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# Drivers of farm business capital structure and its speed of adjustment: evidence from Western Australia's Wheatbelt

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The viability and profitability of a farm business can be influenced by how it chooses to fund its operations and capital investments either using debt or internal funds. This study examines the determinants and speed of adjustment of the capital structure of broadacre farm businesses in Western Australia's Wheatbelt. Results show that prior period cash flow and equity, farm size and farm location are significant determinants of observed capital structures. Farm businesses are found to quickly adjust their capital structure to desired target levels, suggesting that adjustment costs are not high. The findings support the view that there is a pecking order in the choice of how farm businesses fund working capital and capital investments.

**Key words:** capital structure, debt, farm business, pecking order, signalling, speed of adjustment.

## 1. Introduction

A firm's capital structure refers to the combination of debt, equity and hybrid securities it uses to finance its operations and investments. A large body of literature has investigated what determines a firm's capital structure and its speed of adjustment (i.e. how quickly a firm's capital structure is adjusted towards a firm-specific target combination of debt and equity), observing that the structure and speed of adjustment may vary across firms based on each firm's investment and risk preference, access to credit and operating environment (Titman and Wessels 1988; Harris and Raviv 1991; Shyam-Sunder and Myers 1999; Korajczyk and Levy 2003; Fan *et al* 2012; Serfling 2016). However, the studies have mainly focused on corporate firms with very limited application to farms.

In production agriculture, the capital structure of a farm business is a key determinant of its overall financial risk, cost of capital and consequently its

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value. Use of high levels of debt relative to equity increases the vulnerability of a farm business to financial distress and bankruptcy. The capital structure of a farm business may influence its ability to access credit for capital investment necessary to adjust to changes in the production environment and adopt new technologies through capital investment. Despite the implications of the capital structure for farm business viability, few studies have investigated what drives the choice of a farm's capital structure (Barry *et al*. 2000; Escalante and Barry 2003; Zhao *et al*. 2008a; Zhao *et al*. 2008b). Even fewer studies have examined the speed with which farm businesses adjust their capital structures towards their desired targets in response to changes in their production environment and operating circumstances (Aderajew *et al*. 2018).

Farm businesses are often privately held companies or sole proprietorships with no access to public or private funding through equity capital markets; their financing options are usually limited to internal cash and external debt provided by commercial lenders. The absence of complex corporate structures amongst farm businesses enables better detection of the creditworthiness of prospective borrowers by lenders (Aderajew *et al*. 2018).

Over the past thirty years, there has been a rapid rise in the indebtedness of farm businesses across the developed world, which has come against a backdrop of climate change (Makuvaro *et al*. 2018), increased competition from emerging country competitors in export markets (Trindade and Fulginiti 2015), and slowing productivity growth (Fuglie et al. 2017; Khan *et al*. 2017). In Australia, farm business debt rose from about A$15 billion in 1993 to be A$70 billion by 2017 (White 2018). This rise can be attributed to low interest rates, high land values, a shift away from less capital intensive wool production to more capital intensive crop production, technological changes and continued consolidation of farm ownership that has increased farm size and working capital requirements (Rural Bank 2017; Martin *et al* 2018).

The objective of this study is to investigate the determinants of farm capital structure and its speed of adjustment towards individual target levels for a sample of 61 commercial farms in Western Australia's Wheatbelt over the period 2002 and 2011. The Wheatbelt accounts for about 60 per cent of Western Australia's agricultural production and approximately one-third of Australia's total grain exports. The study is the first in an Australian context to investigate farm-level capital structure, its determinants, and its speed of adjustment. The study adds to the literature on capital structure in agriculture by controlling for farm location, based on rainfall zones, as climatic differences across regions may affect the choice of farm business capital structure. Insights from this analysis are relevant for enabling farm businesses to make better decisions on capital investment.

The results show that prior period cash flow and equity, and the location of farms in the medium as opposed to low rainfall region have a significant and inverse relationship with farm business debt-to-asset ratios; larger farm businesses are found to have higher debt-to-asset ratios compared to smaller farms. We find evidence of dynamics in the choice of capital structure amongst farm businesses and that the speed of adjustment to target debt-to-asset ratio is relatively fast. The findings lend support to established capital structure theories, described later in Section 2, in explaining the capital structure decisions of the sampled farm businesses.

The paper proceeds with a brief review of capital structure theories and their applications in the context of farm businesses in Section 2. The empirical method is presented in Section 3 followed by a description of the study region and data in Section 4. Section 5 discusses the empirical results and section 6 offers conclusions and policy implications.

## 2. Literature review

Several theories have been proposed in the corporate finance literature to explain the capital structure choices of businesses. Prominent amongst these are the agency theory (Jensen and Meckling, 1976), free cash flow theory (Jensen 1986), pecking order theory (Myers 1984; Myers and Majluf 1984), trade-off or partial-adjustment theory (Miller 1977), signalling theory (Spence, 1973; Ross 1977), market timing theory (Baker and Wrugler, 2002) and managerial inertia theory (Welch 2004). This paper follows the lead of Aderajew *et al.* (2018) in acknowledging that the capital structures of farm businesses lend themselves to the application of only specific theories. We focus on the pecking order and signalling theories.

The pecking order theory (Myers 1984; Myers and Majluf 1984) posits that less risky funds are preferred to finance new investments and operational activities. Under the pecking order theory, internal cash (cash on hand) is considered less costly and preferred to external sources of funds like debt from a commercial bank loan. In the use of external funds, debt is preferred to equity, because it is less costly although it is noted that most farm businesses do not have access to equity capital markets. Myers (1984) identifies two costs as firms progress through the pecking order of finance options (i.e. internal funds to debt): (i) the prospect of financial distress increases and (ii) the likelihood that a positive net present value project shall be passed up as the cost of security issuance rises. The pecking order theory proposes a negative contemporaneous relationship between cash flow and leverage (Shenoy and Koch 1996).

