

Gender-biased technological change: Milking machines and the exodus of women from farming.*

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Abstract

This paper studies how gender-biased technological change in agriculture affected women's work in 20th-century Norway. After WWII, dairy farms began widely adopting milking machines to replace the hand milking of cows, a task typically performed by young women. We show that the adoption of milking machines pushed young rural women out of farming in dairy-intensive municipalities. The displaced women moved to cities where they acquired more education and found better-paid employment. Our results suggest that the adoption of milking machines broke up allocative inefficiencies across sectors, which improved the economic status of women relative to men.

Keywords: Technological change; rural-to-urban migration; gender effects

JEL Codes: J16, J24, J43, J61, N34, O14, O33

*The authors gratefully acknowledge comments by Ran Abramitzky, Daron Acemoglu, Reidar Almås, Leah Boustan, Lou Cain, Harald Espeli, James Fenske, Martin Fernández Sánchez, Dan Fetter, David Green, Walker Hanlon, Yuzuru Kumon, Emi Nakamura, Josef Sigurdsson, Nancy Qian, Matti Sarvimäki, Paul Sharp, Johannes Stroebel, Mathias Thoenig, Nico Voigtlaender, Céline Zipfel, and various seminar and workshop participants at the University of Bergen, Norwegian School of Economics, Bonn, Groningen, Heidelberg, Helsinki GSE, Konstanz, Northwestern, Mannheim, St Andrews, Stanford, IESEG, Institutt for samfunnsforskning, Statistics Norway (SSB), the Long-Run Dynamics in Economics Workshop in Rouen, Uppsala, the CEPR Economic History Symposium in Odense, and the ES 2023 Winter Meeting in Manchester. Stefan Leknes and Jørgen Modalsli generously shared electricity power station data with us for the project. This work was partially supported by the Research Council of Norway through project No. 275800 and through its Centres of Excellence scheme, FAIR project No. 262675.

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1 Introduction

Between 1950 and 2000, agricultural employment fell by 75% in Europe and the United States, mostly due to the adoption of labor-saving technologies that automated traditional farming tasks.¹ Because traditional farming was subject to a strong gender division of labor (e.g., [Alesina et al., 2013](#); [Voigtländer and Voth, 2013](#)), the various labor-saving technologies introduced during the second half of the 20th century likely displaced male and female farm workers at different rates, depending on which farming tasks were automated. However, despite the extensive literature on the drivers of structural change (e.g., [Herrendorf et al., 2014](#); [Gollin and Kaboski, 2023](#)), the consequences of this *gender-biased* technological change are still not well understood. To what extent did this process contribute to the transformation of women’s work in the 20th century? Has the automation of farming tasks brought economic hardship or gains to affected workers by pushing them out of agriculture?

This paper attempts to make progress on these questions by analyzing the relationship between gender-biased technological change, the reallocation of labor across sectors, and the long-term earning opportunities of displaced farm workers. We focus on one of the largest gender-biased automation shocks in modern agriculture: the adoption of milking machines. Since the 1950s, European dairy farmers have widely adopted milking machines to replace hand milking of cows—the most common job for hundreds of thousands of young rural women.² Ex-ante, the long-term effects of milking machines on young rural women are unclear. Although women had a comparative advantage in producing services (e.g., [Goldin, 1990, 2006](#); [Ngai and Petrongolo, 2017](#)), there were large barriers to moving out of rural areas leading to the misallocation of labor across sectors (e.g., [Munshi and Rosenzweig, 2016](#); [Nakamura et al., 2021](#)).³ We find that the adoption of milking machines after WWII broke up these allocative inefficiencies and, despite its short-run costs, increased the return to education and long-term earning opportunities for young women who grew up in dairy-intensive municipalities.

Our study focuses on Norway, which provides an ideal setting in which to evaluate the economic consequences of the introduction of milking machines. Dairying was the cornerstone of Norwegian agriculture. Like other European dairy regions, Norway experienced a sharp and widespread increase in the use of milking machines after WWII, which coincided

¹Economic historians have vividly described how the mechanization of agriculture has transformed farms and displaced workers throughout the 20th century (e.g., [Olmstead and Rhode, 2001](#)).

²For centuries, dairying and milking the cows were common jobs for young, unmarried women in the dairy regions of Europe ([Snell, 1981](#); [Schultz, 1985](#); [Osterud, 2014](#); [Lampe and Sharp, 2019](#)).

