State-trading enterprises and productivity:
Farm-level evidence from Canadian agriculture

By RYAN CARDWELL and PASCAL L. GHAZALIAN [§]

March 2022

**** PRELIMINARY DRAFT – PLEASE DO NOT CITE OR SHARE WITHOUT PERMISSION ****

Abstract: The Canadian Wheat Board (CWB) was a state-trading enterprise that controlled the sale and distribution of wheat and barley produced in Western Canada from 1935 to 2012. The CWB's regulatory and bureaucratic structures have been investigated as sources of several market effects, including prices and spatial production patterns. We investigate the effects of the CWB on productivity using farm-level data, and identify how deregulation of the CWB affected total factor productivity (TFP) for CWB-regulated crops. Farm-level production and input data for 13,000 grain farms over 15 years are used to generate a within-farm difference-in-difference (DiD) estimator that identifies how relative TFP changed between CWB and non-CWB crops after deregulation. Cereal farm operators typically grow several (CWB and non-CWB) crops in a single season, allowing us to estimate production functions for multiple crops at the same farm in the same year. Our within-farm DiD empirical strategy identifies the effects of deregulation on changes in relative TFP between crops, while controlling for many of the confounding factors that complicate TFP measurement in other approaches, such as unobserved differences between farms and unobserved changes within farms over time. This research makes a methodological contribution to the productivity literature by developing a within-farm DiD estimator, and contributes to the understanding of how policy interventions affect farm-level productivity.

Keywords: Productivity, Agriculture, Agricultural Policy

[§] Cardwell: University of Manitoba (email: ryan_cardwell@umanitoba.ca). Ghazalian: University of Lethbridge (email: pascal.ghazalian@outlook.com).

1. Introduction

The supply chains for wheat and barley in Western Canada were controlled through a state-trading enterprise (STE) called the Canadian Wheat Board (CWB) from 1943 to 2012. Producers of regulated crops were required to sell to the CWB, which then marketed crops on behalf of farmers. Farmers received an initial payment upon delivery, and then a subsequent payment based on a pooled price from the CWB's sales during the marketing season. Because the single-desk authority of the CWB was mandated through legislation, farmers were obliged to sell to the CWB and could not enter contracts with other buyers in Canada or abroad.

The CWB affected every stage of the supply chain, from farmers to processors, railways, and foreign buyers (Brewin 2014). Its single-desk authority provided the CWB with monopsony buying power over producers, market power in negotiations with elevation and transportation companies, and a voice in Canadian agricultural subsidy and international trade policies.

The CWB was a lightning rod for debate in Canadian agricultural policy for decades, most prominently about whether the CWB provided farmers with higher returns than they would have received in an unregulated market. Some studies found that the CWB's monopoly power in selling Western-Canadian wheat into foreign markets allowed it to extract rents from foreign buyers (Groenewegen, 1986; Veeman, 1987; Furtan *et al.* 1999). Others countered that price premiums did not exist, or that any premiums were dissipated by higher marketing and administrative costs at the CWB before being passed on to producers (Carter, 1993; Johnson & Wilson, 1995; Carter *et al.* 1998).

The single-desk authority of the CWB was removed in 2012, which allows us to use post-CWB-era data to investigate unanswered questions about the effects of the STE regulatory framework. We investigate how the single-desk authority affected the productivity of farmers in Manitoba, using deregulation as a quasi-experimental policy change to the regulatory framework under which producers operate. We develop a novel empirical approach to identify the effects of the CWB on the productivity of regulated crops *at the farm level* using the unique production characteristics of field crops. Specifically, we use an empirical approach that includes farm-by-year fixed effects, and allows us to recover an estimate of the CWB's effect on the productivity of regulated crops. This is achieved through a difference-in-difference (DiD) strategy that identifies the change in productivity of regulated crops relative to unregulated crops at the farm level.

Our study contributes to the productivity literature through the development of an empirical methodology to estimate policy effects on farm-level productivity, while controlling for the myriad unobservable farmspecific and time-specific factors that typically confound such investigations. We observe changes in relative productivity between regulated and unregulated crops at the same farm in the same year.

We also contribute to the debate about the effects of the CWB on markets, and the effects of market regulations on productivity more generally. We find that the CWB had a small negative effect on farm-level productivity of regulated crops. Our results suggest that the CWB exerted downward pressure on spring wheat productivity (a CWB-regulated crop) relative to canola productivity (an unregulated crop). We take care to control for important confounding factors, such as different (non-CWB related) underlying productivity trends between crops, and demonstrate that our results are robust across specifications.

The remainder of this paper is organised as follows. Section two describes related literature about the effects of policy interventions on agricultural productivity, and how the CWB affected markets. Section three describes our empirical methodology, our data, and how the unique characteristics of field crop production facilitate our DiD approach. Section four explains our empirical results, and section five closes with conclusions and a discussion.