The signalling theory posits (Spence, 1973; Ross 1977) that in the presence of informational asymmetry, lenders evaluate prospective borrowers based on the ‘signals’ they provide. The desired signal from a potential borrower can help the lender assess whether the borrower is a high risk or low risk. Positive signals can include high cash flows (Shenoy and Koch 1996), managerial competency (Backes-Gellnerm and Werner, 2007), the structure of management contracts (Levine and Hughes, 2005) or prior borrowing history (Ross 1977). Negative signals for lenders can include unfavourable macroeconomic conditions such as rising unemployment (Dinterman *et al.* 2018), poor business cash flow (Boyle and Gutherie, 2003), low levels of collateral and incidences of delays in debt repayment by prospective borrowers (Cadot 2013).

Only a few studies have explored the applicability of capital structure theories to farm businesses. In an empirical investigation of Illinois farms between 1990 and 1994, Barry *et al.* (2000) found that farm businesses adjust to long-run financial targets for equity, debt and leasing and that financing needs follow the pecking order where internal cash is used before resorting to using debt. In another study of Illinois farms, Zhao *et al.* (2008a) show that the willingness of lenders to provide credit to farm businesses depends on measures of past cash flows and profitability. High-quality borrowers signal their creditworthiness by providing lenders with information about the financial health status of their businesses. Zhao *et al.* (2008b) developed a stochastic multi-period simulation model to show that adherence to the pecking order benefits short-term capital structure choices and that the signalling facilitates the implementation of risk-adjusted interest rates by lenders to farm businesses. In studying the impact of debt structure on production efficiency and financial performance of broadacre farms in Western Australia, Mugera and Nyambane (2014) found evidence of signalling theory where farm businesses with higher returns on assets were perceived to be of lower default risk by lenders. Most recently, Aderajew *et al.* (2018), through an examination of a panel of 1,500 Dutch farms between 2001 and 2015, found that both the pecking order theory and signalling theory explain the observed dynamics of farm-level capital structure.

Several studies in both developed and developing countries have examined factors that influence the choice of capital structure, as well as the drivers for resorting to debt and demand for credit at the farm level. In a study of U.S. farms, Katchova (2005) found that the likelihood of farms using debt was influenced by gross farm income, risk management strategies, and the primary operator's age and risk aversion. In a study of food crop farmers in Akwa Ibom in Nigeria, Nwaru *et al.* (2011) found that farm income, profit, human capital and interest payable were significant determinants of debt demand. In an analysis of a nationally representative survey of farm businesses in Ireland, Howley and Dillon (2012) found that farmer personal characteristics such as age and education, as well as farm characteristics, such as farm size and farming system, strongly affected the choice of using debt to finance capital investment. The study also found that farmers were not driven solely by business-related goals such as maximising profits but also by productivist tendencies (i.e. maximising production volumes) and perceived lifestyle benefits derived from farm work.

In an analysis of loan data from a major German development bank, Fecke *et al.* (2016) found that loan demand was significantly influenced by the choice of different types of capital investment, loan structures and business climate expectations. In an examination of the effect of declining commodity prices on the use of debt by soybean and corn farmers in the United States, Prager *et al.* (2018) found that, following commodity price shocks, farm businesses with higher debt-to-asset ratios increased their non-real estate debt relative to those with less debt intensive capital structures, while off-farm income reduced reliance on external debt. Aderajew *et al.* (2018) found that earnings volatility, profitability, asset tangibility and growth opportunities were important determinants of farm-level capital structure.

The speed of adjustment of capital structure refers to the rate at which capital structure is adjusted towards a firm's target level. It indicates the agility of farm businesses in adapting their financing choices to changing production and market conditions. In the presence of imperfect capital markets (i.e. where transaction costs and/or informational asymmetry exist between borrowers and lenders), Frank and Goyal (2007) hypothesised that the speed of capital structure adjustment depends on both the costs of adjusting towards a firm's optimal capital structure and the costs of deviating from the optimal capital structure. They observed that the speed of adjustment was slow where the costs of adjustment towards the optimal capital structure were high. Östekin (2015) and Drobetz *et al.* (2015) both found that the speed of adjustment varies across financial systems, with firms in better institutional environments having lower costs of adjustment and adjusting faster. Hackbarth *et al.* (2006) found that firms operating under more favourable macroeconomic conditions adjusted faster, a finding supported by Cook and Tang (2010) and An *et al.* (2015). In a study of deregulation in the U.S. financial sector, Rahman (2020) found that firms that were dependent on banks rather than public markets for finance exhibited faster speeds in capital structure adjustment in less regulated environments. In a study of the speed of capital structure adjustment amongst Indian firms, Ghose and Kabra (2020) found that more profitable firms adjusted towards their capital structure faster than less profitable firms. In a related study, Ghose and Kabra (2019) found that firms experiencing greater growth adjusted their capital structure faster than low growth firms.

The pecking order theory offers an alternative explanation of the speed of capital structure adjustment, hypothesising that if firms prefer internal funds that are less costly than external funds, the speed of adjustment will depend on the financial surplus or deficit of firms (Devos *et al.* 2017). The dynamic pecking order models of Viswanath (1993) postulate that the speed of adjustment will be asymmetric and will be lower when less costly internal funds are in surplus.

Despite the prospective benefits of understanding how rapidly farm business adjusts their capital structures, few agricultural studies have examined the speed of adjustment of capital structure in farm businesses. Barry *et al.* (2000) in their research of farm businesses in Illinois found that adjustments in short-term debt were rapid, whereas long-term debt adjusted slowly. Aderajew *et al.* (2018) in their study of over 15,000 Dutch farms found that adjustments in the capital structure were slow and they attributed this to the high costs of adjustment.

This study builds upon the existing literature by being the first to investigate drivers of farm business capital structure and its speed of adjustment in an Australian setting. In a global context, this is the first study to examine how differences in rainfall amongst farm businesses impact their capital structures.