³Typical examples of moving costs for rural workers include borrowing constraints, losing access to extended family networks or informal insurance networks, or social norms.

with an exodus of women from farming and a spike in urbanization (Almås, 1983). The number of milking machines increased from 6,357 to 39,924 in the 1950s, while female employment in agriculture fell by 80% between 1948 and 1961.⁴ However, more so than in other countries, the location of dairy farms in Norway is primarily determined by its unique geography, thereby facilitating the identification of the diffusion of milking machines at the local level. Moreover, the detailed Norwegian *individual-level* registry data and official agricultural statistics on the uptake of milking machines at the *municipality level* provide a rare opportunity to study the short- and long-run effects of gender-biased technological change at the micro-level.

Compared to studies on the macroeconomic consequences of structural change, our rich microdata allow us to isolate the effects of a specific labor-saving technology shock—the uptake of milking machines—and evaluate its causal impact on affected individuals. Instead of looking at the effect of technological change in the aggregate (e.g., across countries or sectors), we can identify whether affected women left agriculture, whether they moved to cities and how they performed in the short- and long-term. This is possible even when women’s last name changes after marriage, as we use a panel of individual-level registry data that allows us to systematically link women over time. Moreover, we can show that the adoption of milking machines differentially displaced men and women out of agriculture and assess whether the diffusion of this technology narrowed the gender gap in Norway.

Our empirical analysis is guided by a simple theoretical model that helps us better understand who was affected by the adoption of milking machines, and, especially, who *complied* to leave farming, move into cities, and invest in human capital. Our model combines the key ideas of comparative advantage (Roy, 1951) to explain rural-to-urban migration, with a task-based production function (Zeira, 1998; Autor et al., 2003; Acemoglu and Autor, 2011) to allow for labor-saving technological change and the gender division of labor in traditional farming tasks.⁵ Based on this theoretical framework, we are in a better position to identify the compliers of our quasi-experiment of gender-biased technological change. In our setting, these are misallocated female workers who have a comparative advantage in the urban sector but remain in agriculture because of moving costs.

Our empirical strategy exploits plausibly exogenous variation in the local uptake of milking machines. To do so, we create an exposure measure to milking machines that combines

⁴This figure is based on the number of female hired workers (see Appendix Figure 3, columns 7 and 8; Central Bureau of Statistics of Norway (1968, Table 78)). Other dairy regions, such as Denmark, France, Switzerland, West Germany, and the Netherlands, experienced similar processes. For example, in the Netherlands, the number of milking machines increased from 4,000 to 39,000 in the 1950s, while female employment fell by 75%; from 169,000 to 41,000 in levels (Bieleman, 2005; Mitchell, 1998).

⁵Nakamura et al. (2021) highlight the importance of comparative advantage for understanding the costs and benefits of moving.

changes in the nationwide adoption of milking machines with local differences in the intensity of the dairying sector during the pre-milking machine era (Figures 1 and 3). We use this exposure measure to instrument for the actual uptake of milking machines at the municipality level. Importantly, we provide evidence supporting the validity of our exposure measure as an instrumental variable. First, we use a Lasso procedure to assess whether our milking machine exposure measure is correlated with any other initial characteristics that might generate differential trends across locations. Reassuringly, our results are robust to adding controls selected by Lasso and flexible accounting for county-specific cohort trends. Second, we present event studies and a placebo test showing that the outcomes of women in more or less exposed rural municipalities evolved similarly in the pre-milking machine era. Third, our estimates are also robust to: (i) alternative definitions of our milking machine exposure measure; (ii) including potential confounders, such as education reforms;⁶ and (iii) accounting for spatial correlation.

The main empirical analysis is based on approximately 380,000 women who lived in rural municipalities at the ages of 16 to 25 between 1930 and 1970. Consistent with the model's predictions, we find that the adoption of milking machines pushed affected young women out of agriculture and into cities. Although the displacement effect entailed substantial short-term income losses,⁷ it improved the economic situation of affected women in the long term. The long-run gains were considerable and compensated for the short-run costs: for a one-standard-deviation increase in milking machines per farm, women climbed up their birth-year-specific income distribution by almost two percentiles. Affected women did not only claim up the income distribution because they were more likely to work as middle-aged adults, but also because they had better paying, high-skilled jobs. Consistent with this result, we also find that affected women invested more in higher education, which is a requirement for many white-collar jobs. Indeed, the migration decisions were partly determined by access to higher education institutions, suggesting that the long-run effects of labor-saving technological change on displaced workers are not institution-independent.

