelation ω are almost non-significant, except rubber price return. In addition, the parameter β is positive and statistically significant for all of the variables in this study. The asymmetry parameters λ is significant and negative for price, but non-significant for dollar, oil and rain, indicating that the rubber price is skewed to the left. Panels B and C present the parameter estimates for different Gaussian and Student-t copula functions. In terms of the values of AIC and BIC, the Student-t dependence structure only exhibits better explanatory power than that of Gaussian dependence between rubber price and temperature; however, Gaussian dependence shows better relation between rubber price and other variables. Moreover, the autoregressive parameter β is not significant between rubber price and dollar index, but is significant between rubber price and other variables, implying the persistence pertaining to the dependence structure between rubber price return with oil index return, temperature, and precipitation.

Table 6: Estimation result of copula based GARCH models

	Price	Dollar	Oil	TempD	Rain
Panel A: Estimation of marginal					
C_0	0.0001	-0.0002	0.0006	0.0235**	0.5000**
	(0.5450)	(-1.6246)	(1.0595)	(2.5059)	(2.1817)
C_1	0.3932***	-0.0322	-0.0302	0.3348***	0.5000***
	(11.7720)	(-1.3327)	(-1.1429)	(10.7974)	(12.0196)
ω	0.0000***	0.0000	0.0000	0.0000	0.0000
	(3.3659)	(1.3483)	(1.3981)	(0.0095)	(0.0001)
α	0.2225***	0.0336***	0.0557***	0.1659***	0.1807***
	(6.2451)	(4.3679)	(2.9826)	(5.6569)	(3.5839)
β	0.7775***	0.9664***	0.9443***	0.8341***	0.8192***
	(19.4185)	(162.7056)	(63.6227)	(23.6985)	(10.7266)
υ	2.8760***	8.4871***	8.6889***	3.2429***	3.3885***
	(21.0916)	(4.5391)	(4.1105)	(19.8588)	(5.0949)
λ	-0.0580**	-0.0276	-0.0504*	0.0408**	0.1602
	(-2.1364)	(-1.0794)	(-1.7154)	(1.9838)	(0.8989)
Panel B: Estimation of Gaussian dependence structure for Price					
α		0.0203	0.0373*	0.0644***	0.0260**
		(0.8943)	(1.6669)	(6.3721)	(2.2771)
β		0.2107	0.7153***	0.8834***	0.8937***
		(0.4645)	(3.4152)	(42.1275)	(17.8009)
ln(L)		0.705	32.052	3190.197	5.099
AIC		2.5907	-60.1044	-6376.3943	-6.1978
BIC		13.3223	-49.3728	-6365.6627	4.5339
Panel C: Estimation of student-t dependence structure for Price					
ω		35.6467	199.4353***	14.9948***	195.8707*
		(0.6129)	(57.1676)	(3.4301)	(1.6967)
α		0.0187	0.0375*	0.0531***	0.0261**
		(0.8354)	(1.6724)	(5.4367)	(2.2998)
β		0.1351	0.7139***	0.9111***	0.8937***
		(0.2289)	(3.4206)	(44.9850)	(17.8794)
ln(L)		1.517	32.021	3202.538	4.951
AIC		2.9652	-58.0420	-6399.0766	-3.9011
BIC		19.0627	-41.9446	-6382.9791	12.1963

Notes: * indicates statistical significance at the 10% level;
** indicates statistical significance at the 5% level;
*** indicates statistical significance at the 1% level.

5. Concluding Remarks

Given that Thailand is the world's top rubber producer and exporter, the sources of price changes must be identified to ensure that the country remains competitive in this market. Both changes in climatic factors as well as volatilities in the exchange rate market and crude oil market are assumed to be related to the fluctuation of Thai rubber price returns. The conditional volatility, covariance, and correlation volatility of rubber price return have been estimated using the VARMA-GARCH and copula-based GARCH models. The VARMA-GARCH model showed that volatility spillovers are evident between the volatility of rubber price return and dollar index return, while the VARMA-AGARCH model showed that the volatility spillovers are evident between the volatility of rubber price return with the volatility of dollar index and oil index returns. The coefficients of the volatility of dollar index return in both models are significant, whereas only the coefficient of the volatility of oil index return in the VARMA-AGARCH model is significant. This indicates that the volatility of dollar index return has a stronger effect on Thai rubber price returns. Furthermore, analysis of the rolling windows shows that the correlation between the volatility of rubber price and volatility of oil index return is smaller than the correlation between the volatility of rubber price and other three variables. The copula-based GARCH model shows that the Gaussian dependence has a better explanatory power than the Student-t dependence structure. Dependencies also exist between rubber price return and oil index return, rubber price return and average temperature, and rubber price return and precipitation.

Based on these results, climatic factors and fluctuations in the exchange rate market and crude oil market have significant effects on Thai rubber price returns in the world market. Therefore, the industry should consider the volatilities in these markets as well as climatic conditions when forecasting the future returns from exporting Thai rubber.

With regards the analysis methods, no single method can provide a complete picture of the dependencies and interrelatedness of the various asset markets. Therefore, a set of robust approaches, as applied here, should be used to obtain a complete picture of the complexities associated with analyses of price volatility. We hope that the results of this study can be used by government agencies, the Thai Rubber Association, farmers, as well as other key stakeholders in the rubber industry.

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บทความที่ 9

Application of Extreme Value copulas to palm oil prices analysis

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Abstract

In this paper we study the tail behavior of the palm oil future markets using the Extreme Value Theory and focusing on the dependence structure between the returns on palm oil future price in three palm oil futures markets, namely Malaysian futures markets (KLSE), Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT) by using the Extreme Value Copulas. The results demonstrated that the returns on palm oil future price among KLSE and SGX-DT have dependence in extreme, whereas the returns on palm oil future price among KLSE and DCE, SGX-DT and DCE do not have any dependence. The results could be beneficial for any person or company wishing to be engaged in the commerce of trading palm oil.

Keywords: Extreme Value Theory, dependence structure, Extreme Value Copulas, Malaysian futures markets, Dalian Commodity Exchange, Singapore Exchange Derivatives Trading Limited, palm oil future price.

1. Introduction

Extreme Value Theory (EVT) is a concept that is concerned with the analysis and modeling of extreme high or low observations. The EVT distributed assumption gives the results for the distribution of the normalized maximum of a high number of observations, or equivalently, the distribution of exceedances of observations over a high threshold (Rakonczai and Tajvidi, 2010). Under EVT assumptions on the underlying distribution of observations, it is often superior to normal distribution in many situations and has been widely used in many fields such as financial, hydrological, insurance and environmental science (Lu et al., 2008). The joint extreme events can have some serious impact on a particular field of study; therefore it needs to be carefully modeled. With a calculation of the probability that there is an observation exceeding a certain benchmark, it requires knowledge of the joint distribution of maximal heights during the forecasting period. This is a typical field of application for EVT (Gudendorf and Segers, 2009).

Copulas method has become rapidly developed and has brought the attention in various fields as a way to overcome the limitations of classical dependence measures as exemplified by the linear correlation. The copulas approach is a statistical tool that is considered as the most general margin-free description of the dependence structure of a multivariate distribution (Segers, 2005). The fact that the theory of multivariate maxima in EVT can be expressed in terms of copulas, its philosophy has been recently acknowledged as a form for application. Copulas is revealed to be a very strong tool in financial risk modeling that deals with different classes of existing risks (Cherubini et al., 2004). Scholars that have implemented the extreme value copulas in their study includes Starica (1999) who had investigated the joint behavior of extreme returns in a foreign exchange rate market, and Lu, Tian and Zhang (2008) who had repeatedly taken up the foreign exchange to analyze the dependence structure between the asset return. The results showed that three copulas are suitable to measure the joint tail risk and tail dependence for markets data. In addition, Longin and Solnik (2001) used EVT to study the dependence structure of international equity markets characterized. An application to the Society of Actuaries medical large claims that the data, in terms of insurance through extreme-value copulas, is the topic of the monograph by Cebrian, Denuit and Lambert (2003)

Palm oil is one of the most important energy-crop in the world (USDA, 2011), its implication as an energy crop is due to being a highly efficient and high yielding source of food and fuel. Palm oil is produced entirely in developing countries. Southeast Asian countries are the largest producing region; palm oil was produced 13.01 million tons in 1992, which increased to 50.26 million tons in 2011, a 286% increase in 19 years (USDA, 2011). Malaysia is one of the world's biggest palm oil producers. The factors involved in setting palm oil prices are quite interesting. According to the relevance of Malaysia's palm oil price to the Chinese and Singapore markets, it is important to examine the relationship between the Malaysian futures markets (KLSE) and two palm oil futures markets, namely Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT). In this paper, we will deal with the tail behavior of the palm oil future markets using the EVT and focusing on the dependence structure between the returns on palm oil future price in three palm oil futures markets, namely KLSE, DCE and SGX-DT by using the extreme value copulas.

The remainder of the paper is organized as followed: Section 2 presents the univariate EVT and Generalized Extreme Value (GEV) distribution, Section 3 reviews the concept of copulas and extreme value copulas. Section 4 explains the data used in the empirical analysis, Section 5 discusses the empirical results, and finally Section 6 offers a conclusion.

2. Univariate EVT and GEV distribution

The main idea of Extreme Value Theory (EVT) is the concept of modeling and measuring extreme events which occur with a very small probability (Brodin and Kluppelberg, 2008). It provides methods for quantifying such events and their consequences statistically. Generally, there are two principal approaches to identifying extremes in real data. The Block Maxima (BM) and Peaks-Over-Threshold (POT) are central for the statistical analysis of maxima or minima and of exceedances over a higher or lower threshold (Lai and Wu, 2007). The BM studies the statistical behavior of the largest or the smallest value in a sequence of independent random variables (Lei and Qiao, 2010; Lei et al., 2011). The POT approach is based on the Generalized Pareto Distribution (GPD) introduced by Pickands (1975) (cited in Lei and Qiao, 2010). These are models for all large observations that exceed a high threshold. In this paper, we will adopt GEV model of the BM method to study the tail behavior of the tail of palm oil futures markets.

let Z_i (i=1,…,n) denote maximum observation in each block. Z_n is normalized to obtain a non-degenerated limiting distribution. The BM is closely associated with the use of Generalized Extreme Value (GEV) distribution with c.d.f:

$$H(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{1}$$

where μ, $\sigma > 0$ and ξ are location, scale and shape parameter respectively. Note that $\xi > 0$ is called Frechet distribution, $\xi < 0$ is called Fisher-Tippet or Weibull distribution and $\xi = 0$ is called Gumble or double-exponential distribution. Under the assumption that Z_1, …, Z_n are independent variables having the GEV distribution, the log-likelihood for the GEV parameters when $\xi \neq 0$ is given by:

$$\ell(\xi, \mu, \sigma) = -n\log \sigma - (1+1/\xi) \sum_{i=1}^{n} \log\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right]^{-1/\xi} \quad (2)$$

provided that $1+\xi\left(\frac{Z_i-\mu}{\sigma}\right) > 0$, for i=1,….,n

The case $\xi = 0$ requires separate treatment using the Gumbel limit of the GEV distribution. The log-likelihood in that case is:

$$\ell(\mu, \sigma) = -n\log \sigma - \sum_{i=1}^{n}\left(\frac{Z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\exp\left\{-\left(\frac{Z_i-\mu}{\sigma}\right)\right\} \quad (3)$$

The maximization of this equation with respect to the parameter vector (μ, σ, ξ) leads to the maximum likelihood estimate with respect to the entire GEV family (see Coles 2001 for detail)

3. Copulas and Extreme Value Copulas

Copulas have become the attention multivariate modeling in various fields. A copula is a function that links together univariate distribution functions to from a multivariate distribution function (Patton, 2007). The relevance of copulas stems from a famous result by Sklar (1959) (cited in Segers, 2005). For simplicity, we confined it to the bivariate case. Let X and Y be the stochastic behavior of two random variables with respective marginal cdf's F(x) and G(y) is appropriately described with joint distribution function

$$H(x,y) = P(X \leq x, Y \leq y) \quad (4)$$

and marginal distribution functions

$$F(x) = P(X \leq x), G(y) = P(Y \leq y) \quad (5)$$

Since F(x) and G(y) are uniformly distributed between 0 and 1, then the joint distribution function C on $[0,1]^2$ for all (x,y) $\in R^2$ such that:

$$H(x,y) = C(F(x), G(y)) \quad (6)$$

where C is called the copula associated with X and Y which couples the joint distribution H with it margins. Equation (6) is equivalent to $H(F^{-1}(u),G^{-1}(v)) = C(u,v)$ as a consequence of the Sklar's Theorem, where u = F(x), v= G(y) are marginal distributions of X,Y. The implication of the Sklar's Theorem is that, after standardizing the effects of margins, the dependence between X and Y is fully described by the copula (Lu, et al, 2008). A comprehensive overview of the copulas properties can referred to the work by Nelsen (1999). In this paper, we combine the copula construction with the extreme value theory.

The extreme value copula family is used to represent the Multivariate Extreme Value Distribution (MEVD) by the uniformly distributed margins. Consider a bivariate sample (X_i,Y_i), i=1,….,n. Denote component-wise maxima by M_n = max(X_1,…,X_n) and N_n = max(Y_1,…,Y_n). The object of interest is the vector of component-wise block maxima: M_c = (M_n, N_n)′. The bivariate extreme distribution H can be connected by an extreme value copula (EV copula) C_o: (Segers, 2005)

$$H(x,y) = C_o(F(x;\mu_1,\sigma_1,\xi_1), G(y;\mu_2,\sigma_2,\xi_2)) \tag{7}$$

Where $\mu_i, \sigma_i \xi_i$ are GEV parameters and F(x) and G(y) are GEV margin. By Sklar's Theorem, the unique copula C_o of H is given by

$$C_o(u^t, v^t) = C_o^t(u,v), t > 0 \tag{8}$$

The EV copula has more family. In this paper, the two family applied are Gumbel and HuslerRiess. (Cited in Lu et al., 2008)

Gumbel copula:

$$C(u,v) = \exp(-[(-\ln u)^r + (-\ln v)^r]^{\frac{1}{r}}) \tag{9}$$

The independence copula is obtained in the limit as r = 1, and complete dependence is obtained in the limit as r = ∞.

HuslerReiss copula:

$$C(u,v) = \exp\left\{ -\tilde{u}\,\Phi\left(\frac{1}{r} + \frac{1}{2} r \ln\left(\frac{\tilde{u}}{\tilde{v}}\right)\right) - \tilde{v}\,\Phi\left(\frac{1}{r} + \frac{1}{2} r \ln\left(\frac{\tilde{v}}{\tilde{u}}\right)\right) \right\} \tag{10}$$

Where $\tilde{u} = -\ln u, \tilde{v} = -\ln v$ and Φ is the standardized normal distribution. The independence copula is obtained in the limit as r = 0, and complete dependence is obtained in the limit as r = ∞. For the estimation of copulas parameters, we used Exact Maximum Likelihood method (EML): the parameters for margins and copula are estimated simultaneously (see Yan 2007 for details).

4. Data

This paper used the times series data from Datastream. We work with daily future prices of palm oil data in three markets, namely the Malaysian future markets (KLSE), Dalian Commodity Exchange (DCE) and Singapore Exchange Derivatives Trading Limited (SGX-DT). We took the daily market prices and converted to a return series. Daily prices are computed as return of market i at time t relatives: $R_{i,t} = \ln(p_{i,t} / p_{i,t-1}) * 100$, where $p_{i,t}$ and $p_{i,t-1}$ are the daily price of futures for days t and t-1, respectively. The study period was from December 2007 till June 2012. We have 1196 observations for each market.

5. Empirical Results

5.1 The parameter estimation of the GEV model

In the GEV model, we focused on the statistical behavior of block maximum data. Therefore, the source data is set of 55 records of monthly maximum in each market.

Table1 presents the estimation of three parameters of GEV model based on the maximum likelihood method. The results show that the standard error estimates are relatively low. It implies that the block size of data is appropriate for the parameter estimation. Figure 1, 2, 3 presents the scattered plot of the monthly maximum return on KLSE, SGX-DT and DCE, respectively.

Table1. The parameter estimation results using the ML method based on GEV model

Market	Parameter estimation	ML Method
KLSE	μ	2.491(0.162)
	σ	1.060(0.135)
	ξ	0.281(0.115)
SGX-DT	μ	2.736(0.186)
	σ	1.249(0.158)
	ξ	0.319(0.099)
DCE	μ	2.827(0.333)
	σ	2.186(0.245)
	ξ	0.035(0.104)

Note: Terms in parentheses are standard errors of parameter estimates.