2. Productivity in agriculture

2.1. Estimating productivity in agriculture

Building on advances in agricultural production theory (*e.g.* Chambers 1988), a large portion of research in estimating and measuring agricultural productivity has been conducted at the aggregate level in efforts to compare productivity changes over time and space. Comparisons of productivity growth across countries has been an important focus in the agricultural development literature (*e.g.* Fuglie 2010). The estimation of agricultural productivity has also been important in studies that investigate the farm size-productivity relationship (*e.g.* Berry & Kline 1979; Barrett, *et al.* 2010).

Our study differs in that we seek to identify the causal effects of a policy change on farm-level productivity. To that end, we use farm-level survey data and rely on the exogenous variation imposed on all producers by the end of the CWB's single-desk regulatory authority.

2.2. Policy change and productivity

Government policies can affect farm-level productivity through their effects on incentives and market structures. Such effects have been analysed in other agricultural markets using survey data from farm operators. For example, Mary (2012) investigates how total factor productivity (TFP) of French farms responded to changes in the structure of European farm subsidies after 1993. This study uses survey data that include farm-level information on inputs and outputs to identify a negative effect of subsidies on farm-level productivity. Bellemare (2013) uses farm-level survey and soil-sample data to investigate the relationship between land tenure rights and farm productivity in Madagascar. Chernoff (2018) examines the effects of a temporary partial deregulation of Canada's dairy market on dairy-farmer productivity. This study also uses a farmer survey to collect input and output data, and estimates a causal effect of changing regulations on the productivity of farmers who participate in the partially-deregulated market. Chernoff (2018) does not find significant causal effects of this policy change on farm-level productivity, but the study is complicated by having to account for the potential selection effects of more-productive farms participating in the temporarily-deregulated market. We do not face these selection issues in our application because deregulation of the CWB was universal across producers in 2012.

The CWB could have affected the incentives of producers because its regulations and market activities transcended the supply chain. For example, Carter & Ferguson (2019) find that peculiarities in the CWB's pricing scheme for barley (a CWB regulated crop) affected the spatial pattern of barley production – deregulation increased production close to processing plants. Also, less-efficient growers were less likely to produce high-quality barley varieties after deregulation, leaving behind a pool of relatively more-efficient farmers. This composition effect manifested as increased average productivity.

One important mechanism through which deregulation could have affected farm-level productivity is a change in output price risk faced by producers. The CWB provided producers a partial initial payment upon delivery of grain, followed by a final payment at the end of the marketing season. This final payment was based on a pooled price determined by the returns generated from selling grain through the marketing year. Deregulation of this pricing system removed the distortions that could have affected the output price risk facing farmers – they no longer share short-run output price risk across growers through the initial payment, or in the longer run through the final pooled price. Risk averse producers could respond to changes in output risk by reducing investment in risky, but productivity-enhancing, endeavours (*e.g.* capital, variable inputs, etc.) (Antle 1983).

A change in the quantity and/or frequency of individual producers growing wheat in response to deregulation could also manifest as a measured change in farm-level productivity. For example, if less-efficient producers were less likely to grow wheat after deregulation, there would be compositional effect on the measured efficiency among remaining wheat producers and we would observe negative effects of the CWB on farm-level productivity. Chernoff (2016) and Carter & Ferguson (2019) examine these types of compositional effects of policy changes on farm-level productivity.

Heterogeneous farm-level characteristics could also impact how deregulation affects estimated productivity. For example, individual farmers played almost no role in marketing their grain prior to 2012; this was done by the CWB on behalf of producers. The incentives of producers with varying levels of (unobserved) marketing skills could have been affected with the transition to a market-based system, in which individual producers are responsible for marketing their output to private grain companies.

These factors can impact farm-level productivity in several ways, sometimes in opposite directions. Increasing output-price risk could apply downward pressure on measured productivity through disincentivizing new investments, while a compositional effect that favoured relatively productive farms could apply upward pressure on measured productivity. Our empirical results present the aggregate effect of these factors, and provide insight into how deregulation affected productivity of regulated crops considering all of these effects.

3. Empirical methodology and data

Our farm-level dataset combined with the production characteristics of prairie grain farms allows us to construct a DiD estimator that identifies how *relative* productivity between CWB and non-CWB crops changed *at the farm level* when CWB regulations were removed. We attribute changes in relative productivity to time variation in CWB regulations.

Most prairie field-crop farms produce multiple outputs each year. For example, most grow a combination of wheat, canola, soybeans, or other crops in a single year. This is common practice for two reasons. First, farmers produce different crops in the same year to manage output price risk across products (Antón *et al.* 2011). Second, there are significant agronomic benefits of rotating crops over time (*e.g.* alternating wheat, canola, and soybeans on the same field over time) (Smith *et al*. 2017). The production characteristics of many field crops, particularly wheat and canola, allow farmers to use the same land, machinery, and labour to produce different outputs. The multiple-output nature of field crop production is important in our context because it allows us to observe individual farms producing both CWB and non-CWB crops in the same year. We use this feature to control for unobserved differences across farms.