## 3. Empirical methods

The current study estimates a dynamic partial-adjustment model to account for dynamics in capital structure that arise in the presence of imperfect capital markets that cause firms to temporarily deviate from their desired or optimal capital structure. Following Aderajew *et al.* (2018), we use farm leverage as measured by the debt-to-asset ratio as a proxy for capital structure[1] to present the forward-looking target debt-to-asset ratio of farm $i$ in period $t$, $DA^*_{it}$ as a function of farm-specific characteristics ($X_{it}$) and time fixed effects ($N_t$)[2]:

$$DA^*_{it} = f(X_{it}, N_t) \tag{1}$$

If perfect capital markets are assumed, then ideally a firm's observed debt-to-asset ratio ($DA_{it}$) is equal to its target debt-to-asset ratio $\left(DA^*_{it}\right)$. However, due to the presence of transaction costs (i.e. the costs of identifying information about a borrower and enforcing conditions of a loan, and the cost of searching for a suitable lender), farm businesses face a trade-off between not operating at their target capital structure (i.e. risks, servicing costs, etc) and adjusting to their target capital structure (in this study represented by the debt-to-asset ratio)[3]. This implies that the adjustment costs may be large enough to keep a farm from attaining its target capital structure for an extended period and, hence, the divergence in observed capital structures across farms. Therefore, farm businesses will progressively adjust towards their target debt-to-asset ratio at a speed of adjustment, $\theta$:

[1] Leverage as measured by the debt-to-asset ratio is used as a proxy for farm capital structure, since farm businesses do not generally have access to equity capital markets (Aderajew *et al.* 2018).

[2] Aderajew *et al.* (2018) also include macroeconomic factors of inflation, government debt relative to GDP and the agricultural employment rate. These measures are constant across all farms, which when included with time dummies presents a problem of collinearity. We have chosen to restrict our focus to farm level characteristics to avoid this issue.

[3] Costs of adjustment are the costs of a business changing its capital structure. These can include such costs as lender process and application fees, as well as the time spent collating information required by lenders.

$$\theta = \frac{DA_{it} - DA_{it-1}}{\left(DA_{it}^{*} - DA_{it-1}\right)} \tag{2}$$

The change in the observed debt-to-asset ratios between periods is equal to the speed of adjustment, $\theta$, multiplied by the difference between the target debt-to-asset ratio for the current period, $DA_{it}^{*}$, and the observed debt-to-asset ratio from the prior period, $DA_{it-1}$. Rearranging equation 2 results in equation 3:

$$DA_{it} = (1-\theta)DA_{it-1} + \theta DA_{it}^{*} \tag{3}$$

When $\theta = 1$, a farm fully adjusts to its target capital structure within one period. If $\theta < 1$, a farm partially adjusts to its target capital structure within a period, while when $\theta = 0$, a farm does not adjust within a period (Lemma and Negash 2014). An estimating equation may be expressed as:

$$DA_{it} = (1-\theta)DA_{it-1} + \theta f(X_{it}, N_t) + \varepsilon_{it} \tag{4}$$

Following the model of Aderajew *et al.* (2018), equation 4 can be restated as a linear combination of farm characteristics and time dummies to form the integrated dynamic partial-adjustment model that motivates our empirical investigation (Chang and Dasgupta 2009):

$$DA_{it} = (1-\theta)DA_{it-1} + \theta\left(\sum_{nm}\beta_n X_{it} + \gamma_m N_t\right) + \varepsilon_{it} \tag{5}$$

We use the generalised method of moments (GMM) to estimate equation 5. This method has been adopted in panel studies of farm debt-based capital investment (Bampasidou *et al.* 2017; Stutzman 2018; Aderajew *et al.* 2018). Though the variables will be discussed in detail in the following section, one specific case of endogeneity that is anticipated is between cash flow and capital structure, since a firm's choice between debt and internal cash to fund its investments and operations can affect its cash flow. Conversely, a firm's cash flow as per the pecking order hypothesis may affect its choice of debt use, since greater availability of internal cash may reduce a firm's need for more expensive external funds. Another expected source of endogeneity arises between farm size as measured by total business assets and the debt-to-asset ratios. GMM is a method that uses the two sets of population moment conditions (i.e. mean and variance) to minimise the asymptotic variance amongst the method of moment estimators of the population mean (Wooldridge 2001). The GMM allows for the presence of lagged variables because of its capacity to address the serial correlation problem (Arellano and Bond 1991). The application of the fixed effects estimator requires the strict assumption of exogeneity. Relaxing the assumption of exogeneity, GMM provides a consistent estimator in the presence of heteroscedasticity, that is the variability of a variable is unequal across a range of values of a second variable that may predict it over time (Baum *et al.* 2003).

This study uses the System GMM (Blundell and Bond 1998, 2000), which estimates a system of simultaneous equations shown in equations 6 and 7:

$$DA_{it} = \varphi' DA_{it-1} + X'_{it}\vartheta + (u_i + v_{it}) \tag{6}$$

$$DA_{it} - DA_{it-1} = \delta'(DA_{it-1} - DA_{it-2}) + (X'_{it} - X'_{it-1})\vartheta + (v_{it} - v_{it-1}) \tag{7}$$

where $\varphi$ and $\vartheta$ are coefficients to be estimated, $\delta = 1 + \varphi$, and $DA_{it} - DA_{it-1}$ is the change in the debt-to-asset ratio of farm $i$ at time $t$. The set of independent variables considered is $X'$, that is the determinants of capital structure to be explored. The error term in equation 7, $(\mu_i + v_{i,t})$ contains two identically and independently distributed components, where $\mu_i$ is the time-invariant unobserved heterogeneity within each production unit and $v_{i,t}$ is the idiosyncratic term. Equation 6 provides an estimator in levels and equation 7 provides an estimator based on first differences. Equation 7 alone is referred to as the Differenced GMM (Arellano and Bond 1991). The System GMM is preferred in this study because it presents the lowest bias and highest precision when the time dimension in the panel (in our case 9 years) is small when compared to other widely used estimators like the fixed effect or the difference GMM. The System GMM overcomes the finite sample bias in the presence of weak instruments that the single-equation Difference GMM is subject to (Wooldridge 2001).

A two-step GMM approach is selected because it has greater asymptotic efficiency than a single-step approach. To overcome the downward bias of the standard errors estimated by the traditional two-step GMM estimator, the finite sample corrected variance estimate as proposed by Windmeijer (2005) is used. To test the specification of the model, the Arellano-Bond test (Arellano and Bond 1991) for autocorrelation is applied to the first differenced errors. The Hansen test (Hansen 1982) is used to test for over-identification restrictions in the model's instruments.