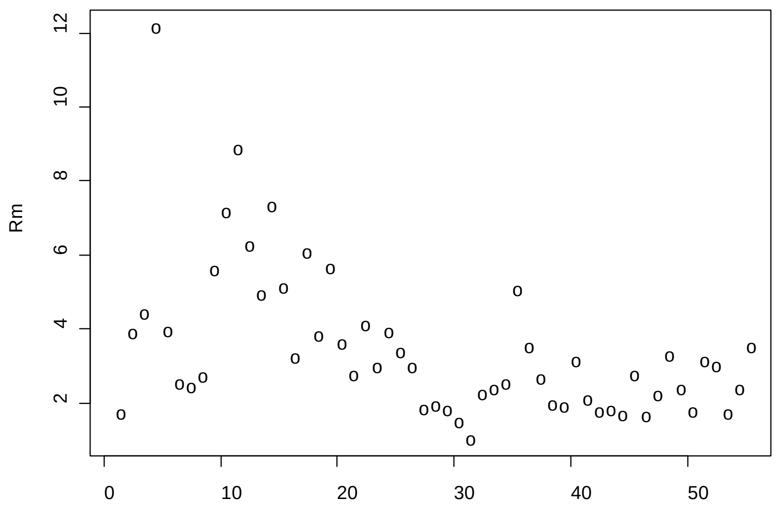

Figure1. The scatter plot of monthly maximum return on KLSE

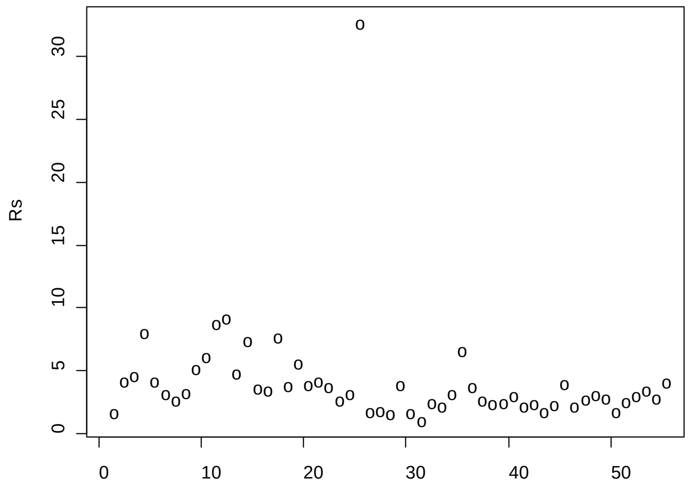

Figure2. The scatter plot of monthly maximum return on SGX-DT

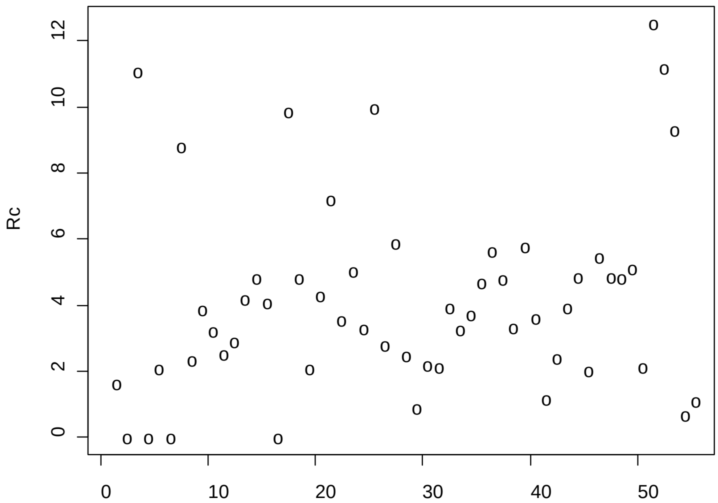

Figure3. The scatter plot of monthly maximum return on DCE

5.2 The parameter estimation of the extreme value copulas.

Table 2. Estimation of copula parameter

Market	Gumbel copula	HuslerReiss copula
KLSE-SGX-DT	3.034(0.473)	2.287(0.414)
KLSE-DCE	0.973(0.084)	0.220(2.721)
SGX-DT-DCE	1.065(0.079)	0.597(0.156)

Note: Terms in parentheses are standard errors of parameter estimates.

Table 2 presents the parameter (r) estimation in the Gumbel and HuslerReiss copula analysis. In the Gumbel copula method, the parameter (r) estimation between KLSE and SGX-DT markets is equal to 3.034, which implies that KLSE and SGX-DT markets have dependence in extreme. Whereas the parameter (r) estimation among KLSE and DCE markets, SGX-DT and DCE markets are equal 0.973, 1.065, respectively, thus indicating that KLSE and DCE markets, SGX-DT and DCE markets have neither dependence or even independence in extremes. In the case of HuslerReiss copula, the parameter (r) estimation between KLSE and SGX-DT markets is equal to 2.287. This means that KLSE and SGX-DT markets have dependence in extreme, while the parameter (r) estimation among KLSE and DCE markets, SGX-DT and DCE markets are equal to 0.220, 0.597, respectively. Thus, there is an indication that KLSE and DCE markets, SGX-DT and DCE markets have neither dependence or even independence in extremes.

6. Conclusion

In this paper, we managed with the tail behavior of return on three palm oil futures prices markets, namely KLSE, DCE and SGX-DT using the univariate EVT and GEV distribution. The study focused on the extreme dependence structure between the returns on palm oil futures prices in three markets using the extreme value copulas. To obtain our results, the paper applied the Gumbel and HuslerReiss copula approach to examine the extreme dependence between KLSE, DCE and SGX-DT markets. The results demonstrated that both methods have a similar outcome. The returns on palm oil future price among KLSE and SGX-DT have dependence in extreme, whereas the returns on palm oil future price among KLSE and DCE, SGX-DT and DCE do not have any dependence. The results could be beneficial for any person or company wishing to be engaged in the commerce of trading palm oil.

Acknowledgements

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บทความที่ 10

Factors affecting palm oil price based on Extremes Value Approach

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Abstract

This study examines the dependence structure of extreme realization of growth rate between palm oil prices and factors affecting, which are soybean oil and crude oil prices. We employ the Bivariate Extreme Value methods for daily palm oil, soybean oil and crude oil prices ranging from July 1988 to January 2012. The results provide that the growth rate of palm oil and soybean oil prices have some dependence in extremes, but growth rate of palm oil and crude oil prices have fairly weak dependence or even independence in extremes. Therefore, the authors of this study hoped that these findings not only have made a contribution to our understanding of what drives palm oil price movement of soybean oil and change in crude oil prices, but also for the practitioner who want to devise an updated model to enhance a further comprehension of the prices that drive these article of trade.

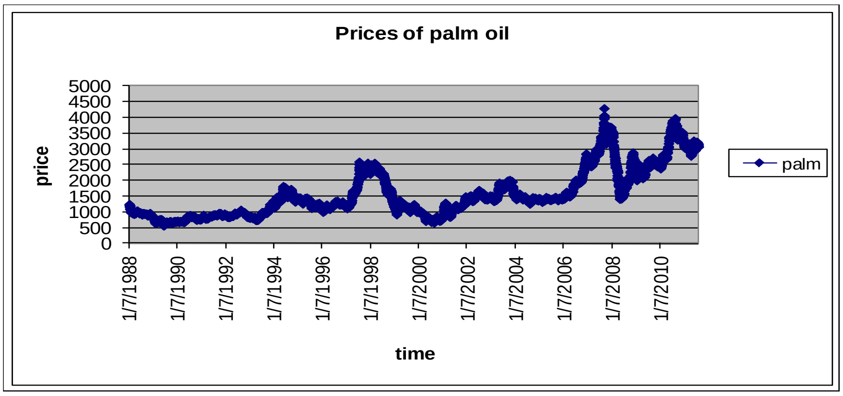
Keywords: Dependence structure, Bivariate Extreme Value, Palm oil prices, Soybean oil prices, Crude oil prices

1. Introduction

In the consumption sector of oil and fats, palm oil is by far one of the highly well-known energy crop leaders in terms of production. The growth of palm oil production can be attributed to the demand of the local consumers as well as a price that is affordable to buy. The process of producing this natural wonder is made from a combination of other energy crops, such as soybean, sunflower, rapeseed and coconut oils (USDA, 2011). The factors that are involved in establishing the prices for palm oil are quite unique. With the rise in an increasing population, rapid economic growth and an elevated production of biodiesel, the worldwide demand for palm oil has brought about a changing shift towards the prices marked in palm oil. Such a rise in the factors will always lead to uncertainty or angst that makes decision making to sway by the extreme side such as hoarding the goods on part of the consumers while leaving scarce items for others (Khaneman, 2011). Nevertheless, it is a compelling fact that when there is an increase in crude oil and soybean oil prices, a recession in the world economy, and variations in the weather, the prices of palm oil tends to fluctuate. Figure 1 demonstrates the prices of palm oil fluctuating on a day to day basis that is based on these factors mentioned. Although uncertainty may be deemed as undesirable for nations that are trying to maintain the stability of palm oil prices, the advantages that it provides for other nations to reap some benefits in the international market are worth the venture. Therefore, for countries like Malaysia who involved in the palm oil plantation, they stand to gain the following: selling a product that is considered as one of the most competitively priced vegetable oil in the global market for the past 20 years and continues to be so today, being assured that the product is in the highest market penetration level of all vegetable oils (Dekeloil, 2012).

With the high price of palm oil, it influences more capital for investment and recruitment of labor to increase the production of palm oil. Since the price of palm oil is determined by many factors, the factor that influences palm oil prices is the availability of substitutes such as the prices of soybean oil. As an oil commodity, it has become an important influence on palm oil prices because of its similar application in the food industry (Rahman, Shariff, Abdullah, & Sharif, 2007). Figure 2 shows the palm oil and soybean oil daily prices series. Moreover, the price of crude oil is also an important factor that influences palm oil prices. Because of the recent price increase in crude oil and growing environmental concerns, biodiesel has become an important alternative fuel that acts as the lifeblood of the retailing industries that are highly depended on the logistics and transportations to deliver their goods on time. Figure 3 demonstrates the daily price series of palm oil and crude oil. This information is of particular importance as it shows the movement of palm oil prices that is affected by the prices of soybean oil and crude oil.

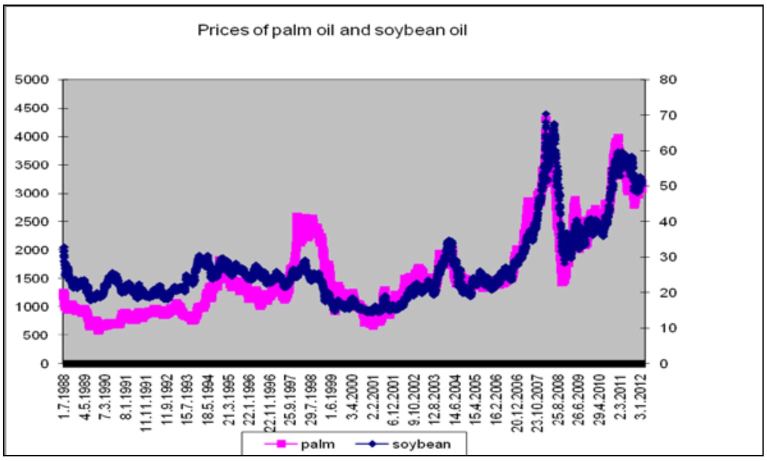
In this study, we attempt to investigate the relationship between palm oil prices and the two factors (soybean oil and crude oil prices) with a daily data. Since the data demonstrates an apparent tendency for non-normal distribution (see in table 1), the way to proceed this is to use the extreme value theory and to model it as the tail of an extreme value distribution. The aim of this paper is to employ the Bivariate extreme value to determine the dependence between the prices of palm oil and soybean oil, as well as the prices between palm oil and crude oil. The rest of the paper is structured as followed: Section 2 gives a literature review, Section 3 presents the data and methodologies, Section 4 discusses the empirical results, and finally Section 5 offers the conclusion.



Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR

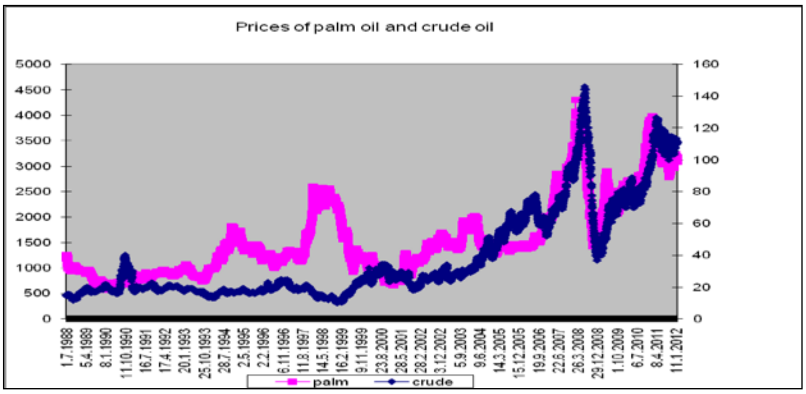
Figure 1. Palm oil daily price, Jul 1988 - Jan 2012



Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR, The Soybean oil price of this paper is Soybean Oil Futures 1-Pos, USD.

Figure 2. Palm oil and Soybean oil daily prices, Jul 1988 - Jan 2012



Source: Ecowin

Note: The Palm oil price of this paper is Palm Oil Futures 1-Pos, MYR, The Crude oil price of this paper is Brent Crude Futures 1-Pos, USD.

Figure 3. Palm oil and Crude oil daily price, Jul 1988 - Jan 2012

2. Literature Review

The authors of the study draw upon the fact that many palm oil producing countries have confirmed involvement with organizations and research institutes. When these two form into a working partnership, they become a unit that generate data and information that adds to the knowledge on oil palm cultivation, palm oil processing, and related applications. We see that Talib & Darawi (2002) have studied upon a structural model for the purpose of describing the Malaysian palm oil industry from 1997 to 1999 by taking into account the total palm oil area, oil palm yield, domestic consumption, exports and imports. In their study, it was proclaimed that the importance of Malaysian economy and its affecting factors were palm oil stock level, price of palm oil, the exchange rate, world population, and the price of soybean oil. According to Wahid, Simeh, & Nordin (2007) who have investigated the development in the world prices for palm oil, their findings considered that the impact of the trends on world palm oil price was derived from consumption, trade, price competitiveness, investment in oil palm/palm oil, and the use of palm oil producing biodiesel. In relevance to this work, the high rise in the trend of the oil palm price had a great implication for the agricultural and industrial sector in producing countries (Pleanjai, Gheewala, & Garivait, 2007). However, it's important to be aware on the fact that the price of oil palm surges over time due to the uncertain price of oil palm. Therefore, the work reminds us that there are risks and unreliability for tree-crop farmers, shareholder, traders, and producers. In order to configure the trends as a way for decreasing risk and uncertainties, there should be some effective risk management strategies implemented to ensure a sound policy to take for action (Karia & Bujang, 2011).

Our review of the work comes across upon other scholars who have studied factors that affect prices of palm oil. There are some studies that indicate an existing relationship between soybean oil and palm oil prices. We refer to Arshad, Shamsudin, & Hameed (2011) who described the soybean oil as a competitor to palm oil. Arhsad and his colleagues used the 'two stage least squares method' to estimate soybean and palm oil prices. With regards to the application employed, their work found that soybean prices would have a positive relationship with world palm oil price. Based on the analysis of relationship with Abdullah, Abas, & Ayatollah (2007), his group reveals that soybean oil and palm oils are two good examples of agricultural commodities that have similar characteristics. They are also substitutable in many applications, and have prices of soybean and palm oil that are highly correlated.

In terms of the relationship between crude oil and palm oil prices, Hameed & Arshad (2009) studied the relationship between the prices of crude oil and selected vegetable oils using the Granger causality test. According to this study, the results show that in the long-run there was a one direction relationship between crude oil price and the prices of each of four vegetable oils, i.e., palm, rapeseed, soybean, and sunflower oils, but the reverse was not true. Moreover, our work points to Hadi, Yahya, Shaari, & Huridi (2011) studying the effect of changes in crude palm oil prices on the price of crude oil. Upon applying the Engle-Granger Cointegration test and Error Correction Model to find a significant long-term result, their work found that the prices of crude palm oil and crude oil are also positively correlated. However, we wish to mention that previous works assume that the data is normally distributed. Therefore, all of the aforementioned studies have suffered from this weakness of normality assumption since the prices of palm oil, soybean oil, and crude oil are assumed to have a non-normal distribution. In this paper we find that the extreme information flows from soybean oil and crude oil prices to palm oil prices.

We assert that the Extreme Value Theory (EVT) provides a strong theoretical basis where we can construct statistical models that are capable of describing extreme events (Gilli & Kellezi, 2006). Extreme value methods have been used in environmental science, hydrology, insurance, and finance. Furthermore, EVT can describe the behavior of random variables both at extremely high or low levels. The theory enables us to describe the performance of the heavy-tail properties of a high frequency time series data, such as financial returns (Onay & Unal, 2012). Univariate extreme value theory was used to analyze and evaluate extreme risks in finance and disaster sector. In addition, the bivariate EVT was used in studied on financial and disaster, such as Brodin & Rootzen (2009) who have used univariate and bivariate extreme value methods for predicting extreme wind storm losses. Based on their study, they believed that the bivariate model provided the most realistic picture of the real uncertainties. To substantiate this idea, Escalante-Sandoval (2007) used bivariate extreme value distribution to analyze the flood frequency. According to his results, it showed that estimating the parameters of marginal distribution with bivariate reduced the standard error of fit than pair of univariate distribution.

3. Data and Methodology

The research instruments used in this study involve bivariate extreme value. Time series data of this paper was obtained from Ecowin. In this paper, the palm oil price is Palm Oil Futures 1-Pos, MYR, the soybean oil price is Soybean Oil Futures 1-Pos, USD and the crude oil price is

Brent Crude Futures 1-Pos, USD. We took daily prices in palm oil, soybean oil and crude oil in local currencies and converted to growth rate of prices. Daily prices are computed as growth rate of prices relatives: $Gr = (p_t - p_{t-1}) / p_{t-1} * 100$, where p_t is the daily futures 1-Pos price at time t. The study period was from July 1988 till January 2012.