We use these distinctive production characteristics to estimate how the removal of CWB regulations affected the productivity of CWB crops relative to non-CWB crops *at the farm level*. We construct a DiD estimator of how productivity of regulated crops changed with the demise of the CWB, relative to how productivity of non-CWB-regulated crops changed over the same period. The DiD estimator is conceptualised as:

$$DiD \equiv \left(\overline{TFP}_{i,t<2012}^{(CWB\_crop)} - \overline{TFP}_{i,t\geq 2012}^{(CWB\_crop)}\right) - \left(\overline{TFP}_{i,t<2012}^{(non\_CWB\_crop)} - \overline{TFP}_{i,t\geq 2012}^{(non\_CWB\_crop)}\right) \tag{1}$$

where $\overline{TFP}_{i,\ t}^{(CWB\_crop)}$ and $\overline{TFP}_{i,\ t}^{(non\_CWB\_crop)}$ are average productivity for farm i during years (t) for CWB and non-CWB crops respectively (CWB regulations were removed in 2012[1]). The CWB regulatory framework was unraveled at the same time for all producers, so its removal was a simultaneous exogenous policy shock to all farms.

Our baseline empirical specification is a Cobb-Douglas production function of the form:

$$lnQ_{it}^{h} = \alpha^{h} + \omega D_t + \theta(D_t \times C^{CWB\_crop}) + BlnX_{it}^{h} + \varepsilon_{it}^{h} \tag{2}$$

where Q_{it}^{h} is output of crop $h = CWB\_crop, non\_CWB\_crop$ on farm i in year t, α^{h} is a crop-specific intercept shifter, D_t is time-varying dummy variable coded as one before 2012 and zero otherwise, $C^{CWB_crop}$is a dummy variable coded as one if the observation is a CWB-regulated crop and zero otherwise, X_{it}^{h} is a vector of inputs (*e.g.* nutrients[2], acreage) on farm i in year t, and ε_{it}^{h} is an error term; θ and B are parameter vectors to be estimated.[3] In this context, θ is the average effect of CWB regulations on productivity of regulated crops relative to non-regulated crops; *i.e.* the DiD conceptualised in equation (1). Table 1 illustrates how the DiD estimate is derived from the parameters in the empirical model.

Our primary dataset is from Manitoba Agricultural Services Corporation (MASC), a crown corporation of the Manitoba Government that provides subsidised agricultural insurance and loans to farmers, and collects production data from participating farmers. The data are administrative for farms that participate in MASC programmes. The dataset covers 2002 to 2018 and includes data for 13,164 farms and 234 different products.

The data we use in estimation are disaggregated beyond the level of individual farm because MASC collects separate production data for every insured field; separate fields owned by the same farmer may grow different crops and be in different municipalities. To account for multiple fields (g) at the farm level (i), we modify equation (2) to:

[1] The CWB remained active as a grain trading company after 2012, but producers were not compelled to sell to the CWB.

[2] We use nitrogen (N) to represent fertilizer application. There is a significant proportion of missing observations for other fertilizer components; we conduct robustness checks to investigate alternative representations of fertilizer use.

[3] This specification is modified below to allow for crop-specific parameters on variable inputs. Note that α^{h} can be alternatively represented as $\alpha^{CWB\_crop}C^{CWB\_crop} + \alpha^{non\_CWB\_crop}C^{non\_CWB\_crop}$ or as $\alpha + \alpha^{non\_CWB\_crop}C^{non\_CWB\_crop}$, where $C^{non\_CWB\_crop}$ is a dummy variable that equals one if the observation is a non-CWB-regulated crop and zero otherwise.

$$lnQ_{git}^{h} = \alpha^{h} + \omega D_t + \theta(D_t \times C^{CWB\_crop}) + BlnX_{git}^{h} + \mathrm{Z}S_g + \varepsilon_{git}^{h} \tag{3}$$

where Q_{git}^{h} is output of crop h on field g belonging to farm i in year t. Variable inputs X_{git}^{h} correspondingly vary across fields, and S_g are soil-type indicator variables[4]. Summary statistics for the two most-frequently grown crops in our dataset (spring wheat, a CWB crop; and canola, a non-CWB crop) are reported in tables 2 and 3.

Producers are not required to report labour and capital inputs to MASC so we do not observe these inputs at the farm level. However, we use the distinctive nature of field crop production to control for differences in capital and labour between farms and over time in our empirical model. The machinery (*e.g.* seeders, sprayers, combine harvesters) used to produce wheat is the same for canola, and a farm typically uses the same machinery to produce both outputs. Likewise, the labour required to produce these crops is very similar; typically the farm operator applying the same number of hours per acre of each crop. Manitoba's government department of agriculture (Manitoba Agriculture and Resource Development, or MARD) produces crop production reports for all major crops each year that include estimated input costs per acre for several crops.[5] These reports reveal that estimated labour and capital costs per acre are the same for spring wheat and for canola; for example, the report for 2018 estimates labour costs of $30 per acre for both crops, and machinery costs (operating, depreciation, and investment) of $74.47 per acre. We use estimates from these reports to justify the assumption that labour and capital inputs per acre on farm i in year t are the same for wheat as for canola. Note this approach still allows for labour and capital input use to vary across farms (i) and over time (t).