## 4. Study region and data

The dataset is a balanced panel from 61 farms located in Western Australia's Wheatbelt region from 2002 to 2011. The region is in the south-west corner of Western Australia and covers a total area of around 197,300 square kilometres, of which over 60% is used for agriculture (Figure 1). In 2015–2016, the gross value of agricultural production in the region was A$4.6 billion, which was over 55% per cent of the total gross value of agricultural production in Western Australia. The farm businesses were clients of a consultancy firm that operates in the study region from whom the data were sourced. The data are a sub-set of data used by Xayavong *et al.* (2015). The data are from farms able to afford an agricultural consultant, so some caution applies to extrapolating findings to the entire population of farms. However, Xayavong *et al.* (2015) checked the representativeness of the sample by comparing it with data from the Australian Bureau of Statistics (2008) agricultural census for the study region. No significant differences in farm characteristics, such as farm size or enterprise mix, were found. Besides, it can be noted that in Western Australia over 40 per cent of broadacre grain farmers use various commercial advisory services including consultant and fee-for-service advisers (Llewellyn and D'Emden 2009; IPSOS-Eureka 2010). Moreover, the annual decline in the number of farms in the study region is only around 1 per cent (Barr 2004), and those exits are mostly not due to unviability. The sampled farms across the study period have a mean revenue of A$1.30 million and an average land size of 3,970 hectares, which is representative of farms in the region; the Planfarm Bankwest Benchmarks (2011) for 2010/2011, the largest comprehensive survey of over 500 farms in Western Australia, shows the average size in 2010/11 was 4,185 hectares and average revenue was A$1.03 million .

Pooled summary statistics for variables included in the estimated models are presented in Table 1. The debt-to-asset ratio is calculated as the ratio of a farm business's total debt divided by its total assets. The measure is on 1

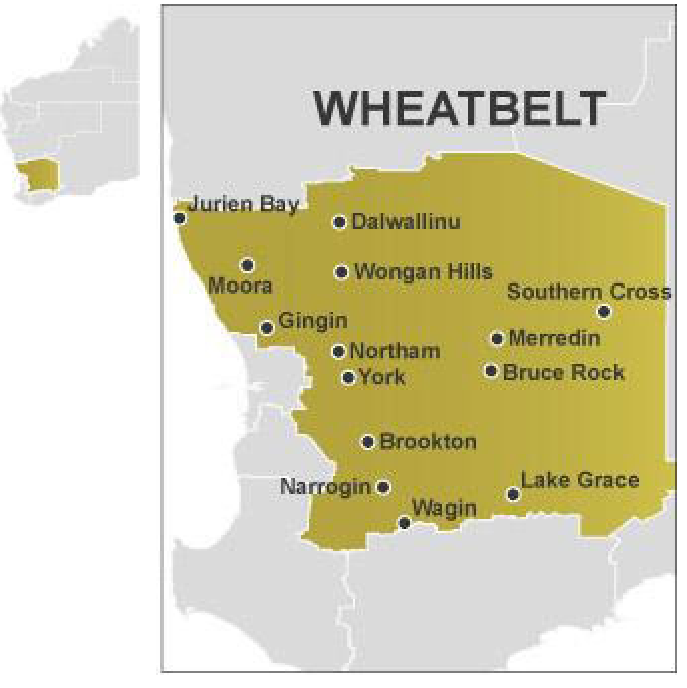


**Figure 1** Western Australia's Wheatbelt Region (http://www.drd.wa.gov.au/regions/Pages/Wheatbelt.aspx). [Colour figure can be viewed at wileyonlinelibrary.com]

**Table 1** Pooled summary statistics (2002–2011)†,‡,§

| Variable | Units | Obs. | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| *Debt-to-asset ratio*$_t$ | | 610 | 0.1776 | 0.1072 | 0 | 0.6011 |
| *Net cash flow*$_t$ | A$ | 610 | −53914 | 389,940 | −2,378,673 | 2,103,550 |
| *Equity*$_t$ | A$ | 610 | 4,163,267 | 3,642,793 | 764,322 | 29,800,900 |
| *Size*$_t$ | A$ | 610 | 5,079,962 | 3,990,873 | 1,041,372 | 33,204,882 |
| *Primary operator age*$_t$ | Years | 610 | 44.3853 | 10.7681 | 19 | 69 |
| *Primary operator education*$_t$ | | 61 | | | | |
| University | | 13 | | | | |
| Non-university | | 48 | | | | |
| *Rainfall zone* | | 61 | | | | |
| Low | | 31 | | | | |
| Medium | | 30 | | | | |

†The normalised measures of net cash flow, equity and size as measured by total business assets are presented in this table.
‡The measures of primary operator age, net cash flow, equity and size as measured by total business assets are not presented in their calibrated form in this table.
§The capital structure is equal to 0 in only 5 of 610 total observations (i.e. the farm business had no debt in a single period). Of these 5 observations, these were split between two individual farm businesses for two years and three years out of ten total years, respectively.

January of the stated year, which is important for interpretation since a change between two years (e.g. 2002 and 2003) is representative of how much the capital structure changed over the calendar year of the first year stated (i.e. 2002). On inspection of the pooled data, we observe that the debt-to-asset ratio ranged from 0 (i.e. the farm had no debt in that single year, which was the case for 5 of the 610 total observations) to 0.6010. The median debt-to-asset ratio was 0.1574 and the mean was 0.1776. Figure 2 shows the box plots for the debt-to-asset ratio by year. The mean debt-to-asset ratio is substantially lower than that observed for the Dutch farms by Aderajew *et al.* (2018) which was 0.363 between 2001 and 2015, as well as for commercial farms in Kansas where the mean debt-to-asset ratio was 0.32 between 2002 and 2012 (Brewer *et al.* 2019). This could be because Australian broadacre farms operate amid variable seasons with little financial support from the government, unlike the case in the EU and North America; the absence of financial support may lead to Australian farm businesses being more risk-averse causing them to have less appetite for debt to finance capital investments. The summary statistics are reported by year in Appendix S1. The distribution of the debt-to-asset ratio is shown to have a skewness of 0.8624 and kurtosis of 3.5780; the pooled distribution is graphically presented in Figure 3 with the distribution graphs of all years provided in Appendix S2.