3.1 Bivariate Extreme Value

The Extreme Value Theory (EVT) is a concept of modeling and measuring extreme events which occur with a very small probability (Brodin & Kluppelberg, 2008). There are two principal approaches to identify extremes in real data, Block Maxima (BM) and Peaks-Over Threshold (POT). BM and POT are central for the statistical analysis of maxima or minima and exceedances over a higher or lower threshold (Lai & Wu, 2007). In this research, we use both bivariate BM and POT models to analyze the relationship between the prices of soybean oil and palm oil, as well as on the prices of crude oil and palm oil.

3.2 Bivariate Block Maxima

This method is concerned with parametric and non-parametric cases. In this study, we choose the parametric models. A brief summary of bivariate BM is given below:

Let (X, Y) denote a bivariate random vector representing the component-wise maxima of an i.i.d. sequence over a given period of time. Under the appropriate conditions the distribution of (X, Y) can be approximated by a bivariate extreme value distribution (BEVD) with c.d.f. G. The BEVD is determined by its two univariate margins G_1 and G_2 respectively, which are necessarily EVD, and by its Pickands dependence function A (Rakonczai & Tajvidi, 2010).

$$G(x, y) = \exp\left\{ \log(G_1(x)G_2(y)) \times A\left(\frac{\log(G_2(y))}{\log(G_1(x)G_2(y))} \right) \right\} \tag{1}$$

A(W) is responsible for capturing the dependence structure between the margins and determines only up to the condition that it is convex, passes through the points (0,1), (1,1) and (1/2,1/2) binds the upper left and right corners. The properties of function A are (1) A(w) is convex, (2) max{(1 − w), w} $\leq$ A(w) $\leq$ 1 and (3) A(0) = A(1) = 1. Rakonczai and Tajvidi, (2010**)** explained in their paper that the lower bounds in the second item of the properties of A corresponds to the complete dependence G(x,y) = min{G1(x),G2(y)}, while the upper bound corresponds to (complete) independence G(x,y) = G1(x)G2(y).

In this BM case, we chose one parametric models form nine models ,which minimizes AIC (Akaike Information Criterion), to use for A(w) is logistic distribution function. Details about these and other models can be found in Stephenson (2011).

The logistic distribution function with parameter dep = r is

$$G(x,y)=\exp[-(x^{\frac{1}{r}}+y^{\frac{1}{r}})^{r}] \tag{2}$$

where $0<r\le 1$. The independence case corresponds to $r=1$. For $r\to 0$, we get complete dependence.

3.3 Bivariate Threshold Exceedances

There are at least two ways of defining exceedances in higher dimensions. In the first definition, a distribution is fitted to the observations $\{(x,y)|(x,y)>(u_x,u_y)\}$ where u_x and u_y are suitable thresholds for each margin. Second definition aims to fit a distribution to $\{(x,y)|(x,y)\nless(u_x,u_y)\}$ where (u_x,u_y) is defined as before. These distributions will be called Type I and Type II bivariate generalized Pareto distributions (BGPD), respectively (Coles & Tawn, 1991), (Coles, 2001).

In this study, the strength of the dependence between extreme prices of palm oil and soybean oil, palm oil and crude oil is estimated by fitting joint exceedances to bivariate extreme value distribution using MGPD type I. From univariate GPD, the details for approximating the tail of X by

$$G(x)=1-\eta_u\left(1+\xi\frac{x-u}{\sigma}\right)^{-\frac{1}{\xi}},x\ge u \tag{3}$$

$$\eta_u=P(X>u)$$

Suppose $(x_1,y_1),\ldots,(x_n,y_n)$ are independent realizations of a random variable (X,Y) with joint distribution function $F(x,y)$ on regions of the from $x>u_x, y>u_y$, for large enough u_x and u_y. The marginal distributions of F each have an approximation of equation (3), with respective parameter sets (η_x,σ_x,ξ_x) and (η_y,σ_y,ξ_y) (Coles, 2001). We can approximate the tail of X and Y for $x>u_x, y>u_y$ with $G(x:\eta_x,\sigma_x,\xi_x)$ and $G(y:\eta_y,\sigma_y,\xi_y)$, respectively. The Bivariate Generalized Pareto Distributions (BGPD) type I is

$$\mathrm{G(x,y)=\exp\{-V(x,y)\},x>0,y>0} \tag{4}$$

The dependence functions of this case use The Husler-Reiss models (palm oil and soybean oil prices) and asymmetric negative logistic models (palm oil and crude oil prices). A brief summary of these models are given below:

The Husler-Reiss (HR) distribution function with parameter dep = r is

$$G(x,y)=\exp(-x\Phi\{r^{-1}+\tfrac{1}{2}r[\log(x/y)]\}-y\Phi\{r^{-1}+\tfrac{1}{2}r[\log(y/x)]\}) \tag{5}$$

where $\Phi(.)$ is the standard normal distribution function and $r>0$. Independence is obtained in the limit as $r\to 0$. Complete dependence is obtained as r tends to ∞.

The asymmetric negative logistic distribution function with parameters dep = r and asy = (t_1,t_2) is

$$G(x, y) = \exp\{-x - y + [(t_1x)^{-r} + (t_2y)^{-r}]^{-1/r}\} \tag{6}$$

where $r > 0$ and $0 < t_1, t_2 \le 1$. When $t_1 = t_2 = 1$, the model reduces to the negative logistic model. Independence is obtained in the limit as either r, t_1 or t_2 approaches zero. Complete dependence is obtained in the limit when $t_1 = t_2 = 1$ and r tends to infinity (Stephenson, 2011).

4. Empirical Results

Table 1 presents the descriptive statistics of the growth rate of palm oil, soybean oil and crude oil prices. An examination of the descriptive table reveals that most of the growth rates of 3 oil prices have excess kurtosis, which indicates the influence of extremes on all growth rates of prices distributions. The Jarque-Bera test rejects normality at 5% level for all distributions.

Table 1. The descriptive statistics of Growth rates of Palm oil, Soybean oil and Crude oil prices

	PALM	SOYBEAN	CRUDE
Mean	0.0277	0.0179	0.0581
Median	0	0	0.0425
Maximum	10.4275	8.3707	14.0545
Minimum	-10.8527	-7.4739	-34.7682
Std. Dev.	1.6032	1.4669	2.2289
Skewness	0.0952	0.1306	-0.5933
Kurtosis	8.2815	5.5438	16.5524
Jarque-Bera	7159.42	1676.162	47440.95
Probability	0	0	0
Observations	6152	6152	6152

4.1 Bivariate Block Maxima

We use the growth rate of prices daily data into blocks of equal length and fit it to the maximums of monthly. In case of BM, we chose the logistic parametric model which minimizes AIC from nine models, to find the dependence functions between growth rate of palm oil and soybean oil prices and between growth rate of palm oil and crude oil prices.

The test results from using bivariate BM are shown in table 2. This table reveals distribution function parameter (r) and estimates for the location (μ), shape (ξ) and scale (σ) parameters. The logistic model between growth rate of palm oil and soybean oil prices has r estimate equal 0.83, which implies that growth rate of palm oil and soybean oil prices has dependence in extremes but not strong enough. Figure 4 shows some dependence between monthly maxima of growth rate of palm oil and soybean oil prices in which figure 5 confirms this information. And the logistic model between growth rate of palm oil and crude oil prices has r estimate equal 0.90, thus indicating that it has dependence but fairly weak or even independence in extremes between palm oil and crude oil prices. There is a fairly weak dependence or even independence between monthly maxima of growth rate of palm oil and crude oil prices; as shown in figure 6 and confirmed by figure 7.

Table 2. Bivariate Block Maxima Palm oil and Soybean oil prices, Palm oil and Crude oil prices

	BM model	AIC	μ_1	σ_1	ξ_1	μ_2	σ_2	ξ_2	r
Palm-soybean	logistic	1,912.587	2.0922 (0.0768)	1.1316 (0.0595)	0.1464 (0.0482)	2.2733 (0.0681)	1.0217 (0.0496)	0.0183 (0.0419)	0.8325 (0.0379)
Palm-crude	logistic	2,138.662	2.0923 (0.0773)	1.1394 (0.0602)	0.1605 (0.0501)	3.1068 (0.0912)	1.3558 (0.0707)	0.1654 (0.0472)	0.9019 (0.0384)

Note: Terms in parentheses are standard errors of parameter estimates.

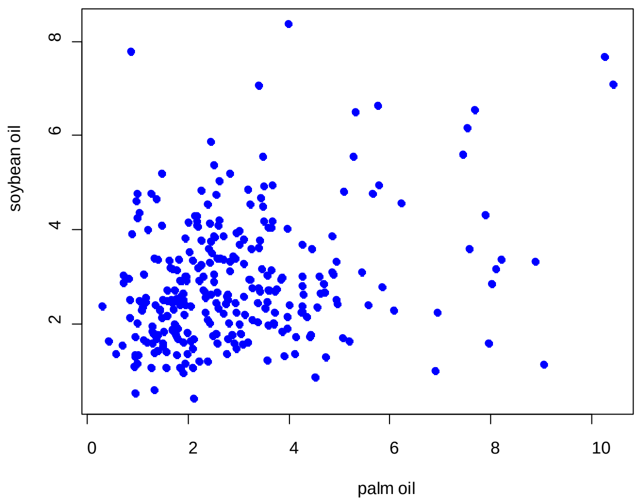


Figure 4. Bivariate monthly maxima of growth rate of palm oil and soybean oil prices

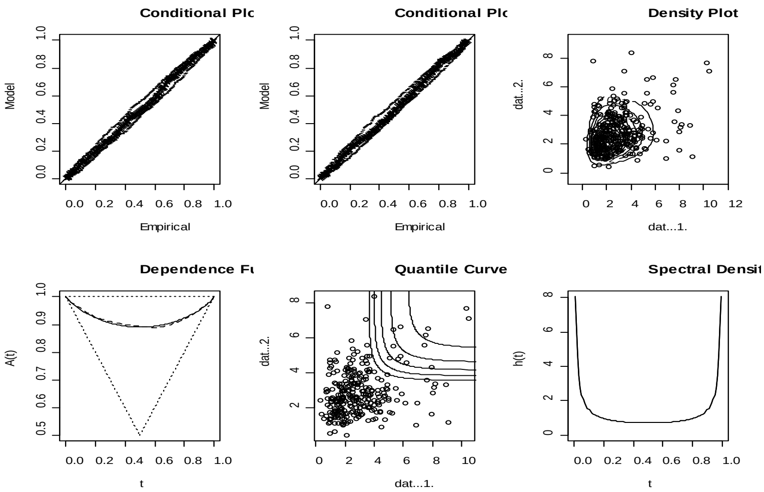


Figure 5. The bivariate logistic distribution function between growth rate of Palm oil and Soybean oil prices.

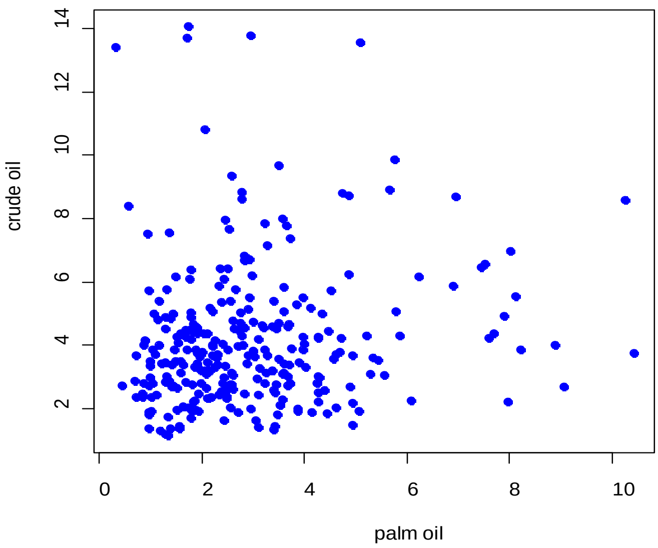


Figure 6. Bivariate monthly maxima of growth rate of palm oil and crude oil prices

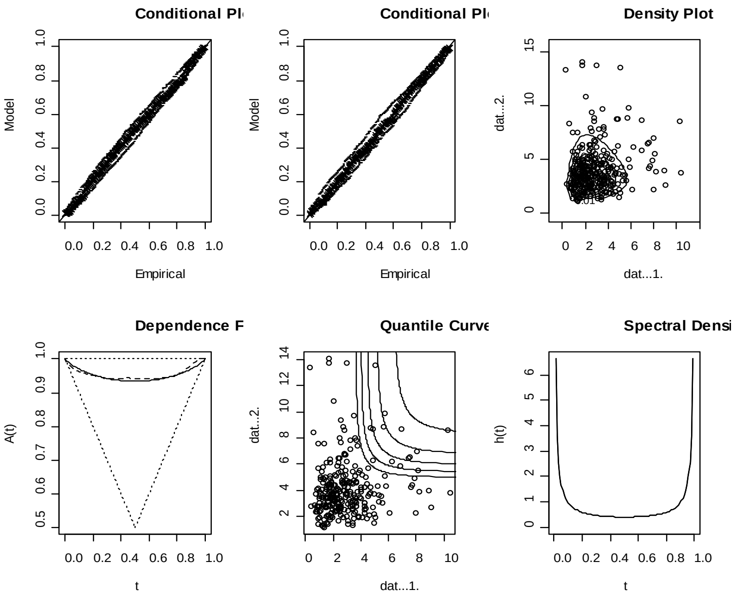


Figure 7. The bivariate logistic distribution function between Growth rate of Palm oil and Crude oil prices.

4.2 Bivariate Threshold Exceedances

We used the growth rate of prices daily data and analyzed the data by modeling exceedances of prices over a threshold. In this case, the dependence in extremes between palm oil and soybean oil prices uses HR models, which minimize AIC from nine models. And the asymmetric negative logistic model is used to find the dependence in extremes between palm oil and crude oil prices.

Table 3 presents the result of the bivariate threshold exceedances analysis of the distribution function parameter (r) and estimates for the shape (ξ) and scale (σ) parameters between growth rate of palm oil and soybean oil prices, growth rate of palm oil and crude oil prices. The HR model has r approach to one that means growth rate of palm oil and soybean oil prices has dependence in extremes. Figure 8 shows dependence in daily growth between palm oil and soybean oil prices and figure 9 provides the information that confirms it. On the other hand, the asymmetric negative logistic model has t_1 , t_2 estimate approach to zero, thus implying that there is independence in daily growth between palm oil and crude oil prices. There is independence in daily growth between palm oil and crude oil prices, where figure 10 presents the data and figure 11 confirms it.

Table 3. Bivariate Threshold Exceedances Palm oil and Soybean oil prices, Palm oil and Crude oil prices

	GPD model	AIC	σ_1	ξ_1	σ_2	ξ_2	t_1	t_2	r
Palm-soybean	HR	6,238.004	1.2265 (0.1070)	0.1005 (0.0651)	0.9939 (0.0850)	0.0437 (0.0636)			0.6605 (0.0358)
Palm-crude	aneglog	6,602.384	1.2023 (0.1047)	0.1037 (0.0663)	1.3726 (0.1218)	0.1773 (0.0684)	0.0256 (0.0132)	0.0795 (0.0477)	3.411 (2.1834)

Note: Terms in parentheses are standard errors of parameter estimates.