To operationalise this assumption, we define a weighting parameter:

$$\varphi_{git}^{h} = \frac{A_{git}^{h}}{A_{it}} \tag{4}$$

that is equal to the number acres of land (A) in field g belonging to farm i in year t that is planted to crop h, as a share of farm i's total planted acres to both crops in year t (where $A_{it} = \sum_g A_{git}^{h}$). The amount of labour (L_{git}^{h}) used to produce crop h in field g belonging to farm i in year t is proportional to the share of farm i's land devoted to producing crop h in field g; this can be represented as $\varphi_{git}^{h}L_{it}$, where L_{it} indicates total labour on farm i in year t. In the context of the variable inputs in our log-linear production function, X_{git}, the labour component would be:

[4] Soil types are classified by MASC as one of ten varieties.
[5] These reports from 2000 to 2020 were provided to the authors by MARD. Tables are available by request, subject to approval from MARD.

$$ln(\varphi_{git}^{h} L_{it}) = ln\varphi_{git}^{h} + lnL_{it}$$

$$= ln(A_{git}^{h}/A_{it}) + lnL_{it}$$

$$= lnA_{git}^{h} - lnA_{it} + lnL_{it} \ .$$

We observe A_{git}^{h} in our dataset and include it in estimation, and lnA_{it} and lnL_{it} are captured in the regression with farm-by-year fixed effects. The same process allows us to control for unobserved farm-by-year variation in capital inputs (K_{git}^{h}). These farm-by-year fixed effects also absorb the D_t variable. Our estimating equation with these farm-by-year fixed effects is:

$$lnQ_{git}^{h} = \alpha^{h} + \delta_{it} + \theta(D_t \times C^{CWB\_crop}) + BlnX_{git}^{h} + \mathrm{Z}S_g + \varepsilon_{git}^{h} \qquad (5)$$

where δ_{it} captures unobserved farm- and time-varying factors including labour, capital, and farmer characteristics such as skill and experience. Farm characteristics embodied in these fixed effects are the same across fields (g) for each farm (i) in year (t), but the estimating equation allows for input variation across fields (g) owned by the same farm (i). The δ_{it} term would normally capture the changes in productivity we seek to estimate in our empirical model. But because we estimate our production function for two crops, we identify the effects of CWB regulations through changes in the difference between productivity of the two (CWB and non-CWB) crops.

Weather is an important determinant of crop yields, and crop production studies often account for time and space variation in growing conditions with indices that include rainfall (Boshrabadi *et al.* 2008) or growing degree and extreme-heat days (Roberts *et al.* 2013). Construction of such indices adds unneeded complication to a model, however, if the focus is not on identifying the effects of weather. We are primarily interested in the effects of the CWB, so we adopt a more general approach to account for time and regional variation in growing conditions. We include municipality-by-time fixed effects (μ_{lt}) in the regression model to capture changes in weather over time and across space:

$$lnQ_{git}^{h} = \alpha^{h} + \delta_{it} + \mu_{lt} + \theta(D_t \times C^{CWB\_crop}) + BlnX_{git}^{h} + \mathrm{Z}S_g + \varepsilon_{git}^{h} \qquad (6)$$

where l indicates municipality.[6]

4. Results

[6] Our dataset includes observations from 99 municipalities in Manitoba.

We present our results across a range of empirical specifications, beginning with the most parsimonious. This allows us to isolate how movements to less-parsimonious, but less-restrictive, specifications affect our primary coefficient of interest (θ).[7]

Columns (1a) and (1b) in table 4 report the baseline results that include farm-level fixed effects and year fixed effects, but not farm-by-year fixed effects. The difference between columns (1a) and (1b) is the inclusion of the $D_t^{CWB} \times C^{CWB\_crop}$ variable in column (1b). The estimated coefficient on the crop-specific dummy variable for canola is negative and significant in both columns, reflecting agronomic differences between the two crops (fewer tonnes per acre, and more chemical inputs per tonne, for canola). The coefficient that reflects the effects of the CWB on wheat productivity in column (1b) is negative and significant at all conventional levels, indicating an estimated effect of 3.26 precent[8] less wheat production. That is, a decline in TFP in the context of our empirical model. As previously noted, this specification does not include farm-by-year fixed effects or weather controls, and our results could be influenced by this omission.