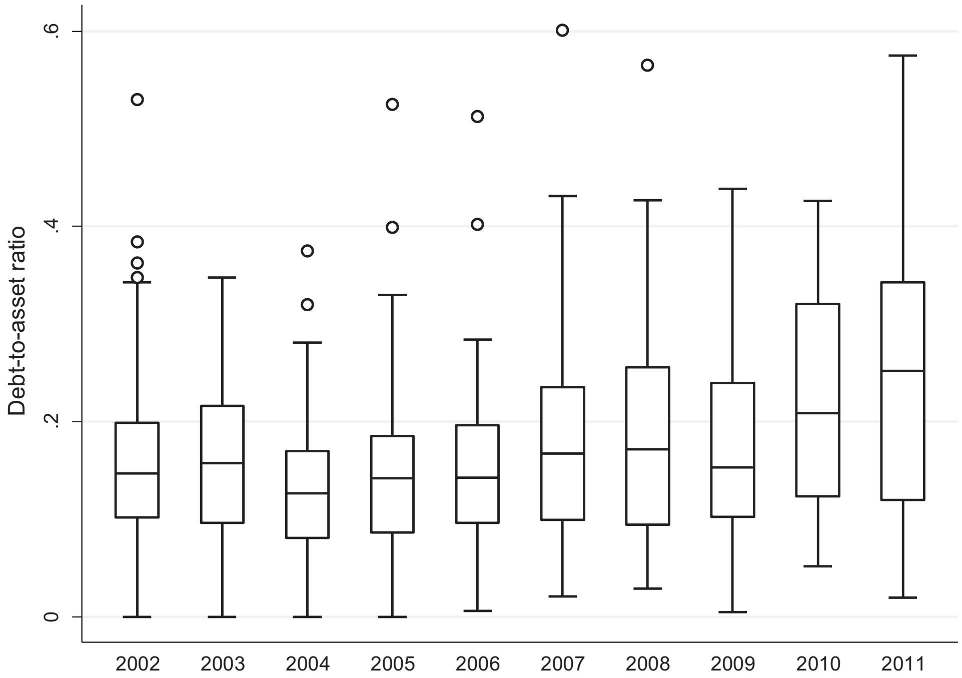


**Figure 2** Box plots of average debt-to-asset ratios (2002–2011).

As shown in Figure 2, though the average debt-to-asset ratio rises over the study period, this is not uniformly positive. Figure 4 presents a scatter plot of the annual changes in capital structure by farm. From the inspection of Figure 4, it is evident that all farms experienced both increases and decreases in their debt-to-asset ratio over the study period.

The first determinant of capital structure considered is the lag of the net cash flow of a farm business. It is calculated as the aggregate revenue minus the aggregate payment over a given period, normalised by the Australian Bureau of Agricultural and Resource Economics Sciences (ABARES) index of consumer prices with 2002 as the base year (ABARES 2012)[4]. The Pecking order theory suggests that higher cash flow in prior periods would reduce debt use since farm businesses would prefer to make use of less costly internal funds instead of external debt (Zhao *et al.* 2008a; Aderajew *et al.* 2018). Improved cash flow can also be interpreted as a positive signal to lenders, which will improve access to debt.

Prior period equity is included to examine the effect of collateral availability on debt use. Farm businesses do not participate in the equity market but use their retained earnings as equity. The measure is taken on 1

[4] The 'lag' of cash flow will be representative of the change in cash position over a given year. As the debt-to-asset ratio is stated effective 1 January of a given year, the cash flow from a given year impacts on the debt-to-asset ratio reported for the next year (i.e. the cash flow over 2002 impacts the debt-to-asset ratio reported at 1 January 2003).