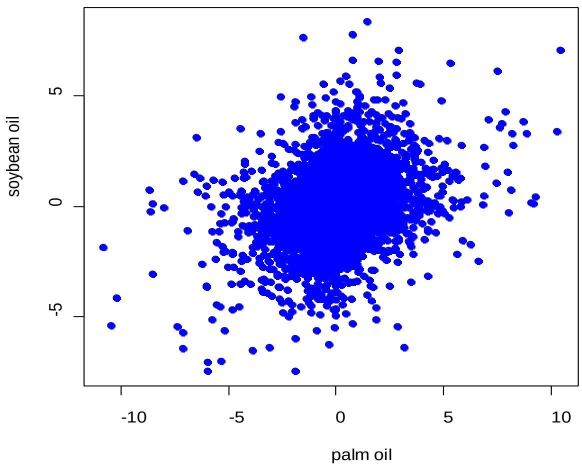


Figure 8. Bivariate threshold exceedances of growth rate of palm oil and soybean oil prices

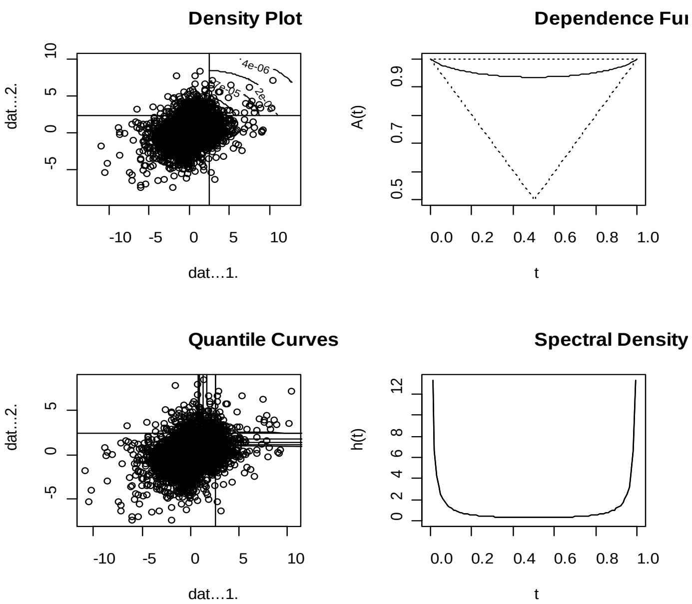


Figure 9. The bivariate HR distribution function between growth rate of Palm oil and Soybean oil prices

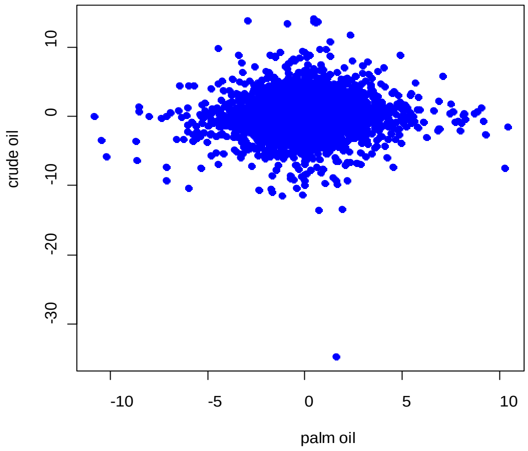


Figure 10. Bivariate threshold exceedances of growth rate of palm oil and crude oil prices

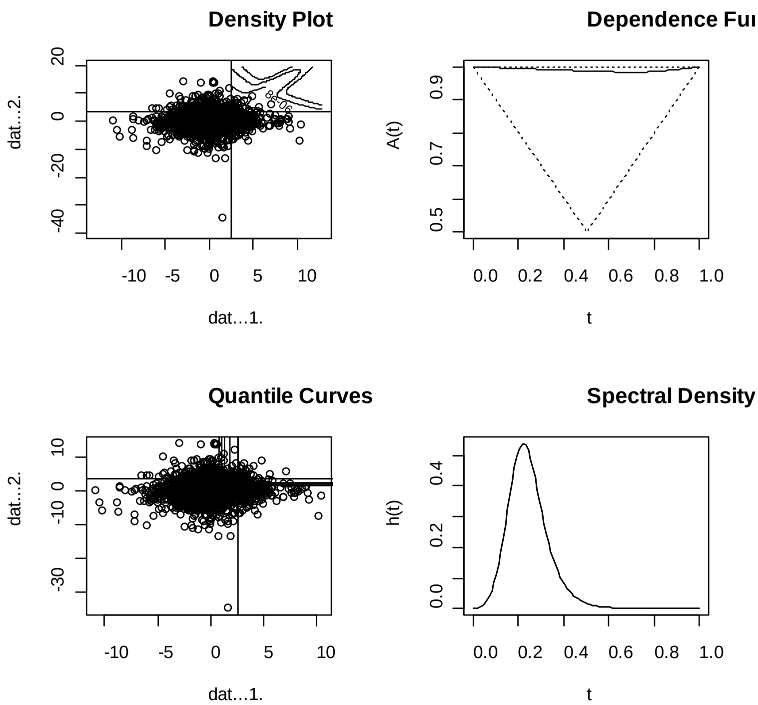


Figure 11. The bivariate asymmetric negative logistic distribution function between growth rate of Palm oil and Crude oil prices

5. Conclusion

This study focuses on the factor affecting palm oil prices. The work attests that there are many factors involved in the movement of palm oil prices. Such a movement has affected the prices of Soybean oil and crude oil as well. The aim of this study is to find the extreme dependence between palm oil and soybean oil prices, palm oil and crude oil prices using the bivariate extreme value. To do this, the paper applies the Bivariate Block Maxima and Bivariate

Threshold Exceedances approach to examine the extreme dependence between the growth rate of palm oil and soybean oil prices, and the growth rate of palm oil and crude oil prices. Based upon our application, we see that the results of this paper show that both methods have a similar outcome. The growth rate of palm oil and soybean oil prices has some dependence in extremes. However, in the case of the growth rate of palm oil and crude oil prices, it has fairly weak dependence or even independence in extremes. Therefore, the authors of this study hoped that these findings not only have made a contribution to our understanding of what drives palm oil price movement of soybean oil and change in crude oil prices, but also for the practitioner who want to devise an updated model to enhance a further comprehension of the prices that drive these article of trade.

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บทที่ 2
การเข้าร่วมนำเสนอบทความ

ในช่วงระยะเวลา 2 ปี (15 สิงหาคม 2553 - 14 สิงหาคม 2555) นักวิจัยได้เข้าร่วมนำเสนอบทความในการประชุมนานาชาติสองแห่งได้แก่ (1) การประชุมนานาชาติ "The 4th International Conference of the Thailand Econometric Society" ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ วันที่ 13 มกราคม 2554 (2) การประชุมนานาชาติ "The Fifth International Conference of the Thailand Econometric Society" ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ ระหว่างวันที่ 12-13 มกราคม 2555 รายละเอียดของการประชุมมีดังนี้

(1) การประชุมนานาชาติ "The 4th International Conference of the Thailand Econometric Society"

ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ วันที่ 13 มกราคม 2554 ผลงานวิจัยที่เข้าร่วมนำเสนอได้แก่ บทความเรื่อง "Spatial Market Integration of Cassava Market and Causality Relationship in Thailand" รายละเอียดของการนำเสนอมีดังนี้

Outline

1 Introduction

2 Conceptual framework

3 Data and Background

4 Empirical Result

5 Conclusion and policy implication

1. Introduction

- Thailand has been the largest cassava exporting country, with a 70% share of export quantities for many years.
- Despite of price instability in the past two decades, and frequent losses incurred to growers, cassava production and export are expected to grow continuously.
- The problem of price instability called for intervention policies such as pledging policy, and **export quotas** to cope with price volatility.

1. Introduction

- Studies of market efficiency in the context of price efficiency are common. Researchers adopt the frame work of **price transmission along a supply chain** and concern with function of agents in each market level as information processors, for example, Vavra and Goodwin (2005); Zhou and Buongiorno (2005); Serra and Goodwin (2003).

- Another framework in the context of market integration, emphasizing on the **spatial dimension** and often used to assess effects of price intervention on price and farmers' income as well as the influence on market efficiency.

- Among others, Ardeni (1989); Yang *et al.* (2000); and Nanang (2000); Liu and Wang (2003) **test price efficiency in the context of spatial market integration based on the LOP**. [If market integration does not exist, these policies are potentially effective, since price levels may respond accordingly.] On the contrary, such policies are ineffective if market integration is strong because price levels can be affected marginally.

4

1. Introduction

- **Empirical evidences in Thailand show that the pledging programs could not effectively raise prices of cassava and rice (Pongpoorsakorn, et al. , 2000; Sriboonchitta, 2000).**

- Spatial (horizontal) market integration studies of Thailand was found in various agricultural product such as pig (Lapboonruang, 2004), rice (Trakulphonnimit, 2002), banana (Visansirikul, 2003), fruit (Issariyathip, 2002), feed corn (Kuntum, 2003), and palm (Kaewchuey, 2007) etc., but not in cassava.

- Previous studies on cassava market in Thailand focused on price transmission along supply chain of various cassava products include Sittikul (1997); Sanguanchur (2002); Apihakit (2004); Poomprasert (2005) and Punkla (2008).

5

1. Introduction

- **Most recently researchers use the cointegration approach as the empirical method for investigating a long run equilibrium relationship. If two spatially separated price series are cointegrated, there is a tendency for them to co-move in the long run according to a linear relationship.**

*• The Johansen and Juselius (1990) maximum likelihood estimator overcomes the use of two step estimators of Engle and Granger (1987) and can test for the presence of multiple cointegrating vectors. Furthermore, this test allows the researcher to test restricted versions of cointegrating vectors, speed of adjustment parameters and it is possible to verify a theory by testing restrictions on the magnitudes of the estimated coefficients.

**• Alternatively, the directed acyclic graph (DAG), a data-determining approach has been adopted to identify directional relationship among markets.

6

1. Introduction

Objectives

- To investigated cassava spatial and symmetric market integration using quantile regression to results of DAG with Johansen multivariate cointegration procedure to test the law of one price (LOP) for seven provincial markets of 3 regions of major producing cassava markets.

7

2. Conceptual framework

- Spatial market integration could be investigated via the transmission of price shocks from one regional market to other horizontally related markets.
- This concept for spatial arbitrage relationship between regions X and Y shown in eq.(1), represents the strong form if $\alpha = \beta_2 = 0$ and represents the weak form when this restriction is removed.
- The parameter $\beta_1 = 1$ indicates perfect transmission of a price change in one market to the second market for both forms.

8

2. Conceptual framework

$$Px_t = \alpha + \beta_1 Py_t + \beta_2 Z_t + e_t \qquad (1)$$

All of variables are in logarithms. Where Px_t and Py_t are prices for homogenous goods at time t in markets X and Y, α is transfer costs between markets X and Y and Z_t denotes non-stochastic factors. Most of recent works employ cointegration modeling to capture long run price relationship and to avoid problem of spurious relationship due to nonstationarity of prices series.

9

2. Conceptual framework

To investigate market integration as modeled in eq. (1) the procedure of this study takes 6 steps as follow:

1. test for structural change using recursive residuals.
2. test for seasonal unit roots for each series under structural change.
3. test for Johansen's multivariate cointegration.
4. conduct innovation accounting analysis (impulse response function and forecast error variance decomposition).
5. investigate of causal relationships among seven markets using directed acyclic graph (DAG)
6. apply quantile regression to DAG results for 3 selectd dependent markets

10

2. Conceptual framework

Hypothesis:

1) It is hypothesized that relative to other markets, contiguous cassava producing provinces engaged in arbitrage should exhibit a higher degree of market integration due to effect of relative lower transportation costs, and better access to information.

2) LOP prevail at all levels of prices. This hypothesis implies symmetric transmission for low and high prices.

11

2. Conceptual framework

2.1 Johansen's cointegration test

The main advantage of the Johansen approach in testing for market integration and the law of one price (LOP) is that it allows hypothesis testing on the coefficients of both α and β using likelihood ratio test. The Johansen cointegration test is based on a vector autoregression (VAR) system. Given a price vector Pt, VAR is carried out using eq. (2) and short term adjustment be written in vector error correction form (VEC) as eq. (3)

$$P_t = A_1 P_{t-1} + A_2 P_{t-2} + \ldots + A_k P_{t-k} + \varepsilon_t \qquad (2)$$

$$\Delta P_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-1} + \varepsilon_t , \qquad t = 1,\ldots, T \qquad (3)$$

where $\Gamma = -\left[I - \sum_{j=1}^{i} A_j \right]$ and $\Pi = -\left[I - \sum_{i=1}^{k} A_i \right]$ **= impact matrix showing LR relationship**

μ accounts for tran. cost/quality price differential with time trend

12

2. Conceptual framework

P_t is (nxn) column vector of m variables, μ is an (nx1) vector of constant terms, Γ and Π represent coefficient matrices, Δ is a difference operator, k denotes the lag length, and ε_t is independently and identically distributed (i.i.d.).

The coefficient matrix Π is known as the impact matrix, and it contains information about the long run relationships.

The following three relevant hypotheses are rank test for number of cointegrating vectors, test of LOP for perfect market and test for weak version of LOP of eq.(1).

13

2. Conceptual framework

(1) Cointegration rank (r) test

Rank of Π , r determines the number of stationary linear combinations of P_t, There are three possibilities:

(1) if r = n, the price variables are stationary in level.

(2) if r = 0, there exists no linear combination of P_t that are stationary.

(3) 0< r <n, there exists r stationary linear combinations of P_t.

- A rank of r = n -1 in a multivariate system with n price series would imply that there is only one stochastic trend driving the behavior of prices in the system.

- **Cointegration rank test under hypothesis** $H_0 : \Pi = \alpha\beta'$ **. test for market intetegration**

14

2. Conceptual framework

- There are two alternative tests that used to identify the number of significant cointegrating vector r, the trace test (λ_{trace}) and maximum eigenvalue test (λ_{max}) as in eq.(4) and (5).

$$\lambda_{Trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}) \qquad (4)$$

Trace test (λ_{trace}) hypothesis is

H_0: cointegration vector $\leq$r, H_a: cointegration vector $\geq$ r

$$\lambda_{max} = -T\ln(1-\hat{\lambda}) \qquad (5)$$

Maximum eigenvalue test (λ_{max}) hypothesis is

H_0: cointegration vector = r, H_a: cointegration vector = r+1

15

2. Conceptual framework

(2) Test of the law of one price (LOP)

- Testing for the law of one price (LOP), restrictions R' can be placed and tested on the parameters in the β matrix under hypothesis $H_0 : R'\beta = 0$.

- If rank of the multivariate system is n-1, the LOP test becomes a test of whether the row in the β matrix sum to zero.

- The hypothesis that the LOP holds for all prices simultaneously is determined by the rank of the system.

  - If r = n (full rank), then the LOP holds for all prices simultaneously.

  - If r < n, then the LOP is rejected for all prices simultaneously, in which case, the second testable hypothesis is that the LOP holds between any two prices

16

2. Conceptual framework

(3) Weak exogeneity test

- Adjustment parameters are related to the concept of weak exogeneity.

- If all adjustment parameters for one variable are zero, then this variable is said to be weakly exogenous to the long run parameters in the remaining equations.

- This implies that the coefficients on the levels of the remaining price series in the system is zero in this particular equation which would mean other price variables are not influencing this variable in the long run.

- The null hypothesis is that each variable does not respond to shock or disequilibrium in the long run relationship ($H_0 : \beta'\alpha = 0$), the i^{th} row of the Π matrix is zero. That is the i^{th} row of α has its element equal to zero.

17

2. Conceptual framework

2.2 Directed acyclic graph (DAG)

The majority of past investigations of causal relationships among economic variables use the Granger causality framework that builds on the knowledge that a cause precedes its associated effect thus an effect does not precede its cause. DAG represents a conditional independence relationship as given by the recursive decomposition as eq. (6)

$$\Pr(v_1, v_2, v_3, \ldots, v_n) = \prod_{i=1}^{n} \Pr(v_i \mid pa_i) \qquad (6)$$

where Pr(.) is the joint probability of variables $v_1, v_2, v_3, \ldots, v_n$ and pa_i represents some subsets of the variables that precede (come before in a causal sense) v_i in order ($v_1, v_2, v_3, \ldots, v_n$).

18

2. Conceptual framework

DAG employed PC algorithms, that proceeds step wise testing. The process of causal determination begins with a complete undirected graph which shows an undirected edge between variables in the system, then remove edges between variables and the assign causal flows on the remaining edges. Fisher's z is used to test whether conditional correlations are significantly different from zero, Fisher's z show as eq. (7)

$$z[\rho(i, j|k), n] = \left[\frac{1}{2}\sqrt{n - |k| - 3}\right] \ln\left\{\frac{|1 + \rho(i, j|k)|}{|1 - \rho(i, j|k)|}\right\}, \qquad (7)$$

where n is the number of observations used to estimate the correlations, $\rho(i, j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and $|k|$ is the number of variables in k. If i, j, and k are normally distribution of $z[\rho(i, j|k), n] - z[r(i, j|k), n]$ is standard normal.

19

3. Data and Background

- The data used for analysis are monthly farm prices during January 1989 - March 2009 obtained from Office of Agricultural Economics (OEA), Ministry of Agriculture and Agricultural Cooperatives (MAAC).

- Prices were deflated by CPI to reflect real price received by growers.

- Seven provinces were selected to represent major markets of 3 regions (northeast, east and west) on the basis of their production areas and availability of data.

- Nakronrachasima (Nak), Chaiyapoom (Cha) and Konkhaen (Kon), are 3 top rank of the northeastern region which rank 1, 3 and 12 of the country. Nak is apparently the largest market both for cassava and processed products of the whole kingdom.

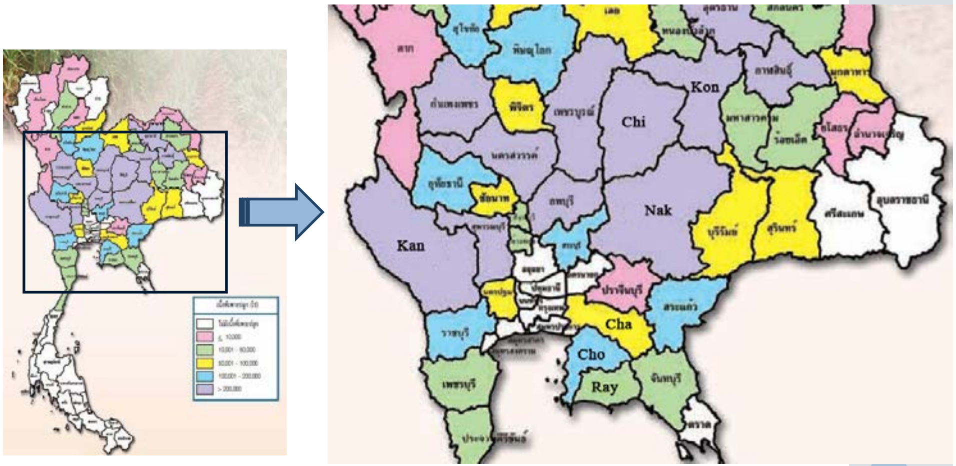
- Chacheongsao (Cha), Chonburi (Cho) and Rayong (Ray) rank 5, 7 and 10 of the country production representing the eastern region and Kanchanaburi (Kan) represents central-western region as it holds the sixth largest production of the country.

3. Data and Background

Table I: Price statistics and characteristics of the selected provinces.