Columns (2a) and (2b) of table 4 include farm-by-year fixed effects and weather controls without, and with, the CWB interaction variable, respectively. These specifications control for potentially-important unobserved heterogeneity across farms and over time. Most results in columns (2a) and (2b) are quantitatively and qualitatively similar to columns (1a) and (1b). Controlling for unobserved heterogeneity results in a slightly larger negative estimated effect of the CWB on wheat productivity, which translates to an output decrease of 3.90 precent.

The results in (1a) and (1b) in table 5 are from a specification that relaxes the assumption of identical coefficients on variable inputs across crops. This is achieved by interacting input quantities (X_{git}^h) with crop-specific dummy variables. Estimated coefficients on interacted variables reveal that more wheat (measured in tonnes) is produced with equivalent quantities of variable inputs. The effect of the CWB on relative productivity is almost identical in this specification, indicating a negative impact of the CWB on wheat output.

One concern about identifying the effects of the CWB by estimating productivity differences between two crops is that underlying trends in wheat or canola yields that derive from seed genetics and breeding improvements (referred to as *genetic gain*) could mistakenly be attributed to the CWB regime change. Figure 1 illustrates how average productivity evolved for wheat and canola in our sample. The lines

[7] Models are estimated in Stata using the **reghdfe** command (Correia 2017), which allows for estimation of high-dimensional fixed effects.
[8] Note: $[1 - exp(-0.0331)] \times 100 = 3.26$

illustrate tonnes per acre averaged across all farms in our dataset. Visual inspection reveals similar short-term volatility for both crops, which is largely a function of weather variation. Our empirical model controls for short-term weather variations, but controlling for underlying trends for each crop could be important in isolating the CWB effect.

To identify the effects of the CWB regime change on changes in relative productivity, we need to control for crop-specific productivity trends deriving from other sources, most importantly genetic gains. One challenge is that the existence of the CWB could affect breeding activity and genetic factors that increase yields, particularly for wheat. Our strategy to deal with this potential confounder is to control for underlying trends in wheat and canola productivity from outside the CWB's geographic jurisdiction.

We use wheat and canola yield data from North Dakota [sourced from the United States Department of Agriculture (USDA)], which borders Manitoba to the south, and has similar growing conditions (weather and soil). The Canadian and US markets for wheat and canola are closely integrated through international trade, but farmers in North Dakota were never subject to the single-desk authority of the CWB, and they operate under different agricultural policies than Manitoba farmers. Figure 2 illustrates average wheat and canola yields in North Dakota from 2002 to 2018. We add measures of US yield growth to our empirical model to control for underlying genetic gains that could affect relative productivity. Our regression equation is modified as:

$$lnQ_{git}^{h} = \alpha^{h} + \delta_{it} + \mu_{lt} + \sum_{h} \gamma^{h} \left(Yld_{t}^{ND,h} \times I^{h}\right) + \theta(D_{t} \times C^{CWB\_crop}) + BlnX_{git}^{h} + \mathrm{Z}S_{g} + \varepsilon_{git}^{h} \qquad (7)$$

Where $Yld_{t}^{ND,h}$ is an index of average yield for crop h (wheat or canola) in year t in North Dakota and I^{h} is an indicator equal to 1 for crop h and zero otherwise.[9]

Results from this specification are presented in column (2a) and (2b) of table 5. We identify a negative effect of the CWB on wheat productivity relative to canola productivity, with results closely aligning to those in columns (1a) and (1b) in table 5. The estimated coefficient on the interacted CWB variable is marginally larger than in column (1b), providing evidence that the inclusion of variables to account for underlying genetic gains is important. The smaller estimated coefficient in column (1b) compared to (2b) (-0.038 compared to -0.045) is due to this coefficient absorbing some of the effects of underlying genetic gain differences between wheat and canola in the specification of column (1b). That is, the negative effects of the CWB on wheat productivity are underestimated without including controls for the genetic gains being made in the absence of the CWB (*i.e.* in North Dakota). This specification estimates a

[9] Index reference year is 2002.

negative effect of the CWB of 4.42 precent. The inclusion of yield data from North Dakota in column (2b) of table 5 allows us to better isolate the CWB effect, and provides us with our preferred specification.

All our specifications paint a similar empirical picture. The existence of the CWB's regulatory framework applied downward pressure on farm-level productivity of wheat. The effects are quantitatively small on an annual basis, but are significant and robust across specifications. These small annual effects add up to large effects on aggregate yields over the long tenure of the CWB, however.

5. Conclusion

The effects of the CWB transcended the grain supply chain in Canada for several decades. It's regulatory and marketing interventions distorted the market and affected incentives from the farm to foreign buyers of Canadian wheat and barley. The demise of the CWB provides us with an opportunity to investigate how sweeping regulatory frameworks affect the economic incentives of actors along the supply chain.