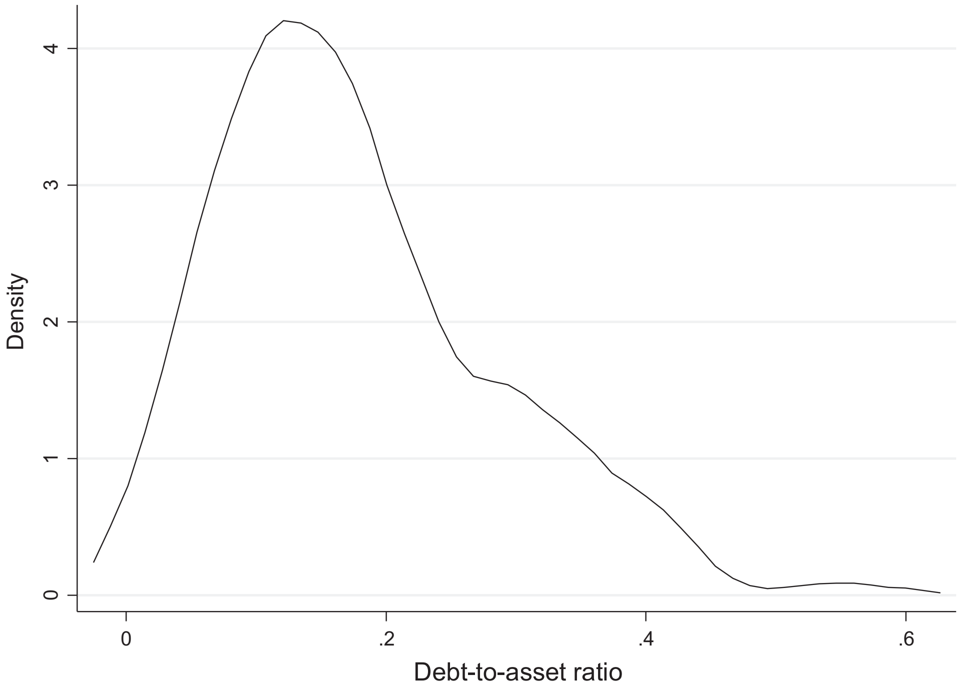


**Figure 3** Pooled density plot of debt-to-asset ratios (2002–2011).

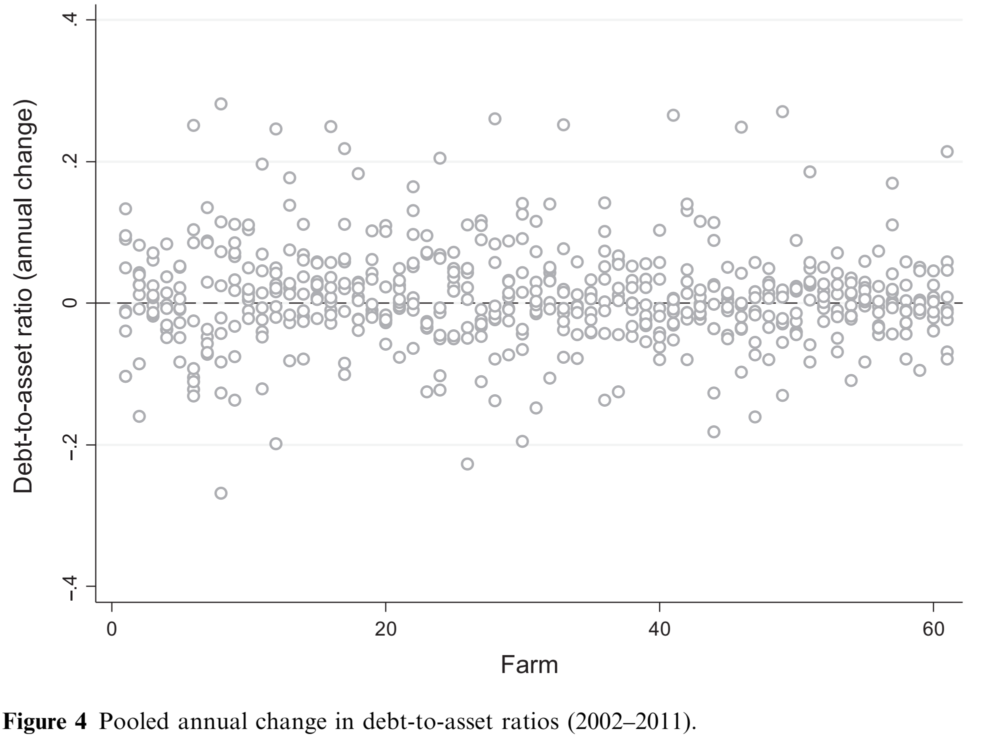


**Figure 4** Pooled annual change in debt-to-asset ratios (2002–2011).

January of the stated year and normalised by the ABARES Consumer Price Index with 2002 as the base year (ABARES 2012). Equity is an important signal to access debt for capital investment where commercial lenders are the primary source of credit (Benjamin and Phimister 2002; Cadot 2013); in Australia, 96% of all rural debt is provided by commercial banks (White 2018). Equity measures farm business net worth, so higher equity values would be expected to positively influence farm business outlook, which has been shown to have a positive impact on loan supply (Fecke *et al*. 2016).

A lag of farm size is included and measured as the lag of total business assets normalised by the ABARES index of consumer prices with 2002 as the base year (ABARES 2012)[5]. Aderajew *et al*. (2018) have observed that large farm businesses have farm assets of higher value than small farm businesses and this has a positive and significant association with the debt-to-asset ratios of horticulture and livestock farms in the Netherlands. For ease of interpretation of estimated parameters, the measures of prior period equity, the lag of net cash flow, and farm size are divided by $10^7$.

The age of the primary farm operator is included as a proxy for management experience. It is measured in years. Operator age is expected to influence the use of debt. Some studies have found that older farm operators have improved access to debt (Zhao *et al*. 2008a) due to longer operational history and lender relationships; other studies have found that younger farm operators were more likely to accumulate debt (Katchova 2005; Howley and Dillon 2012) than older operators who were less likely to over-invest in capital assets (Skevas et al. 2018).

A dummy variable is constructed to group primary operators as either university-educated or not. Howley and Dillon (2012) found that educational attainment is positively associated with debt use amongst Irish farms whereas Katchova (2005) found a negative association between educational attainment and the demand for debt amongst farm businesses in the United States. Educational attainment may be interpreted by lenders as a signal of managerial competency.

As the survey area is a dryland farming region, expected income and its variability, as well as a farm business operator's risk appetite, may be influenced by the rainfall zone in which farm businesses are located (Kingwell and Farré 2009). To capture this effect, a dummy variable is constructed based on the Western Australian Department of Agriculture and Food's rainfall zone classification. Farms located in the medium rainfall zone average 325–450 mm of rainfall per annum, while farms in the low rainfall zone average less than 325 mm each year. Farm businesses located in low rainfall regions may experience frequent poor seasons, lowering production and profitability. They may have more debt intensive capital structures as they struggle to finance production operations from internal cash flow and become

[5] The lag is chosen because the size of the farm business would be expected to impact the farm business's ability to borrow.

**Table 2** Expected relationship between debt-to-asset ratio and potential determinants

| Determinant of debt-to-asset ratio | Pecking Order | Signalling |
|---|---|---|
| Net cash flow$_{t-1}$ | − | + |
| Equity$_t$ | − | + |
| Size$_t$ | N/A | + |
| Primary operator age$_t$ | N/A | + |
| University education (primary operator) | N/A | + |
| Medium rainfall zone | − | + |

more prone to loan default. This may lead to the location of farm businesses in low rainfall zones serving as a negative signal to lenders, who might view businesses in these regions as less climatically secure and more likely to have greater variability in investment returns. The anticipated signs of the relationships between the debt-to-asset ratio and its potential determinants (excluding the autoregressive component), as hypothesised by both the pecking order and signalling theories, are presented in Table 2.

## 5. Empirical results

This section reports the determinants of the debt-to-asset ratio and the speed of adjustment for a sample of farm businesses in Western Australia's Wheatbelt. All the estimates were obtained using Stata 13 and Microsoft Excel. The GMM estimation results are presented in Table 3. The results of a pooled ordinary least squares regression and a fixed effects regression are reported in Appendix S3 for the robustness check of the results obtained from the GMM estimation.