Stat.	Northeast			East			West
	Nak	Chi	Kon	Cha	Cho	Ray	Kan
mean	1,309.4	1,251.4	1,257.4	1,179.5	1,183.3	1,200.5	1,117.4
median	1,256.0	1,204.6	1,197.6	1,091.8	1,134.3	1,124.2	1,071.3
maximum	2,539.3	2,442,6	2,386.4	2,430.5	2,043.5	2,206.2	2,054.3
minimum	677.0	617.6	574.6	654.5	704.8	664.9	563.6
Production area (country rank)	1	3	12	5	7	10	6
Absorption rank* (rai/merchant)	2 (22,482)	4 (12,469)	3 (20,514)	7 (7,028)	5 (8,619)	1 (30,580)	6 (8,066)
Proximity to port (rank)	4	6	7	2	1	3	5

Note * Absorption capacity = total production area ÷ number of merchants.



22

3. Data and Background

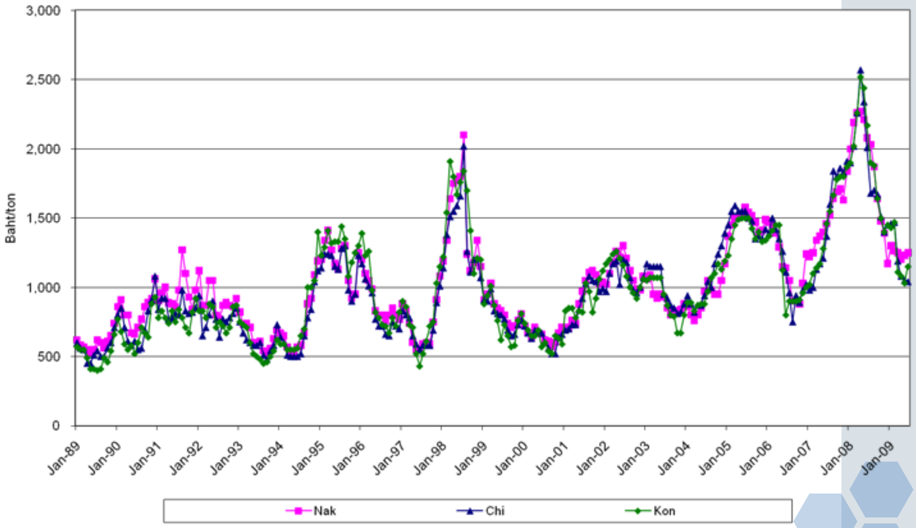


Figure 1 Farm prices of cassava in Northeastern provinces

23

3. Data and Background

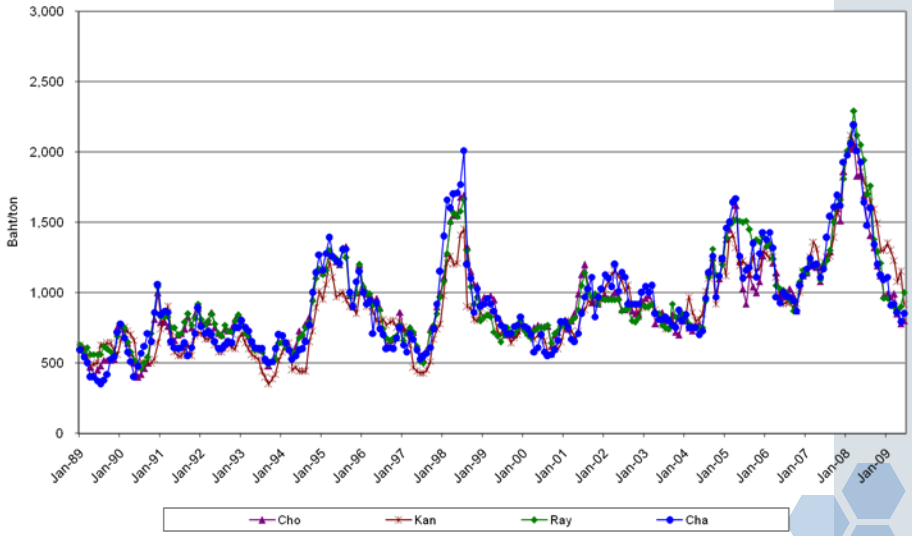


Figure 2 Farm prices of cassava in Eastern and Western provinces

4. Empirical Result

4.1 Johansen cointegration test and the LOP test

- The results of standard rank tests using λ_{trace} (and λ_{max}) reveal 6 (and 2) cointegration vectors in sub period 1 and only vector normalized by Ray was selected for further analysis (based on AIC and SIC criteria). For sub period 2, both λ_{trace} and λ_{max} indicate existence of only one stable long run equilibrium relation in the series.

- For sub period 1, the estimation results of cointegrating vector (β) and adjustment parameter (α) after normalization for each period are shown (in Table II) that 4 markets (Kan, Cho, Cha, Nak) determine price in Ray and having long term relationship. As implied by β_s, (0.23 to 1.00) the market exhibit poor to high degree of integration. In sub period 2, most markets are moderately integrated (β_s range from 0.35 to 0.7). Surprisingly Nak, the largest market did not determine the price in Ray as did in the sub period 1.

4. Empirical results

Table II: Normalized cointegrating vectors (β) and short run adjustment parameter (α) from unrestricted cointegration model.

variables	Sub period 1 (1989:01-2002:12)		Sub period 2 (2003:01-2009:06)	
	cointegration equation (normalized by Pray)		cointegration equation (normalized by Pkon)	
	β	α	β	α
Pkon	0	0.044	1	-1.009***
Pray	1	0.121	0.066	0.552*
Pkan	0.478***	0.412***	0.695***	0.185
Pcho	1.048***	0.363***	0.630***	1.069***
Pcha	0.234***	0.152	0.711**	0.467*
Pchi	0.095	-0.138	0.352***	-0.140
Pnak	0.737***	-0.223*	0.039	0.193
constant	0.015	-	-	-

Note: *,**,*** indicates significance at 10% 5% and 1% level
Source: Analysis by Eviews 6

4. Empirical results

- The test for the LOP $(\beta'\alpha = 0)$ of cointegration equation in sub period 1 can not be rejected for all of pairs while sub period 2, the LOP hold for some pairs (pkon-pkan and pkon-pcha) but multivariate test for the LOP, shows that LOP hold for all market except Ray (pray) and Nak market (pnak).

- Results of testing hypothesis $H_0 : \beta'\alpha = 0$ for weak exogeneity of α in sub period 1 and 2 are summarized in Table III and Table IV. In sub period 1, $\alpha_2, \alpha_4, \alpha_7$ are significantly different from zero, indicated that only Ray (high concentrated market) Cho (closet to the port) and Nak (**largest market and market center**) responded to shock in the long run relationship (cointegrating vector). In sub period 2, only Kon (the smallest market) and Cho market that responded to perturbations in the long run relations.

4. Empirical results

Table III: Test of hypotheses for sub period 1

hypothesis		χ^2 statistic	result
Test of hypotheses of LOP and weak exogeneity test in sub period 1			
H_0: test of market integration hypothesis or LOP $(H_0 : R'\beta = 0)$			
$\beta_2 + \beta_3 = 0$	[pray=1, pkan= -1]	4.60	F
$\beta_2 + \beta_4 = 0$	[pray=1, pcho= -1]	0.10	F
$\beta_2 + \beta_5 = 0$	[pray=1, pcha= -1]	4.064	F
$\beta_2 + \beta_6 = 0$	[pray=1, pchi= -1]	3.13	F
$\beta_2 + \beta_7 = 0$	[pray=1, pnak= -1]	7.16	F
$\beta_2 + \beta_3 + \beta_4 + \beta_6 + \beta_7 = 0, \beta_1 = \beta_5 = \beta_7 = 0$		8.33	F

i = 1-7 markets, j^{th} = 1-2 cointegrating vectors
Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis
Source: Analysis by Eviews 6

28

4. Empirical results

Table III: Test of hypotheses for sub period 1 (continued)

hypothesis			χ^2 statistic	result
Test of hypotheses of LOP and weak exogeneity test in sub period 1				
H_0: test of weak exogeneity of adjustment coefficients $(H_0 : \beta'\alpha = 0)$				
$\alpha_{1j} = 0$	for j = 1, 2	$(\alpha_1 = pkon)$	4.76	F
$\alpha_{2j} = 0$	for j = 1, 2	$(\alpha_2 = pray)$	10.22	R
$\alpha_{3j} = 0$	for j = 1, 2	$(\alpha_3 = pkan)$	5.48	F
$\alpha_{4j} = 0$	for j = 1, 2	$(\alpha_4 = pcho)$	10.18	R
$\alpha_{5j} = 0$	for j = 1, 2	$(\alpha_5 = pcha)$	4.80	F
$\alpha_{6j} = 0$	for j = 1, 2	$(\alpha_6 = pchi)$	7.038	F
$\alpha_{7j} = 0$	for j = 1, 2	$(\alpha_7 = pnak)$	10.49145	R

i = 1-7 markets, j^{th} = 1-2 cointegrating vectors
Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis
Source: Analysis by Eviews 6

29

4. Empirical results

Table IV: Test of hypotheses for sub period 2

hypothesis		χ^2 statistic	result
Test of hypothesis $H_0: R'\beta = 0$ and $H_0: \beta'\alpha = 0$ in sub period 2			
H_0: test of market integration hypothesis $(H_0 : R'\beta = 0)$			
$\beta_{11} + \beta_{13} = 0$	[pkon=1, pkan= -1]	2.897311	F
$\beta_{11} + \beta_{12} = 0$	[pkon=1, pray= -1]	13.66343	R
$\beta_{11} + \beta_{14} = 0$	[pkon=1, pcho= -1]	17.82320	R
$\beta_{11} + \beta_{15} = 0$	[pkon=1, pcha= -1]	1.142098	F
$\beta_{11} + \beta_{16} = 0$	[pkon=1, pchi= -1]	19.33641	R
$\beta_{11} + \beta_{17} = 0$	[pkon=1, pnak= -1]	17.39124	R
$\beta_{11} + \beta_{13} + \beta_{14} + \beta_{15} + \beta_{16} = 0, \beta_{12} = \beta_{17} = 0$		9.902597	F

i = 1-7 markets, j[th] = 1 cointegrating vector
Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis
Source: Analysis by Eviews 6

30

4. Empirical results

Table IV: Test of hypotheses for sub period 2 (continued)

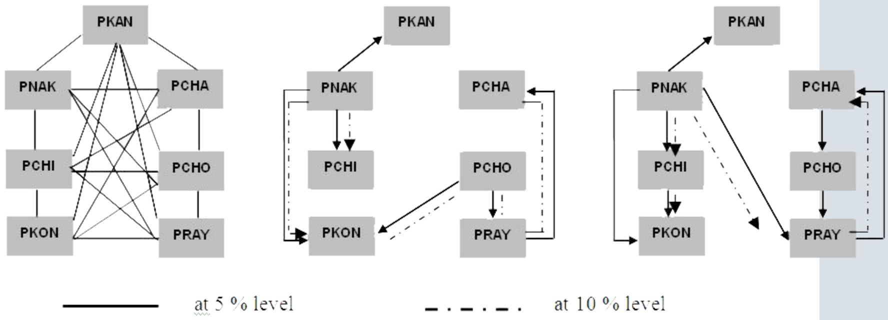
hypothesis		χ^2 statistic	result
Test of hypothesis $H_0: R'\beta = 0$ and $H_0: \beta'\alpha = 0$ in sub period 2			
H_0: test of weak exogeneity of adjustment coefficients $(H_0 : \beta'\alpha = 0)$			
$\alpha_{1j} = 0$ for j = 1, 2	$(\alpha_1 = pkon)$	14.64515	R
$\alpha_{2j} = 0$ for j = 1, 2	$(\alpha_2 = pray)$	4.321000	F
$\alpha_{3j} = 0$ for j = 1, 2	$(\alpha_3 = pkan)$	0.559749	F
$\alpha_{4j} = 0$ for j = 1, 2	$(\alpha_4 = pcho)$	9.918984	R
$\alpha_{5j} = 0$ for j = 1, 2	$(\alpha_5 = pcha)$	3.807929	F
$\alpha_{6j} = 0$ for j = 1, 2	$(\alpha_6 = pchi)$	0.184414	F
$\alpha_{7j} = 0$ for j = 1, 2	$(\alpha_7 = pnak)$	0.447487	F

i = 1-7 markets, j[th] = 1 cointegrating vector
Note: R = rejection of the null hypothesis, and F = failure to reject the null hypothesis
Source: Analysis by Eviews 6

31

4. Empirical results

4.2 Result of causality test using directed acyclic graph (DAG)



(a) Complete undirected graph (b) DAG (1989:01-2002:12) (c) DAG (2003:01-2009:06)

Figure 3 Causality test by directed acyclic graphs (DAGs)

4. Empirical results

Table V: Quantile regression of PKan

Variable	Quantile				
	10%	25%	50%	75%	90%
constant	-0.169***	-0.076***	0.028**	0.117***	0.200***
PNak	0.709***	0.787***	0.803***	0.808***	0.798***
Pseudo R-squared	0.466	0.504	0.575	0.629	0.650
Quantile dependent var	-0.333	-0.156	0.026	0.309	0.542

Note: *,**,*** indicates significance at 10% 5% and 1% level
Source: Analysis by Eviews 6

Quantile Slope Equality Test (Wald test)		
total	χ^2_4 = 1.85	p = 0.56
period 1	χ^2_4 = 1.52	p = 0.82
period 2	χ^2_4 = 3.11	p = 0.54

4. Empirical results

Table VI: Quantile regression of PChi

Variable	Quantile				
	10%	25%	50%	75%	90%
constant	-0.139***	-0.058***	0.011	0.072***	0.144***
PNak	1.004***	0.997***	0.973***	0.949***	0.997***
Pseudo R-squared	0.688	0.707	0.756	0.764	0.737
Quantile dependent var	-0.388	-0.217	0.000	0.413	0.694

Note: *,**,*** indicates significance at 10% 5% and 1% level
Source: Analysis by Eviews 6

Can not reject H_0: slope equality for all periods.

34

4. Empirical results

Table VII: Quantile regression of PKon

Variable	Quantile				
	10%	25%	50%	75%	90%
constant	-0.199***	-0.100***	0.011	0.126***	0.204***
PNak	1.034***	1.058***	1.009***	1.040***	1.045***
Pseudo R-squared	0.626	0.643	0.664	0.674	0.679
Quantile dependent var	-0.445	-0.231	0.073	0.389	0.702

Note: *,**,*** indicates significance at 10% 5% and 1% level
Source: Analysis by Eviews 6

Quantile Slope Equality Test (Wald test)		
total	χ^2_4 = 2.96	p = 0.56
period 1	χ^2_4 = 3.34	p = 0.50
period 2	χ^2_4 = 1.36	p = 0.85

35

4. Empirical results

Table VIII: Quantile regression of PRay

Variable	Quantile				
	10%	25%	50%	75%	90%
constant	-0.214***	-0.114***	0.010	0.112***	0.203***
PNak	0.881***	0.885***	0.872***	0.871***	0.841***
Pseudo R-squared	0.553	0.543	0.576	0.622	0.644
Quantile dependent var	-0.375	-0.173	0.018	0.321	0.635

Note: *,**,*** indicates significance at 10% 5% and 1% level
Source: Analysis by Eviews 6

Can not reject H_0: slope equality for all periods.

36

5. Conclusion and policy implication

- cointegrating vectors in periods 1 and 2 can not reject the multivariate test for law of one price in periods 1 and 2. (except the pair wise tests in period 2 can reject H_0 of LOP only for 2 out of 6 pairs.) This indicates that growers in all markets receive the same prices. But there is tendency for some markets becoming less efficient. That is merchants could have gain power from their growing business.

- Causal direction results from DAG clearly indicate that the largest market (Nak) with relatively high market concentration is the price leader and plays dominant roles in price transmission not only to within the region but possibly to major markets of other regions.

37

5. Conclusion and policy implication

- The geographical proximity among contiguous provinces and between each province to the main port exhibit significant price links.
- A possible reason is relative lower transportation costs allow trades of fresh cassava and dry chips among contiguous provincial markets.
- The growth of cassava production and business expansion of merchants owning drying places (chip processors) lead to high market concentration and market power.

38

5. Conclusion and policy implication

- For this empirical result, intervention policy for cassava market of Thailand (pledging policy) found not to impede market integration.
- The income guarantee program by itself generates compensation to growers based on prevailing market price and thus the program has no effect on price distortion.
- Evidently, the concentrated (Ray) and/or large (Nak) markets as well as Cho (close to the main port) responded to price perturbation in period 1 but not in period 2.
- Only the small markets (Kon and Cho) adapted to respond to price shock in period 2. This further confirms existence of significant role of large markets.
- Existence of symmetric price transmission for low and high price changes confirms that growers in all markets have been equally affected by price shocks. This does not imply that positive and negative changes in prices of products would have the same effect to farm prices. Hence, vertical price transmission is required.