We develop a novel empirical methodology that controls for unobserved differences between farms and over time with fixed effects, but still allows us to identify how an exogenous policy change affected farm-level productivity. We find that the CWB exerted downward pressure on farm-level productivity of spring wheat (the most prominent CWB-regulated crop) of approximately 4 percent. This finding contributes to the literature on the effects of the CWB, and more generally to the literature on how government regulations affect firm performance.

Our empirical approach can be useful for other productivity studies applied to firms with multiple outputs. Including firm-by-year fixed effects in these studies can strengthen identification of causal effects (of policy change in our case), and lessen concerns about the confounding effects of unobserved firm-level and time-varying characteristics.

References

Antle, J. M. (1983). Incorporating risk in production analysis. *American Journal of Agricultural Economics*, 65(5), 1099-1106.

Antón, J., S. Kimura and R. Martini. (2011). "Risk Management in Agriculture in Canada", *OECD Food, Agriculture and Fisheries Working Papers*, No. 40, OECD Publishing.

Bellemare, M. F. (2013). The productivity impacts of formal and informal land rights: Evidence from Madagascar. *Land Economics*, 89(2), 272-290.

Berry, R. A., & Cline, W. R. (1979). *Agrarian structure and productivity in developing countries: a study prepared for the International Labour Office within the framework of the World Employment Programme*. Johns Hopkins Univ. Press.

Barrett, C. B., Bellemare, M. F., & Hou, J. Y. (2010). Reconsidering conventional explanations of the inverse productivity–size relationship. *World Development*, 38(1), 88-97.

Boshrabadi, H. M., Villano, R., & Fleming, E. (2008). Technical efficiency and environmental-technological gaps in wheat production in Kerman province of Iran. *Agricultural Economics*, 38(1), 67-76.

Brewin, D. G. (2014). Limitations on the market power generated by the single desk of the Canadian Wheat Board. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 62(4), 491-517.

Carter, C. A. (1993). Canada's grain-marketing system. In: Cramer, G. L., & Wailes, E. J. (Eds.). *Grain Marketing* (Second Edition). Westview Press, Boulder, CO.

Carter, C. A., & Ferguson, S. M. (2019). Deregulation and regional specialization: Evidence from Canadian agriculture. *Canadian Journal of Economics/Revue canadienne d'économique*, 52(4), 1497-1522.

Carter, C. A., Loyns, R. M. A., & Berwald, D. (1998). Domestic costs of statutory marketing authorities: the case of the Canadian Wheat Board. *American Journal of Agricultural Economics*, 80(2), 313-324.

Chambers, R. G. (1988). *Applied production analysis: a dual approach*. Cambridge University Press.

Chernoff, A. (2016). *Essays on Firm Heterogeneity with Empirical Applications in Economic History and Agricultural Economics* (Doctoral dissertation).

Correia, Sergio. 2017. "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator" Working Paper. http://scorreia.com/research/hdfe.pdf.

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. *The shifting patterns of agricultural production and productivity worldwide*, 63-95.

Furtan, W. H., Kraft, D. F., & Tyrchniewicz, E. W. (1999). Can the Canadian Wheat Board extract monopoly rents? The case of the spring wheat market. *International Journal of the Economics of Business*, 6(3), 417-437.

Groenewegen, J. R. (1986). A perspective on Canadian Wheat Board exports, price pooling, and West Coast capacity constraints. *Canadian Journal of Agricultural Economics*, 34(3), 331-346.

Johnson, D. D., & Wilson, W. W. (1995). Competition and policy conflicts in Canada-US barley trade. *Journal of Agricultural and Resource Economics*, 20(1), 1-18.

Manitoba Agricultural Services Corporation (MASC). Production data provided to the authors.

Mary, S. (2013). Assessing the impacts of pillar 1 and 2 subsidies on TFP in French crop farms. *Journal of Agricultural Economics*, 64(1), 133-144.

Roberts, M. J., Schlenker, W., & Eyer, J. (2013). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics*, 95(2), 236-243.

Smith, E. G., Zentner, R. P., Campbell, C. A., Lemke, R., & Brandt, K. (2017). Long-term crop rotation effects on production, grain quality, profitability, and risk in the northern great plains. *Agronomy Journal*, 109(3), 957-967.

United States Department of Agriculture (USDA). National Agricultural Statistics Service online database. Available at https://www.nass.usda.gov.

Veeman, M. M. (1987). Hedonic price functions for wheat in the world market: implications for Canadian wheat export strategy. *Canadian Journal of Agricultural Economics*, 35(3), 535-552.

Table 1. Difference-in-Difference (DiD) estimate

	CWB era (before 2012)	Post-CWB era (2012 onward)	Difference in D_t^{CWB}
CWB crop	$\alpha^{CWB\_crop} + \omega + \theta$	α^{CWB_crop}	$\omega + \theta$
Non-CWB crop	$\alpha^{Non\_CWB\_crop} + \omega$	$\alpha^{Non\_CWB\_crop}$	ω
Difference between crops	$\alpha^{CWB\_crop} + \theta - \alpha^{Non\_CWB\_crop}$	$\alpha^{CWB\_crop} - \alpha^{Non\_CWB\_crop}$	DiD: θ

Note: DiD estimate = [Difference in pre- and post-treatment outcomes for treated group (CWB crop)] minus [Difference in pre- and post-treatment outcomes for control group (non-CWB crop)]. The coefficient θ captures the effects of CWB.