The Wald test rejects the null hypothesis that the parameters of interest are simultaneously equal to zero. The Arellano-Bond test indicated no first or second-order autocorrelation in the first differenced errors. This means the use of instruments from the $t-2$ period and prior in these models is acceptable. The null hypothesis for the Hansen test proposes that the over-identification restrictions imposed in the model are valid, where the instruments used are uncorrelated with the error term and the excluded instruments are correctly omitted from the estimated equations. The Hansen test results for our model show that the null hypothesis cannot be rejected for each equation at the 10% level. Following Bond (2002), the estimated coefficient of the autoregressive debt-to-asset ratio for the System GMM model (0.4015) is found to lie between the upwardly biased pooled ordinary least squares autoregressive coefficient estimate (0.7098) and the downwardly biased fixed effects regression autoregressive coefficient estimate (0.3617).

The estimated coefficient for the lagged debt-to-asset ratio reported is positive and highly significant. The estimate of 0.4015 is between 0 and 1, which implies that the debt-to-asset ratio of farm businesses in the study region would converge towards their target levels over time. It further

**Table 3** Generalised method of moments estimation results—overall sample

| GMM | Debt-to-asset ratio | |
|---|---|---|
| | Coefficient | Robust Standard Error |
| Debt-to-asset ratio$_{t-1}$ | 0.4015*** | 0.1216 |
| Net cash flow$_{t-1}$ | −1.1330*** | 0.0231 |
| Equity$_{t-1}$ | −0.8807*** | 0.2515 |
| Size$_{t-1}$ | 0.7763*** | 0.2278 |
| Primary operator age$_t$ | −0.0008 | 0.0005 |
| University education | −0.0169 | 0.0128 |
| Medium rainfall zone | −0.0271*** | 0.0088 |
| Year dummies (Base: 2003) | | |
| 2004 | −0.0044 | 0.0164 |
| 2005 | 0.0244* | 0.0133 |
| 2006 | 0.0138 | 0.0126 |
| 2007 | 0.0222 | 0.0174 |
| 2008 | 0.0166 | 0.0154 |
| 2009 | 0.0101 | 0.0165 |
| 2010 | 0.0463*** | 0.0178 |
| 2011 | 0.0300** | 0.0150 |
| Constant | 0.0983*** | 0.0330 |
| Number of Instruments | 52 | |
| Number of Groups | 61 | |
| Wald Test | $\chi^2(17)$ | $\Pr > \chi^2$ |
| | 504.46 | 0.000 |
| Arellano-Bond | z | $\Pr > z$ |
| First Order Test | −4.61 | 0.000 |
| Second-order Test | 1.24 | 0.215 |
| Over identification Tests | $\chi^2(34)$ | $\Pr > \chi^2$ |
| Hansen Test | 44.50 | 0.107 |

Significance Level: ***−1%, **−5%, *−10%.

confirms the presence of dynamics in the capital structure choices of the farms (Aderajew *et al.* 2018). From equation 4, the speed of adjustment is 59.85%[6], which corresponds to a half-life of approximately 0.76 years, that is it will take approximately 9 months[7] for a farm business to adjust its capital structure half-way to its target capital structure. In comparison to the only other study in agricultural economics to estimate the speed of capital adjustment of farm businesses via a comparable procedure (Aderajew *et al.* 2018), our finding suggests that farm businesses in Western Australia's Wheatbelt adjust their capital structure far more rapidly towards their target level than the dairy, field crop and livestock farms in the Netherlands. The estimated speed of adjustment is approximately the same as the horticultural farms in the Netherlands. Aderajew *et al.* (2018) attributed the slow speed of capital structure adjustment amongst Dutch farms to high adjustment costs. The faster speed of adjustment amongst the surveyed farm businesses

[6] From equation 4, the speed of adjustment is equal to 1 minus the coefficient for the lag of observed capital structure (0.4015)

[7] The half-life is calculated as $\ln(0.5)/\ln(0.4015)$

suggests that they face lower costs of adjustment compared to farms in the Netherlands. In seeking to explain these lower costs of adjustment, we note that the surveyed farms had substantially lower debt-to-asset ratios than the Dutch farms. It is plausible that the low debt-to-asset ratios of the surveyed farms made it easier for these farm businesses to adjust faster towards their target capital structure because lenders would perceive these businesses as being of lower risk. Further, the surveyed farms were family-owned and operated businesses with small overheads and flexible wage costings that allowed cash operating surpluses to be more easily committed to debt-servicing.

The results in Table 3 show a negative and significant relationship between the observed debt-to-asset ratio and prior period cash flow. These results lend support to the applicability of pecking order theory to the choice of capital structure amongst farm businesses in the survey region, as farm businesses would be expected to reduce their debt use in periods of improved cash flow. An increase in prior period equity is found to be negatively and significantly associated with debt-to-asset ratio. This appears consistent with the pecking order theory since where farms have higher equity levels, which is generated from retained earnings, they would be expected to seek less debt. It is also possible that those farm businesses with higher equity levels would target to maintain low debt-to-equity ratios as they are risk-averse. Farm size, as measured by total business assets, is found to have a significant and positive relationship with the debt-to-asset ratio, suggesting that lenders prefer to lend money to larger farm businesses. This finding is consistent with the results of the study by Aderajew *et al.* (2018) that found large dairy and livestock farm businesses in the Netherlands to have a positive relationship with debt-to-asset ratios. A negative and significant relationship is found between the medium rainfall dummy variable and the debt-to-asset ratio. The coefficient of −0.0271 indicates that holding all else constant, farm businesses located in the medium rainfall regions have a lower debt-to-asset ratio compared to those in the low rainfall region. We compared the change in the mean debt-to-asset ratios over the survey period for farm businesses in each region. In low rainfall regions, the mean debt-to-asset ratio increased from 0.1592 in 2002 to 0.2675 in 2011; in medium rain regions, the mean debt-to-asset ratio increased from 0.1787 to 0.2170. Between 2002 and 2011, the mean of farm business debt rose by 232% for farm businesses in low rainfall regions, as opposed to 171% for farm businesses in medium rainfall regions. By contrast, the mean value of farm business assets increased 135% in medium rainfall regions, as opposed to 121% in low rainfall regions.