39


Thank You
40

(2) การประชุมนานาชาติ "The Fifth International Conference of the Thailand Econometric Society"

ณ คณะเศรษฐศาสตร์ มหาวิทยาลัยเชียงใหม่ ระหว่างวันที่ 12-13 มกราคม 2554 ผลงานวิจัยที่เข้าร่วมนำเสนอมีจำนวน 3 บทความได้แก่ 1) บทความเรื่อง "Predicting price of palm oil using Extreme Value" 2) บทความเรื่อง "An application of EVT to analyze US corn market" และ 3) บทความเรื่อง "Modeling the Volatility of Rubber Price Return using VARMA GARCH Model"

Program: Thursday January 12th, 2012

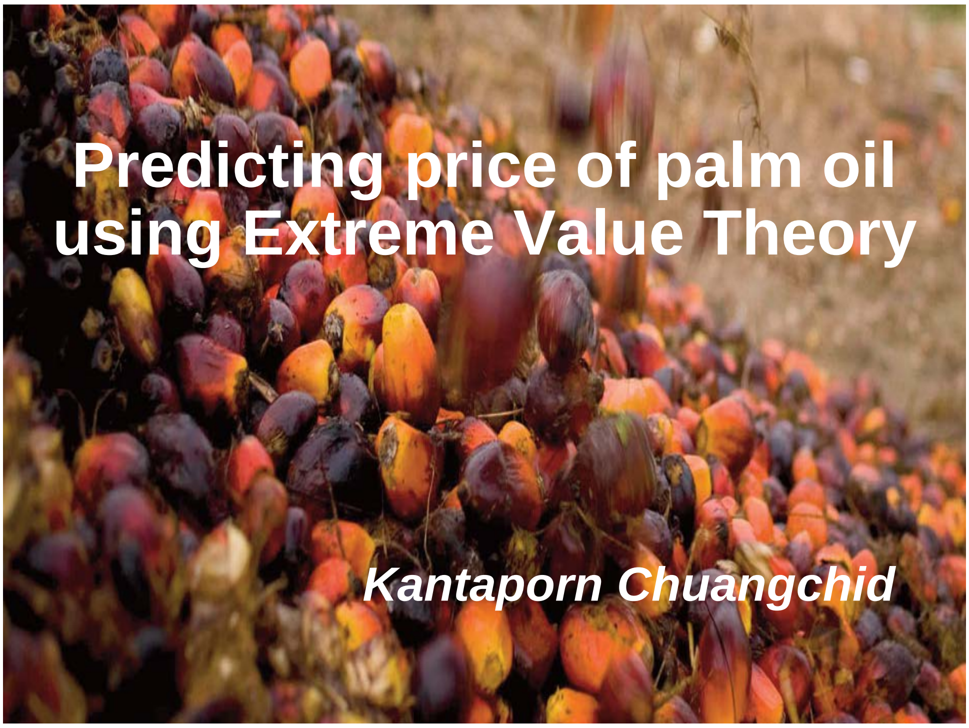
Time	Main Hall	Room ECB 1201	Room ECB 1202	Room ECB 1207	Time
08:00-09:00	Registration				08:00-09:00
09:00-09:30	Opening Ceremony				09:00-09:30
09:30-10:30	Keynote Speech: "Four theorems and a financial crisis" by Prof. Paul Embrechts *at the Main Hall*				09:30-10:30
10:30-11:00	Coffee break				10:30-11:00
11.00 - 11.45	Measuring Correlations of Integrated but not Cointegrated Variables - A Semiparametric Analysis of Volatility Spillover Effects *(Yiguo Sun, Cheng Hsiao*, and Qi Li)*	MARC-MARS: Modeling Asset Returns via Conditional Multivariate Asymmetric Regime-Switching *(Marc S. Paolella* and Pawel Polak)*	The Establishment of Assessment Indicators of Environmentally Sustainable Development and Its Application in National Park *(Wan-Tran Huang*, Chun-Yu Chien, Yun Jhang, Ya-Hsuan Hsu, and Han-Shen Chen)*	Economic Factors Influencing the Urban Real Estate Price in the People's Republic of China *(Lianting Cheng*, Prasert Chaitip, and Chukiat Chaiboonsri)*	11:00-11:30
				Does Price Matter? The FMOLS Estimation of Rich Countries Tourist Outbound to Four ASEAN Countries *(Komkrit Wongkhae* and Chukiat Chaiboonsri)*	11:30-12:00
11.45 - 12.30	Macroeconomic Determinants of Stock Market Volatility and Volatility Risk-Premiums (Valentina Corradi, Walter Distaso, and Antonio Mele*)	Testing for Monotonicity in Expected Asset Returns *(Joseph Roman and Michael Wolf*)*	Do We Still Need to Finance Energy until Next 10-20 Years? : An Energy Model giving a Brief Picture of Our 2010 Policy *(Apirada Chinprateep)*	Predicting price of palm oil using Extreme Value Theory *(Kantaporn Chuangchid*, Aree Wiboonpongse, Sanzidur Rahman, Yaovarate Chaovanapoonphol, and Songsak Sriboonchitta)*	12:00-12:30
12:30-14:00	Lunch				12:30-14:00
14.00 - 14.45	Prediction in Econometrics: Towards mathematical justification of simple (and successful) heuristics *(Vladik Kreinovich*, Hung T. Nguyen, and Songsak Sriboonchitta)*	On Permutation Tests for Serial Independence (Lanh Tran* and Jiexiang Li)	Does off-balance sheet activities affect the banks' profit efficiency? Empirical evidence from the Indian banking sector *(Sunil Kumar)*	Analysis of Equilibropathy Acupuncture Involving Chronic Pain Treatment and Healing Rates *(Sangkhae Sutthi*, Songsak Sriboonchitta and Pathairat Pastpipatkul)*	14:00-14:30
				Dynamic correlations between local APIs and corresponding regional, national levels in China *(He Zhanqiong)*	14:30-15:00
14.45 - 15.30	Statistics with Fuzzy Data in Econometrics *(Berlin Wu)*	Smooth Transition Quantile Capital Asset Pricing Models with Heteroscedasticity *(Cathy W.S. Chen*, Simon Lin, and Philip L.H. Yu)*	Banking reforms and total factor productivity growth in the banking industry: evidence from India *(Rachita Gulati and Sunil Kumar*)*	A Study of Seasonality and Dynamic Correlations between Local and Regional, National APIs Level *(He Zhanqiong)*	15:00-15:30
15:30-16:00	Coffee break				15:30-16:00
16.00 - 16.45	Detecting Changepoints in Segmented Linear Regression Heteroscedastic Models by Empirical Likelihood Methods *(Hualing Zhao and Hanfeng Chen*)*	Forecast combination for discrete choice models: predicting FOMC monetary policy decisions *(Laurent L. Pauwels* and Andrey Vasnev)*	The relationship between Leisure Participated Motivation and Constraints on Senior Students *(Cheng-Chuan Chen*, Chih-Chuan Wang, and Rui-Cheng Hong)*	Modeling the effects of community-based tourism on household income and poverty alleviation in thailand with econometric treatments of endogeneity and selection bias problems *(Komsan Suriya)*	16:00-16:30
			A New Approach on Standard Setting in Education with Fuzzy Statistical Analysis *(Mingchuan Hsieh)*	Effects of microcredit on povertyreduction in Thailand using propensity score matching and average treatment effect model *(Siwaporn Fongthong* and Komsan Suriya)*	16:30-17:00
16.45 - 17.30	Fuzzy modeling of survival function from interval or censored observations (Andrzej Szymanski* and Agnieszka Rossa)	An Innovative Financial Time Series Model: The Geometric Process Model *(Jennifer S.K. Chan1, Connie P.Y. Lam and S.T. Boris Choy*)*	Performance Evaluation in After School Care Policy *(Huang-Yu Shih)*	Determinants of Borrowers and Loan Sizes of Microcredit for Villages and Urban Communities in Thailand *(Siwaporn Fongthong* and Komsan Suriya)*	17:00-17:30
17:30-18:00				An optimal model of monetary and fiscal policy interaction in the case of indonesia *(Haryo Kuncoro* and K. Dianta A. Sebayang)*	17:30-18:00

Program: Friday January 13th, 2012

Time	Main Hall	Room ECB 1201	Room ECB 1202	Room ECB 1207	Time
08:00-09:00	Registration				08:00-09:00
09:00-10:30	Keynote Speech: "Granularity Adjustment for Risk Measures: Systematic vs Unsystematic Risks" by Prof. Christian Gourieroux *at the Main Hall*				09:00-10:30
10:30-11:00	Coffee break				10:30-11:00
11.00 - 11.45	Statistical inference from ill-known data using belief functions *(Thierry Denoeux)*	Structural Breaks in Stock Returns Volatility: Evidence from the Stock Exchange of Thailand *(Yuthana Sethapramote and Suthawan Prukumpai)*	Estimation and Decomposition Agricultural Productivity Growth in Asia *(Supawat Rungsuriyawiboon)*	Charitable giving behavior in Thailand and Mukdaharn Province: Tobit vs. double-hurdle models *(Jintanee Jintranun*, Peter Calkins, Songsak Sriboonchitta, and Chukiat Chaiboonsri)*	11:00-11:30
				Modeling the Volatility of Rubber Price Return using VARMA GARCH Model *(Wei Chen Sang*, Wan Tran Huang, Aree Wiboonpongse, Sanzidur Rahman, Yaovarate Chaovanapoonphol, and Songsak Sriboonchitta)*	11:30-12:00
11.45 - 12.30	Modelling Risk Premium using Capital Asset Pricing Model with Asymmetric Error Distributions *(Nuttanan Wichitaksorn and S.T.Boris Choy*)*	The Dependence Measures of South East Asian Countries' Currency : Using Copulas Approach *(Kanchana Chokethaworn, Jittaporn Sriboonjit, Songsak Sriboonchitta, Prasert Chaitip, and Chukiat Chaiboonsri*)*	Does information and communication technology increase production efficiency? A comparison among service industries *(Sophia P. Dimelis* and Sotiris Papaioannou)*	Modeling the volatility in China's railway freight volume based on conditional volatility model *(Dai Jing*, Songsak Sribookchitta, and Li Ting)*	12:00-12:30
12:30-14:00	Lunch				12:30-14:00
14.00 - 14.45	Behavioral Decision Analysis using Fuzzy Target *(Van-Nam Huynh* and Yoshiteru Nakamori*)*	Analysis of Dependence Structure between House Prices and Stock Indexes Using Archimedean Copulas *(Jianxu Liu*, Songsak Sriboonchitta)*	Mental Health, Happiness, and Income *(Pungpond Rukumnuaykit)*	A State Space Frame Work for Modeling and Forecasting Time Series *(Muhammad Kashif* and Muhammad Inayat Khan)*	14:00-14:30
				New Approach on Core Human Capital Resource Evaluation with Soft Computing Techniques *(Xingyu Yuan*, Jiechen Tang, and Berlin Wu)*	14:30-15:00
14.45 - 15.30	Efficiency Improvement by Local Moments in Grouped Data Analysis *(Kohtaro Hitomi, Qingfeng Liu*, Naoya Sueishi, and Yoshihiko Nishiyama)*	Value at Risk Analysis of Gold Price Returns Using Extreme Value Theory *(Kittiya Chaithep*, Songsak Sriboonchitta, Chukiat Chaiboonsri, and Patirat Paspipatkul)*	Hold a Mirror Up to Nature : A newapproach on Correlation Evaluation with Fuzzy Data and its Applications in Econometrics *(Chih Ching Yang*, Berlin Wu, and Songsak Sriboonchitta)*	House Prices and Economic Growths in People's Republic of China Using Panel Data *(Wenjuan Huang*, Prapatchon Jariyapan, Piyaluk Buddhawongsa, and Chaiwat Nimanussornkul)*	15:00-15:30
15:30-16:00	Coffee break				15:30-16:00
16.00 - 16.30	Maximum Entropy Test of Autoregressive Models *(Sangyeol Lee)*	Solving nonlinear Black-Scholes equations by using the homotopy perturbation method *(Hsuan Ku Liu* and Liang Tao)*	An Application of Metafrontier Cost Model Measuring the Cost Efficiency and metatechnology Ratio in Credit Department of Farmers' Association *(Wan-Tran Huang, Yu-Han Hsu, Chun-Yu Chien*, Wei-Yi Chen, and Yung-Hsiang Lu)*	New Services Development and Pricing Strategy of Rail Transporters to Deliver Products of Small and Medium-Sized and Community Enterprises in Chiang Mai, Thailand: An Analysis with Binary Logit and Hedonic Price Models *(Komsan Suriya*, et.al)*	16:00-16:30
16.30 - 17.00	Generalized Mean-Risk Preferences *(Daniel Schoch)*	Capital Inflows and Inflation Nexus: Evidence from Nonlinear Cointegration and Causality Tests *(Abdul Rashid)*	Factors effecting output in developed country: panel sample selection approach *(Warattaya Chinnakum*, Songsak Sriboonchitta and Pathairat Pastpipatkul)*	Detection of regime switching in stock prices before "window dressing" at the year end using genetic algorithm *(Tatcha Sudtasan* and Komsan Suriya)*	16:30-17:00
17.00 -17.30	Prediction Interval of AR(1) Model with a Linear Trend after Preliminary Unit Root Test (Monchaya Chiangpradit* and Sa-aat Niwitpong)	An application of EVT to analyse US corn market *(Gong Xue*, Aree Wiboonpongse, Sanzidur Rahman, Yaovarate Chaovanapoonphol, and Songsak Sriboonchitta)*	Foreign Direct Investment, Human Capital and Economic Growth in People's Republic of China: Using Panel Data Approach *(Xianghong Cao*, Prapatchon Jariyapan, Piyaluk Buddhawongsa, and Chaiwat Nimanussornkul)*	Can Rising Tourism Income Compensate Fading Agricultural Income? A General Equilibrium Analysis of Income Distribution and Welfare in a Rural Village in Northern Thailand *(Pakpicha Pathompituknukoon*, Purich Khingthong*, and Komsan Suriya)*	17:00-17:30

รายละเอียดของการนำเสนอมีดังนี้

(1) บทความเรื่อง ”Predicting price of palm oil using Extreme Value”



Outline

1. Introduction
2. Objective
3. Literature Review
4. Methodology
5. Empirical results
6. Conclusion

Introduction

-The last few years have seen an increase in the production of renewable fuels because of rising crude oil prices, limited supplies of fossil fuel and increased concern about global warming.

-Palm oil is a type of fatty vegetable oil derived from the fruit of the palm tree. It is used for both food and non-food.

-The world palm oil production was 13.01 million tons in 1992 which has increased to 50.26 million tons in 2011, a 286% increase in 19 years (USDA, 2011).

-The major world producers and exporters are Malaysia and Indonesia.

-The major world importers are India, China and the European Union.

-Figure 1

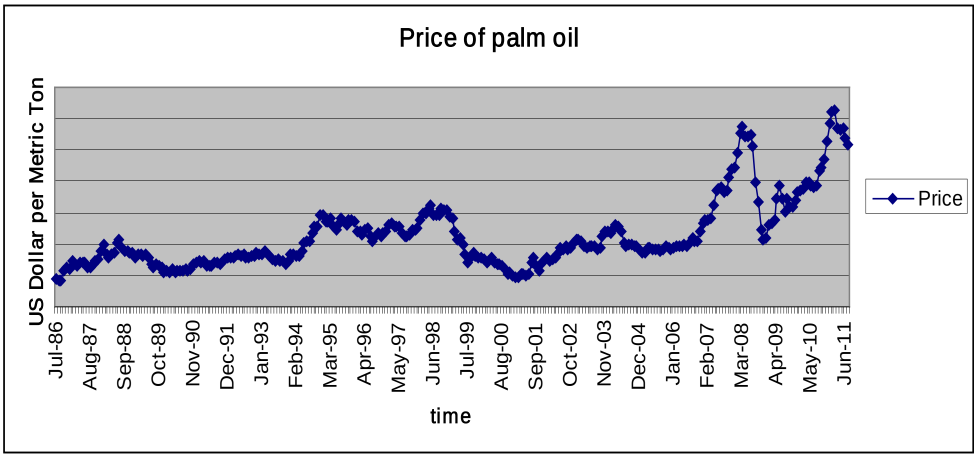
-Palm oil price can be significantly affected in two ways, fluctuation in nature and world demand.

Products from palm oil

Food Products

Non-Food Products

Figure 1



Introduction

-In risky conditions and between price instability, forecasting is very important in helping to make informed decisions.

-Forecasting of agricultural price has traditionally been carried out by applying an econometric model such as ARIMA, ARCH, GARCH based on historical data. Using such approach ignores the possibility of extreme event.

-The palm oil price prediction involves determining the probability of extreme event.

-Extreme Value Theory enables to describe the behavior of random variables both at extremely high or low levels.

Objective

Using the Extreme Value Theory focus on the Block Maxima (BM) and Peak-Over-Threshold (POT) modeling to predict extreme price events and forecast extreme value of palm oil price in the future.

Literature Review

A number of studies exist on forecasting palm oil prices using various technique.

-Alias and Tang (2005)

-Abdullah et al., (2007)

-Fatimah and Roslan (1986)

-Rangsan and Titida (2006)

EVT provides a strong theoretical basis with which we can construct statistical models that are capable of describing extreme events (Manfred and Evis, 2003). Extreme value methods were used in environmental science, hydrology, insurance and finance.

Literature Review

for examples;

-Bensalah (2000)

-Silva and Mendes (2003)

-Bekiros and Georgoutsos (2004)

-Zuo-xiang et al., (2005)

In disaster studies,

-Li-Hau and Pei-Hsuan (2005)

-Xu and Zhang (2010)

Methodology

The Extreme Value Theory (EVT)

EVT is a method for modeling extreme values. The main idea of this theory is the concept of modeling and measuring extreme events which occur with very small probability (Erik and Claudia, 2006).