Table 2. Summary statistics (spring wheat)

	Mean	Std. Dev.	Min	Max
Yield (mt)	130.28	86.13	0	2025
Acres	98.35	49.73	0.5	1178
N (lb/ac)	80.27	26.50	0	890
P (lb/ac)	29.79	11.96	0	401
K (lb/ac)	7.00	11.11	0	338
S (lb/ac)	3.45	6.66	0	600
Soil type (indicator)	4.45	1.67	1	10

n = 390,500
12,752 farms

Table 3. Summary statistics (canola)

	Mean	Std. Dev.	Min	Max
Yield (mt)	81.06	53.52	0	1160
Acres	98.74	49.73	0.4	1044
N (lb/ac)	92.22	29.67	0	900
P (lb/ac)	29.93	12.27	0	390
K (lb/ac)	6.18	11.48	0	386
S (lb/ac)	14.35	9.35	0	715
Soil type (indicator)	4.53	1.71	1	10

n = 473,368
11,906 farms

Table 4. Empirical results

	(1)		(2)	
	Baseline		Farm-year FE & weather	
	(a)	(b)	(a)	(b)
CWB × Wheat		-0.0331***		-0.0398***
		(0.00374)		(0.00342)
ln(Acres)	1.019***	1.019***	1.016***	1.016***
	(0.00103)	(0.00103)	(0.000875)	(0.000876)
ln(Acres) × Wheat				
ln(N)	0.0360***	0.0359***	0.0318***	0.0316***
	(0.00244)	(0.00244)	(0.00271)	(0.00271)
ln(N) × Wheat				
Canola	-0.500***	-0.519***	-0.498***	-0.521***
	(0.00214)	(0.00281)	(0.00211)	(0.00278)
Wheat Yield Index (US)				
Canola Yield Index (US)				
Farm FE	YES	YES		
Year FE	YES	YES		
Farm-Year FE			YES	YES
Municipality-Year FE			YES	YES
Observations	859,869	859,869	846,999	846,999
Categories	13,028	13,028	12,155	12,155
R-squared	0.824	0.824	0.924	0.924

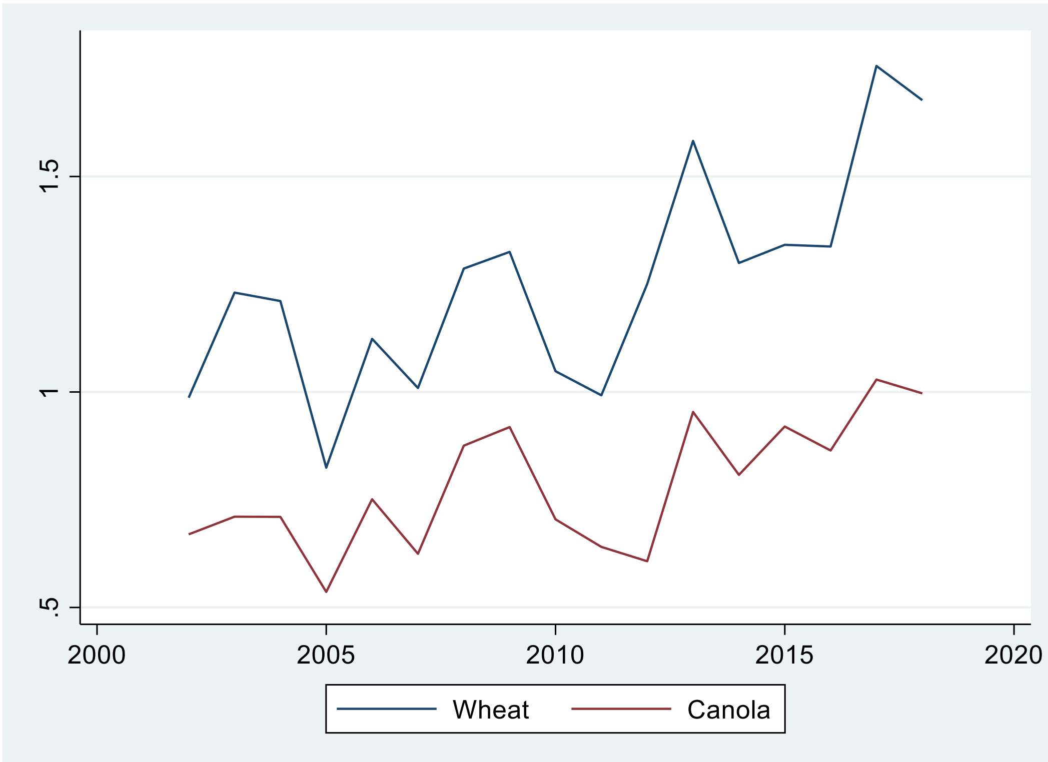
Dependent variable is log of tonnes
Intercepts and soil-type coefficients are suppressed
Robust standard errors in parentheses
Errors clustered at Farm level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Empirical results, cont.