Analysis of the year fixed effects in the System GMM estimation shows few years are statistically significant, with only 2010 significant at a 1% level and 2011 at a 5% level, both having positive signs. This indicates that over the 2009 and 2010 years, the debt-to-asset ratios for the farm businesses were higher than the base year. These results are consistent with the graph of the average debt-to-asset ratio presented in Figure 2 where sharp rises in the

**Table 4** Observed versus predicted mean and standard deviation values by rainfall region and farm size

| | Observed | | Predicted | |
|---|---|---|---|---|
| | Medium | Low | Medium | Low |
| Large | 0.1457 (0.1138) | 0.1990 (0.1155) | 0.1304 (0.1309) | 0.1877 (0.1068) |
| Small | 0.1919 (0.0881) | 0.1919 (0.0983) | 0.1584 (0.0625) | 0.1759 (0.0631) |

debt-to-asset ratio were observed in 2009 and 2010. This rise in debt-to-asset ratios coincides with a sharp decline in key crop prices, from the high prices experienced in 2007 and 2008, and below average rainfalls being experienced across the survey region in 2009 and 2010 that lowered production yields, with parts of Western Australia's Wheatbelt experiencing their lowest rainfall on record in 2010.

To examine the usefulness of our GMM estimation results in predicting the debt-to-asset ratios of farm businesses across farm size and rainfall region, the means and standard deviations of the observed and predicted results are presented in Table 4:

Table 4 shows that for all categorisations, although the predicted mean results are lower than the observed values, the magnitude of these differences is minor. Large farms are categorised as those that have A$4,000,000 or greater in business assets (normalised against the study's base year of 2002), which constitutes 300 of the 540 total observations. For both observed and predicted values, farm businesses in low rainfall regions have a higher mean debt-to-asset ratio than farm businesses in medium rainfall regions. Large farm businesses in low rainfall regions have a higher mean debt-to-asset ratio than small farm businesses. By contrast, small farm businesses in medium rainfall regions have a higher mean debt-to-asset ratio than large farm businesses in medium rainfall regions. The results lend support to the findings of the regression analysis that farm businesses in low rainfall regions hold more debt relative to their assets as compared to those in medium rainfall regions. Additional plots of the relationship between debt-to-asset ratio and farm characteristics are provided in Appendix S4.

## 6. Discussion and Conclusion

This study estimated a System GMM model to investigate the determinants of farm capital structure and its speed of adjustment towards an optimal target for a sample of 61 farm businesses in Western Australia's Wheatbelt over the period 2002–2011. To the best of our knowledge, this is the first study in Australia to focus on determinants of farm capital structure and the speed of capital structure adjustment in a dynamic production environment. Further, this is the first study globally to investigate the impact of rainfall availability on farm business capital structures.

The main finding is that prior period cash flow and equity, together with farm location in the medium rainfall region, have a strong negative and significant association with observed debt-to-asset ratios of farm businesses. Those findings are consistent with the postulates of the pecking order and signalling theories. Consistent with the pecking order theory, we find that farm businesses will use internal funds (equity generated from high retained earnings) to reduce their debt burdens. Farm size, as measured by the value of farm business assets, has a positive and significant association with debt-to-asset ratio, suggesting that larger farms can secure debt more easily that small farms, possibly because they can signal their creditworthiness by offering farm assets as collateral. This may also suggest that farm businesses normally use debt financing to increase their asset holdings. The finding is consistent with the signalling theory hypothesis and the observation made by Aderajew *et al.* (2018) for Dutch farm businesses.

Our results show that farm businesses appear to adjust their capital structure over time towards their target level and the speed of adjustment is much faster compared to Dutch farm businesses observed by Aderajew *et al.* (2018), the only prior study to consider the speed of capital structure adjustment amongst farm businesses. A possible explanation for this is that the cost of adjustment for the sample of farms in our study is lower than that of the Dutch farms. The fast speed of capital structure adjustment implies that farm businesses in Western Australia are operating in a favourable economic environment with strong institutions and potentially benefitting from a deregulated banking environment. Western Australian farm businesses may also have benefitted from having lower starting debt-to-asset ratios than Dutch farmers, allowing them to adjust their capital structures more readily.

For policymakers, the finding that farm businesses in the survey region appear to adhere to the pecking order theory in their use of debt implies that implementing policies that help farm business operators to increase cash flows while reducing cash flow variability can keep farm indebtedness low and improve the speed with which capital structure can be adjusted to target levels. An example of such a policy is the Australian Government's Farm Management Deposit Scheme, which allows eligible primary producers to set aside pre-tax income in higher income years so that it may be drawn down in lower income years. This may have the benefit of improving production output in the longer term by lowering the amount of money directed away from production to debt service costs. Another example is the implementation of revenue contingent loans or income-contingent loans as proposed by Botterill *et al.* (2017). Such loan structures would allow income smoothening by farm businesses to concentrate on debt repayments in periods of better financial performance, potentially reducing farm reliance on debt in future periods. Policymakers can also focus on identifying and implementing measures (such as interventions to reduce informational asymmetry between borrowers and lenders) that reduce adjustment costs for farm businesses trying to reach their target capital structures. This can provide incentives for achieving economies of scale through mechanisation and other farm innovations. Policymakers should pay close attention to increases in the debt-to-asset ratios of farm businesses in low rainfall regions, as more debt intensive capital structures may limit the ability of these farm businesses to further adapt to climate change. Future empirical studies of farm businesses can explore how macroeconomic factors, such as interest rates, drive capital structure choices and speed of adjustment to target levels.

## Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article:

**Appendix S1: Table S1.** Debt-to-asset ratio- summary statistics (2002–2011).

**Appendix S2: Figure S1.** Density plots of debt-to-asset ratio by year (2002–2011).

**Appendix S3: Table S1.** Pooled ordinary least squares regression estimation results- overall sample.

**Appendix S3: Table S2.** Fixed effects regression estimation results- overall sample.

**Appendix S4: Figure S1.** Lowess plot of pooled debt-to-asset ratios against lag of cash flow (2002–2011).

**Appendix S4: Figure S2.** Lowess plot of pooled debt-to-asset ratios against one period lagged equity (2002–2011).

**Appendix S4: Figure S3.** Average debt-to-asset ratio and one period lag of normalised average business assets (2003–2011).

**Appendix S4: Figure S4.** Density plot of pooled debt-to-asset ratios by rainfall region (2002–2011).

**Data S1**Farm level data (2002–2011).