There are two principal approaches

1. **Block Maxima Model (BM)**

The BM studies the statistical behavior of the largest or the smallest value in a sequence of independent random variables (Xu and Zhang, 2010). One approach to working with extreme value data is to group the data into blocks of equal length and fit the data to the maximums of each block: assuming we have identified n blocks let Zi (i=1,…,n) denote maximum observation in each block(Coles, 2001).

Methodology

The BM is closely associated with the use of Generalized Extreme Value (GEV) distribution with c.d.f:

$$G(z) = \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

The log-likelihood for the GEV parameters when $\xi \neq 0$ is (Coles, 2001) is given by:

$$\ell(\xi, \mu, \sigma) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\xi\left(\frac{Z_i-\mu}{\sigma}\right)\right]^{-1/\xi}$$

Methodology

The case ξ = 0 requires separate treatment using the Gumbel limit of the GEV distribution (Coles, 2001). The log-likelihood in that case is:

$$\ell(\mu, \sigma) = -n\log \sigma - \sum_{i=1}^{n}\left(\frac{Z_i-\mu}{\sigma}\right) - \sum_{i=1}^{n}\exp\left\{-\left(\frac{Z_i-\mu}{\sigma}\right)\right\}$$

Methodology

2. **Peaks-Over-Threshold Model (POT)**

The POT approach is based on the Generalized Pareto Distribution (GPD) introduced by Pickands (1975). These are models for all large observations that exceed a high threshold. If the block maxima has an approximate distribution of GEV, then for large enough threshold, u, the distribution function of (X-u), conditional on X > u, is approximately

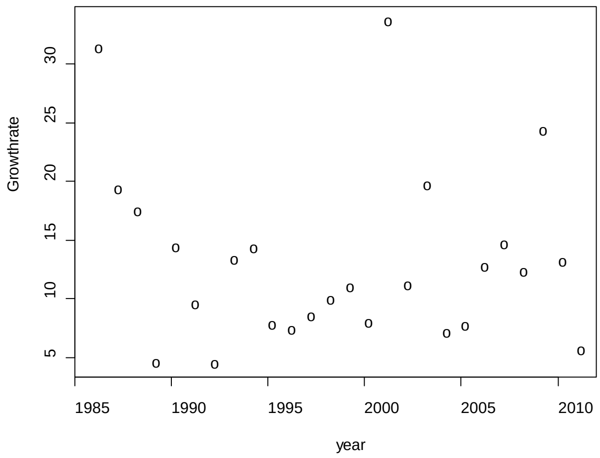
$$H(y) = 1-\left(1+\frac{\xi y}{\sigma}\right)^{-1/\xi}$$

For $\xi \neq 0$ the log-likelihood is (Coles 2001)

$$\ell(\sigma, \xi) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log\left(1+\xi y_i/\sigma\right)$$

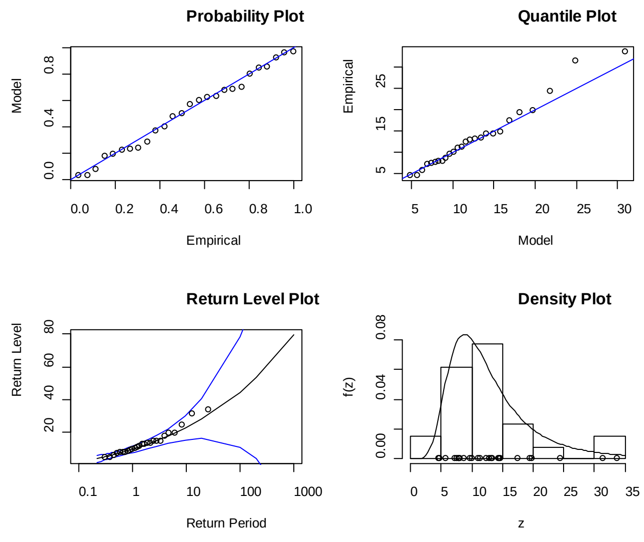
Empirical results

1. **The results from the BM model**



The scatter plot of annual maximum palm oil price growth rate (PPGR)

Diagnostic Plots for GEV fit to the annual maximum PPGR

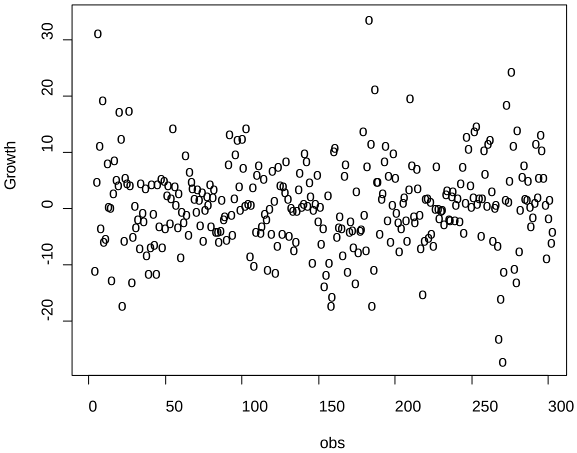


T-year return level based on GEV model

Item	GEV fit	95%
ξ	0.2106	
σ	4.5000	
μ	9.6435	
Year-5	17.5810	(14.0515,24.4286)
Year-10	22.5982	(17.5190,37.5984)
Year-25	30.1837	(21.8648,67.3767)
Year-50	36.8748	(24.9560,105.3495)
Year-100	44.5726	(27.8615,165.6797)

Empirical results

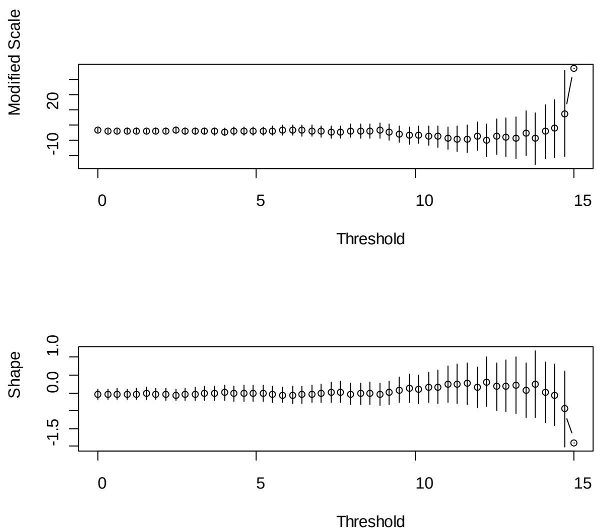
2. **The results from the POT model**



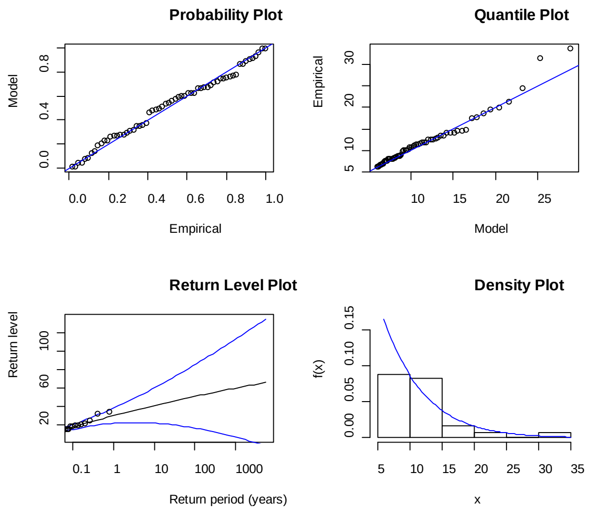
The scatter plot of PPGR

Mean Residual Life Plot of PPGR

Parameter stability plots for PPGR



Diagnostic plots for GPD fit to PPGR



T-year return level based on GPD model

Item	GPD fit	95 %
ξ	-0.0435	
σ	6.0619	
Year-5	37.6226	(29.1853,76.9672)
Year-10	40.8219	(30.7610,94.3344)
Year-25	44.9058	(32.4901,122.6481)
Year-50	47.8887	(33.5656,149.0050)
Year-100	50.7830	(34.4789,180.5439)

Conclusion

-The aim of this study is to predict extreme events in the price of palm oil in the future using the best possible method that overcomes previous shortcomings in the literature dealing with palm oil price predictions.

-Using BM and POT approaches of extreme value modeling technique, we fit GEV and GPD models to the growth rate of the palm oil price covering a 25 year period (Jul, 1986 to Jul, 2011).

-Both GEV and GPD found that palm oil price will have higher extremes in the next 5, 10, 25, 50 and 100 year period with acceleration in values towards longer future periods.

(2) บทความเรื่อง “An application of EVT to analyze US corn market”

An application of EVT to analyze US corn market

Gong Xue, Aree Wiboonpongse, Sanzidur Rahman, Yaovarate Chaovanapoonphol, Songsak Sriboonchitta

Structure of Presentation

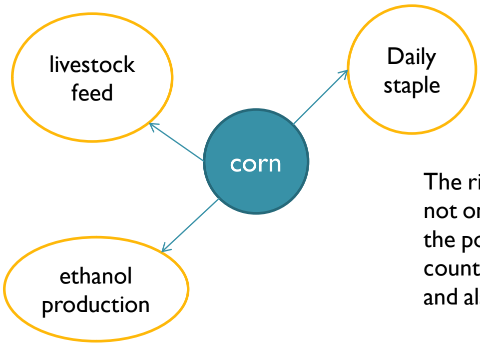
- 1. Introduction
- 2. Econometric Analyse
- 3. Empirical Results
- 4. Conclusion

Research Question

- Nowadays the agricultural price (such as the corn) kept increasing, and fairly volatile.
- In our study, we want to answer the question like "What are the likely future trends of corn price? How large the risk of the corn market?"

Motivation

Agricultural commodity price is significant important because:



The risk of corn market not only influence the interest of the poor in low-income import countries, famers in USA, and also everyone's daily life.

Discuss Earlier Work

1. There are a large number of literatures based on EVT focus on finance, energy, insurance.

But a few of them on the agricultural commodities price.

There are a large number of literatures based on EVT focus on finance, energy, insurance.

Field	Author	Publication	Main content
Finance	Bekiros, 2005	Mathematics and Economics	used BMM and POT to calculate the VaR of three exchange rate indices. After comparing the results with traditional methods on three different markets, they concluded that EVT-based method produces the most accurate forecasts of extreme losses.
Energy	Marimoutou, 2009	Energy Economics	applied the Garch-EVT model in the oil market, modeled VaR for long and short trading positions by applying both unconditional and conditional EVT models(Garch-EVT model) to forecast VaR. However the conditional EVT models are not superior to the others
Insurance	Vandewalle, 2006	Mathematics and Economics	On estimation of insurance premiums for excess-of-loss reinsurance policies in excess of a high retention level ... with special attention to heavy-tailed distributions and Wang' s premium principle as a generalization to the net premium principle

Some similar papers focus on the agricultural commodity price, but…

- John Cotter, Kevin Dowd, Wyn Morgan. (2008) study the US. corn and soybeans future market price, and use POT method to estimate the risk in agricultural market. However, this paper only focus on estimating the agricultural price by using EVT but never compare the results with other traditional methods. Therefore it can not say EVT works better. Besides, the time span of this study is about ten years, much shorter than ours. Otherwise, they never provide any policy suggestions to the government.

Risk Measures Tools in Extreme value Theory

- Here we introduce several Terminology
- Extreme Value Theory(EVT):
- The theory summaries the law of the movement of extreme events.
- Return Level: to what degree the extreme events will happen again in next few decades. (ten years)
- VaR (Marimoutou.el, 2009): how much we can lose with a given probability over a certain time horizon.
- Expected Shortfall: (Tsay, 2010) if the loss occurs, the expected value of the loss.

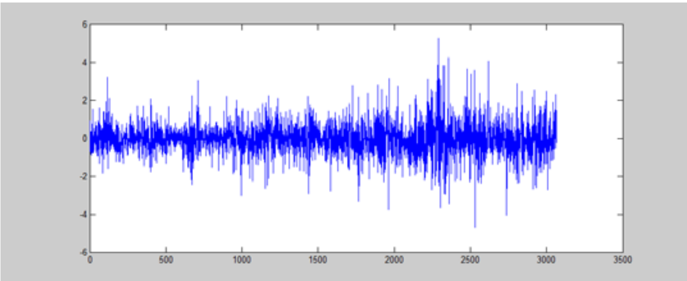
Our Steps in Estimation

- We analyse the three methods in EVT as followed:
- 1. Unconditional model:
- Block Maxima Method (BMM), Peaks Over Threshold (POT) (Coles, 2001)
- 2. Conditional Model:
- GARCH-EVT model (Alexander J. McNeil, Rüdiger Frey, 2000)
- We compare the results of EVT family methods with the other traditional methods (such as GARCH-normal, and GARCH-t)

Empirical Study

- Data set: corn U.S No.2 yellow.
- This quotation is the leading benchmark price.
- Data source: USDA
- Time span: 1st January 1979 to 29th September 2011

Fig. the corn return plot



The Results of Return Level

			Return Level(ten year)
BMM	monthly		4.881
	quarterly		4.366
	yearly		4.137
POT	threshold= 1.132	r=2	4.803
		r=4	4.739
	threshold= 0.771	r=2	4.714
		r=4	4.671

POT results of VaR

		VaR(5%)	VaR(1%)	ES(5%)	ES(1%)
threshold: 1.132	r=2	3.233	4.804	4.247	6.086
	r=4	3.337	4.927	4.358	6.183
threshold: 0.771	r=2	2.73	4.114	3.616	5.189
	r=4	2.878	4.319	3.797	5.41

The 1% and 5% VaR and ES estimates are not varied much in two thresholds. Given threshold equal to 1.132, i.e u=95% in the negative return, declustering r=2 we can predict tomorrow's loss for corn. U.S is 3.233% and if this happens the corresponding expected loss will be 4.247%.

The Results of Empirical Study

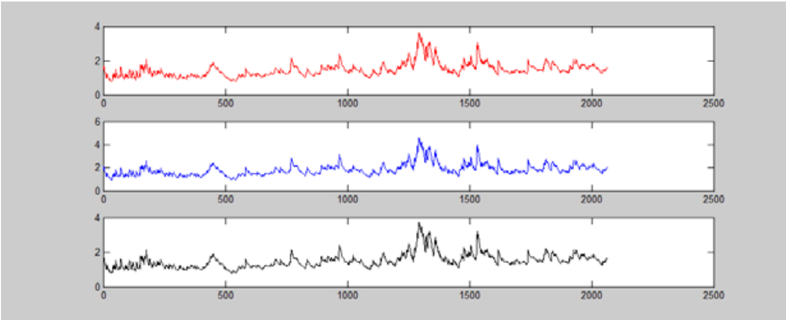


Fig. the 1% VaR Estimate of Three Dynamic Models: GARCH-normal, GARCH-t and GARCH-EVT

The Results of Empirical Study

	0.95 quantile	0.99 quantile	0.995 quantile
Expected	103	20	10
Conditional EVT	99(0.048)	23(0.011)	11(0.005)
Conditional Normal	108(0.052)	41(0.019)	25(0.012)
Conditional t	108(0.052)	37(0.017)	25(0.012)

The Main Findings of This Study

- 1.The shape parameters in the BMM and POT estimation is positive, which confirms the necessity to use the EVT in this study.
- 2. Comparing with the traditional approaches such as the GARCH-normal and GARCH-t models to calculate the VaR, the GARCH-evt model performs better in the corn returns by backtesting.
- 3. The corn percent change return level in next ten year and the VaR is higher when using the EVT methods which indicates that in the future the price has rising trend than expecte.

The policy implication for the poor countries: increase the investment in Agriculture.

- For the long term, it is necessary to improve the purchasing power of poor food buyers since price trend is increasing higher, increase the investment in agriculture may be the best way to cut poverty and stimulate economic activity. In others, there may equally be a need to diversify the structure of the economy. In many cases, investments in improving the overall environment in which agriculture operates may be most appropriate – improving basic governance systems, macroeconomic policy, infrastructure, technology, education, health, etc

Important Contribution

- This paper use the corn market as an example to analyze the corn returns exhibit extreme behavior which help the US. governments to design the best agricultural strategies and also for the low-income import countries to help the poor.

Conclusion

- As the volatility in the corn markets increases, implement risk measures became a necessity. In this study we focused on the extreme market risk of USA corn return in the period 1979 to 2011.The Return Level, VaR, and ES tools were used to assess extreme tail events and market risk. We also give some useful suggestions to the governments, especially the US and the low-incoming countries.