	(1) Het. input effects		(2) Genetic gain trends	
	(a)	(b)	(a)	(b)
CWB × Wheat		-0.0382***		-0.0452***
		(0.00341)		(0.00438)
ln(Acres)	1.010***	1.010***	1.010***	1.010***
	(0.00113)	(0.00113)	(0.00113)	(0.00113)
ln(Acres) × Wheat	0.00855***	0.00686**	0.01252***	0.01208***
	(0.00286)	(0.00284)	(0.00171)	(0.00171)
ln(N)	0.0287***	0.0291***	0.0288***	0.0289***
	(0.00289)	(0.00290)	(0.00289)	(0.00290)
ln(N) × Wheat	0.0130***	0.0120***	0.01001***	0.00925***
	(0.00172)	(0.00171)	(0.00290)	(0.00288)
Canola	-0.403***	-0.437***	-0.518***	-0.644***
	(0.0149)	(0.0150)	(0.0176)	(0.0203)
Wheat Yield Index (US)			0.01267***	0.01005***
			(0.00047)	(0.00052)
Canola Yield Index (US)			0.48383***	0.47457***
			(0.01588)	(0.01588)
Farm FE				
Year FE				
Farm-Year FE	YES	YES	YES	YES
Municipality-Year FE	YES	YES	YES	YES
Observations	846,999	846,999	846,999	846,999
Categories	12,155	12,155	12,155	12,155
R-squared	0.924	0.924	0.925	0.925

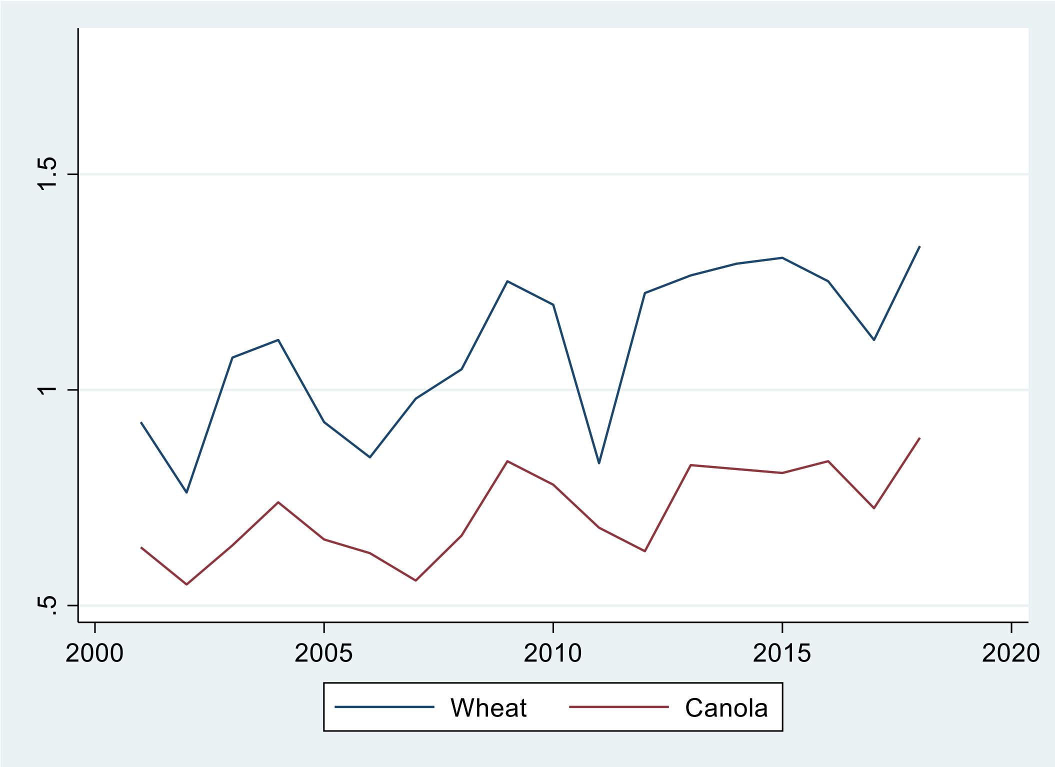
Dependent variable is log of tonnes
Intercepts and soil-type coefficients are suppressed
Robust standard errors in parentheses
Errors clustered at Farm level
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. Average yield, Manitoba (tonnes/acre)



Source: Authors' calculations based on data from MASC

Figure 2. Average yield, North Dakota (tonnes/acre)



Source: Authors' calculations based on data from USDA