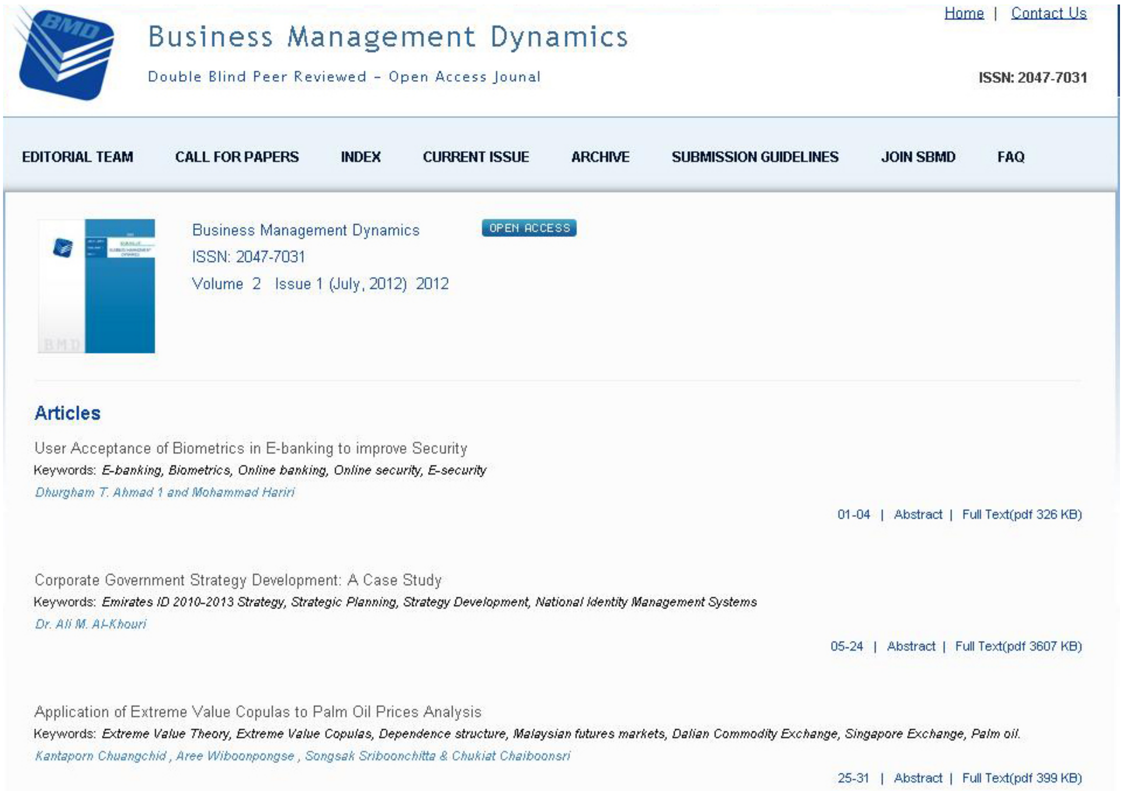
- Thank you everyone!!!

บทที่ 3
การส่งบทความเพื่อตีพิมพ์ในวารสารวิชาการระดับนานาชาติ

คณะวิจัยได้ทำการส่งบทความเพื่อตีพิมพ์ในวารสารต่างประเทศ 7 ฉบับ ได้แก่

(1) Business Management Dynamics

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Application of Extreme Value copulas to palm oil prices analysis ซึ่งขณะนี้ได้รับการตีพิมพ์แล้วใน Business Management Dynamics, Vol.2, No.1, Jul 2012, pp.25-31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Keywords: *E-banking, Biometrics, Online banking, Online security, E-security*
Dhurgham T. Ahmad 1 and Mohammad Hariri
01-04 | Abstract | Full Text(pdf 326 KB)

Corporate Government Strategy Development: A Case Study
Keywords: *Emirates ID 2010-2013 Strategy, Strategic Planning, Strategy Development, National Identity Management Systems*
Dr. Ali M. Al-Khouri
05-24 | Abstract | Full Text(pdf 3607 KB)

Application of Extreme Value Copulas to Palm Oil Prices Analysis
Keywords: *Extreme Value Theory, Extreme Value Copulas, Dependence structure, Malaysian futures markets, Dalian Commodity Exchange, Singapore Exchange, Palm oil.*
Kantaporn Chuangchid , Aree Wiboonpongse , Songsak Sriboonchitta & Chukiat Chaiboonsri
25-31 | Abstract | Full Text(pdf 399 KB)

ที่มา: http://bmdynamics.com/recent_issue.php?id=16

(2) International Journal of Agricultural Management

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Predicting Malaysian palm oil price using Extreme Value Theory ซึ่งขณะนี้ได้รับการตีพิมพ์แล้วใน International Journal of Agricultural Management, Volume 2, Number 2, January 2013, pp. 91-99(9)

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Predicting Malaysian palm oil price using Extreme Value Theory

Authors: Chuangchid, Kantaporn; Sriboonchitta, Songsak; Rahman, Sanzidur; Wiboonpongse, Aree

Source: International Journal of Agricultural Management, Volume 2, Number 2, January 2013 , pp. 91-99(9)

Publisher: Institute of Agricultural Management

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Abstract:

This paper uses the extreme value theory (EVT) to predict extreme price events of Malaysian palm oil in the future, based on monthly futures price data for a 25 year period (mid-1986 to mid-2011). Model diagnostic has confirmed non-normal distribution of palm oil price data, thereby justifying the use of EVT. Two principal approaches to model extreme values - the Block Maxima (BM) and Peak-Over-Threshold (POT) models - were used. Both models revealed that the palm oil price will peak at an incremental rate in the next 5, 10, 25, 50 and 100 year periods. The price growth level in Year-5 is estimated at 17.6% and 44.6% in Year-100 using BM approach. Use of the POT approach indicated a growth rate of 37.6% in Year-5 and 50.8% in Year 100, respectively. The key conclusion is that although the POT model outperformed the BM model, both approaches are effective in providing predictions of growth in prices caused by extreme events. The results could serve as a useful guide to farmers, exporters, governments, and other stakeholders of the palm oil industry informing strategic planning for the future.

References: 4 references open in new window

Articles that cite this article?

Keywords: Price forecasting; Extreme Value Theory; Block Maxima model; Peak-Over-Threshold model; Malaysian palm oil

Document Type: Research article

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(3) International Journal of Marketing Studies

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Factors Affecting Palm Oil Price Based on Extremes Value Approach ซึ่งขณะนี้ได้รับการตีพิมพ์แล้วใน International Journal of Marketing Studies, Vol. 4, No. 6, 2012

International Journal of Marketing Studies

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Factors Affecting Palm Oil Price Based on Extremes Value Approach

Kantaporn Chuangchid, Aree Wiboonpongse, Songsak Sriboonchitta, Chukiat Chaiboonsri

Abstract

This study examines the dependence structure of extreme realization of growth rate between palm oil prices and factors affecting, which are soybean oil and crude oil prices. We employ the Bivariate Extreme Value methods for daily palm oil, soybean oil and crude oil prices ranging from July 1988 to January 2012. The results provide that the growth rate of palm oil and soybean oil prices has some dependence in extremes, but the growth rate of palm oil and crude oil prices has fairly weak dependence or even independence in extremes. Therefore, the authors of this study hoped that these findings not only have made a contribution to our understanding of what drives palm oil price movement of soybean oil and change in crude oil prices, but also for the practitioner who want to devise an updated model to enhance a further comprehension of the prices that drive these article of trade.

Full Text: PDF DOI: 10.5539/ijms.v4n6p54

International Journal of Marketing Studies ISSN 1918-719X(Print) ISSN 1918-7203(Online)

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(4) International Journal of Intelligent Technologies and Applied Statistics

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH Model ซึ่งขณะนี้ได้รับการตีพิมพ์แล้วใน International Journal of Intelligent Technologies and Applied Statistics, Vol.5 No.3 (2012/09), pp. 251-266

Subject Catagory>Social Science>Statistics>International Journal of Intelligent Technologies and Applied Statistics>Vol.5 No.3

Total Pages: 16 Full-text: Download

ID	2592143
Subject/Title	Forecasting the Volatility of Futures Return in Rubber and Oil Using Copula-Based GARCH Model
Author	Wei-Chen Sang;Songsak Sriboonchitta;Wan-Tran Huang;Aree Wiboonpongse
Journal Title	International Journal of Intelligent Technologies and Applied Statistics
Parallel Title	IJITAS
Vol./Publishing Date	Vol.5 No.3 (2012/09)
Page(s)	251-266
Language	English
Abstract	This paper tries to use the Copula-based GARCH model to find out the relationships between the volatility of rubber futures returns in AFET and four other variables. The results show that the Student-t dependence structure exhibits better explanatory ability than the Gassusian dependence structure in determining the volatility of rubber futures in AFET and two rubber futures in SICOM and TOCOM. However, the Gassusian dependence shows better explanatory ability in the volatility of rubber futures in AFET and two kinds of oil futures in TOCOM. For the multivariate Copula model, all the parameters between AFET and other variables are significant.
Keyword(s)	Volatility,Rubber futures return,Crude oil futures return,Gas oil futures return,Copula-based GARCH model
CEPS Category	Subject Catagory>Social Science>Statistics Subject Catagory>Natural Science>There is no row at position 0.SELECT isNull(descriptionEn,description) as descriptionEn FROM journalSubCat WHERE ptype_id = 3 AND type_id=1295 Subject Catagory>Applied Science>General

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(5) 財金論文叢刊

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Modeling volatility and interdependencies of Thai rubber spot price return with climatic factors, exchange rate and crude oil markets ซึ่งขณะนี้ได้รับการตีพิมพ์แล้วใน 財金論文叢刊, No.16 (2012/06). pp. 1-20

財金論文叢刊>No.16

Total Pages: 20 Full-text: Download

ID	2591535
Subject/Title	Modeling Volatility and Interdependencies of Thai Rubber Spot Price Return with Climatic Factors, Exchange Rate and Crude Oil Markets
Author	Wei-Chen Sang;Songsak Sriboonchitta;Sanzidur Rahman;Wan-Tran Huang;AreeWiboonpongse
Journal Title	財金論文叢刊
Vol./Publishing Date	No.16 (2012/06)
Page(s)	1-20
Language	English
Abstract	Thailand is a leading producer and exporter of rubber in the world market. The interdependencies and volatility of Thai rubber price return with climatic factors (precipitation and temperature), exchange rate, and crude oil market returns are determined in this paper. Vector autoregressive moving average process with generalized autoregressive conditional heteroscedasticity (VARMA-GARCH), VARMA with generalized autoregressive conditional heteroscedasticity (VARMA-AGARCH), and copula-based GARCH models were employed for the analyses. The results demonstrated the interdependencies of Thai rubber price return with dollar and crude oil returns as well as with crude oil return and climatic factors in the VARMA-AGARCH and the copula-based GARCH models, respectively. We conclude that the volatility of Thai rubber price return is linked with volatility in the exchange rate and crude oil markets as well as climatic factors. Thus, stakeholders in the rubber industry should consider movements in those markets when forecasting Thai rubber price returns. Using a set of robust approaches is also recommended to obtain a complete picture of the volatilities and interdependencies of the asset markets.
Keyword(s)	Thai rubber spot price return,climatic factors,crude oil index return,dollar index return,VARMA-GARCH,VARMA-AGARCH model,Copula-based GARCH model
TEPS Category	Subject Catagory>Social Science>Economics

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(6) International Journal of Approximate Reasoning

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Modeling Volatility and Dependency of Agricultural Price and Production Indices of Thailand: Static versus Dynamic Copulas ซึ่งขณะนี้ได้รับการตีพิมพ์ทางเว็ปไซต์ในวันที่ 1 กุมภาพันธ์ 2556

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Available online 1 February 2013

In Press, Corrected Proof — Note to users

Modeling volatility and dependency of agricultural price and production indices of Thailand: Static versus time-varying copulas

Songsak Sriboonchitta[a], Hung T. Nguyen[b], Aree Wiboonpongse[c], Jianxu Liu[a]

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[b] Department of Mathematical Sciences, New Mexico State University, United States

[c] Department of Agricultural Economics and Agricultural Extension, Faculty of Agriculture, Chiang Mai University, Chiang Mai 50200, Thailand

http://dx.doi.org/10.1016/j.ijar.2013.01.004, How to Cite or Link Using DOI

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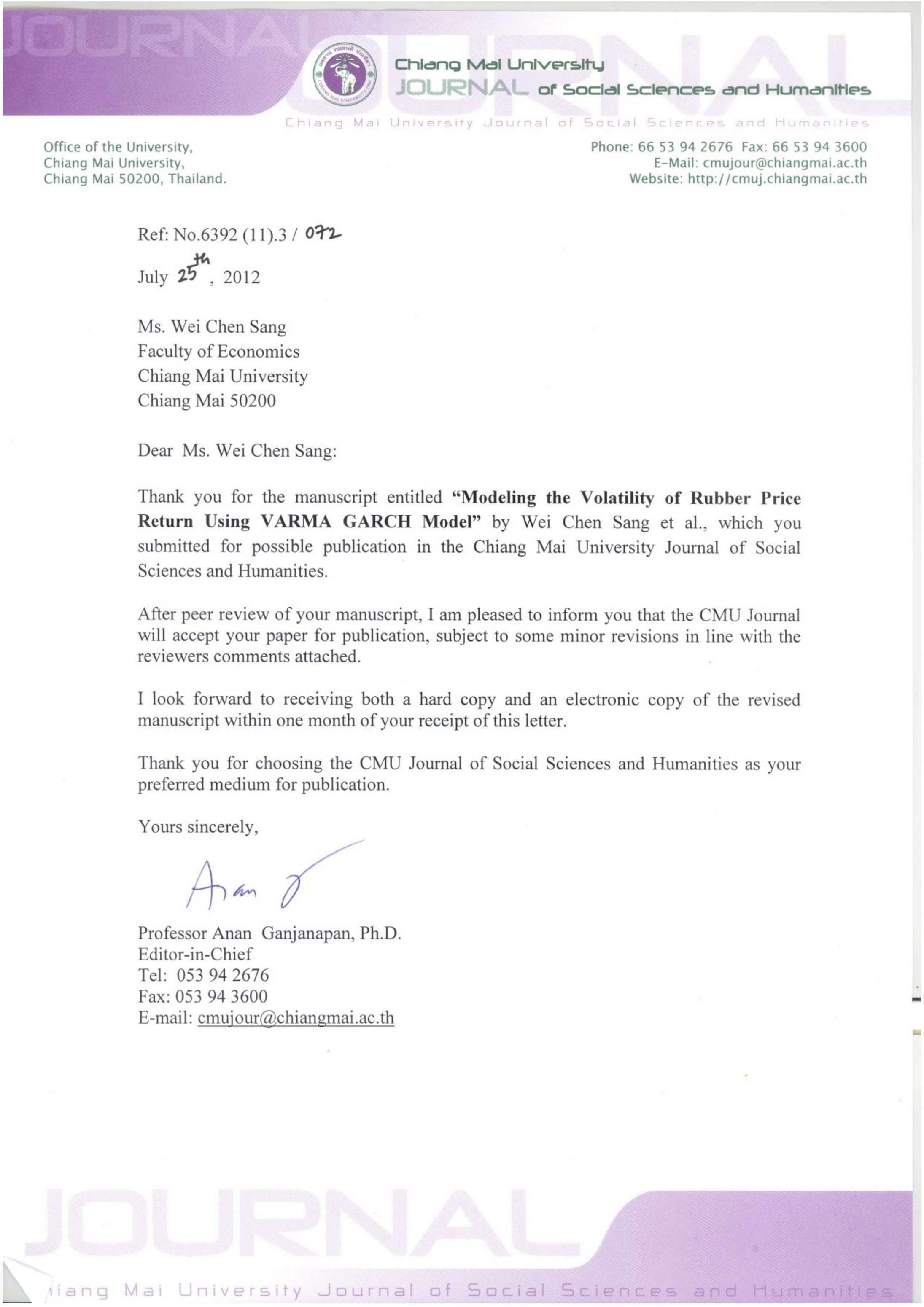
Abstract

Volatility and dependence structure are two main sources of uncertainty in many economic issues, such as exchange rates, future prices and agricultural product prices etc. who fully embody uncertainty among relationship and variation. This paper aims at estimating the dependency between the percentage changes of the agricultural price and agricultural production indices of Thailand and also their conditional volatilities using copula-based GARCH models. The motivation of this paper is twofold. First, the strategic department of agriculture of Thailand would like to have reliable empirical models for the dependency and volatilities for use in policy strategy. Second, this paper provides less restrictive models for dependency and the conditional volatility GARCH. The copula-based multivariate analysis used in this paper nested the traditional multivariate as a special case (Tae-Hwy and Xiangdong, 2009) [13]. Appropriate marginal distributions for both, the percentage changes of the agricultural price and agricultural production indices were selected for their estimation. Static as well as time varying copulas were estimated. The empirical results were found that the suitable margins were skew *t* distribution and the time varying copula i.e., the time varying rotate Joe copula (270°) was the choice for the policy makers to follow. The one-period ahead forecasted-growth rate of agricultural price index conditional on growth rate of agricultural production index was also provided as an example of forecasting it using the resulted margins and time-varying copula based GARCH model.

ที่มา: http://www.sciencedirect.com/science/article/pii/S0888613X13000066

(7) the Chiang Mai University Journal of Social Sciences and Humanities

คณะวิจัยได้ทำการส่งบทความจำนวน 1 บทความได้แก่ Modeling the Volatility of Rubber Price Return Using VARMA GARCH Model ซึ่งขณะนี้กำลังอยู่ในระหว่างการตีพิมพ์



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Ref: No.6392 (11).3 / 072

July 25th, 2012

Ms. Wei Chen Sang
Faculty of Economics
Chiang Mai University
Chiang Mai 50200

Dear Ms. Wei Chen Sang:

Thank you for the manuscript entitled **"Modeling the Volatility of Rubber Price Return Using VARMA GARCH Model"** by Wei Chen Sang et al., which you submitted for possible publication in the Chiang Mai University Journal of Social Sciences and Humanities.

After peer review of your manuscript, I am pleased to inform you that the CMU Journal will accept your paper for publication, subject to some minor revisions in line with the reviewers comments attached.

I look forward to receiving both a hard copy and an electronic copy of the revised manuscript within one month of your receipt of this letter.

Thank you for choosing the CMU Journal of Social Sciences and Humanities as your preferred medium for publication.

Yours sincerely,

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