Our second set of findings shows that, because of the traditional gender division of labor in agriculture, introducing labor-saving technologies can have major and long-lasting *gender-specific* effects. We find that while displaced young women moved to cities, invested in their human capital, and found higher-skilled employment, most young men remained in the same rural areas, which offered high returns on the skill sets they had already acquired. This result

⁶Recent work by [Porzio et al. \(2022\)](#) shows that educational reforms contributed to increased schooling and a decline of agricultural employment of affected cohorts using data for multiple countries.

⁷This finding is consistent with workers' fears that labor-saving technological progress curtails employment and lowers wages; see [Caprettini and Voth \(2020\)](#) for a historical setting, and [Acemoglu and Autor \(2011\)](#) and [Acemoglu and Restrepo \(2020\)](#) for a modern setting.

is consistent with the historical narrative and with the predictions of our model. Overall, our findings show that the adoption of milking machines significantly reduced gender differences in labor force participation rates and income in the long term. Income differences between these men and women were reduced by about 2 percentile ranks, and differences in labor force participation rates dropped by almost 4 percentage points.

Our paper contributes to a growing literature on the effects of automation on labor markets (Restrepo, 2023) by empirically documenting the long-term effects of automation. We provide evidence that migration and task reinstatement can lead to long-term welfare gains for affected workers.⁸ Our finding that affected rural women acquire more education to take high-skilled jobs in Norway’s expanding service sector also complements the insights from Atkin (2016), who shows that expansions in low-skill export-manufacturing jobs increased the opportunity costs of staying in school.

We also add to the literature on the evolution of female labor participation over the 20th century in industrialized countries (e.g., Goldin, 1994, 2006; Olivetti, 2014; Olivetti and Petrongolo, 2016). The adoption of milking machines pushed women out of rural areas and transformed women’s work by increasing their educational attainment and occupational status. Our results suggest that this gender-biased technology shock reduced the gender gap by breaking up deeply rooted gender norms within labor markets (e.g., Alesina et al., 2013; Fernández, 2013; Giuliano, 2015, 2018).

Our work relates to studies of the drivers and effects of structural change (e.g., Herrendorf et al., 2014; Gollin and Kaboski, 2023).⁹ A small branch of the literature studies the gender effects of structural change in the context of middle and high-income countries from a macroeconomic perspective (e.g., Olivetti, 2014; Moro et al., 2017; Ngai and Petrongolo, 2017; Rendall, 2018). We complement this literature by using the rich Norwegian individual-level registry data that allow us to identify how a specific technology shock in agriculture changed women’s work and thus contributed to the process of structural transformation.

Finally, there is also a large body of work that considers barriers to migration and the selection of workers into specific locations as the main reasons behind rural-urban wage gaps (e.g., Gollin et al., 2014; Munshi and Rosenzweig, 2016; Bryan and Morten, 2019). A few studies rely on forced migration or natural disasters to study the misallocation of labor across sectors and places (Nakamura et al., 2021; Sarvimäki et al., 2022), whereas we consider the

⁸Recent examples are Acemoglu and Restrepo (2019), Atack et al. (2019), and Feigenbaum and Gross (2022). We refer readers to Restrepo (2023) for a recent survey of the automation literature.

⁹The focus of recent empirical studies has been on evaluating the consequences of increases in agricultural productivity on structural change (e.g., Bustos et al., 2016; Carillo, 2021; Gollin et al., 2021). It is worth noting that negative productivity shocks in agriculture unrelated to technological change can also trigger structural change (e.g., Ager et al., 2020).

large-scale adoption of milking machines as a quasi-natural experiment that substantially reduced the barriers to moving by eliminating the job opportunities for women on farms, thereby facilitating structural transformation.¹⁰

2 Historical background

This section provides a brief overview of Norway’s structural transformation during our period of study (1930-1970), followed by a detailed discussion of the widespread adoption of milking machines on dairy farms after WWII.

In 1930, less than 30 percent of Norwegians lived in cities and agriculture was still a key sector.¹¹ Agricultural employment decreased substantially when Norway experienced unprecedented economic growth between WWII and 1970.¹² This period saw an acceleration in the mechanization of agriculture similar to that in other parts of Scandinavia, Western Europe, and the United States. Agricultural production became more capital-intensive (see Appendix Figure 1), in part due to rising labor costs and the removal of trade barriers. Concomitantly, primary-sector employment declined by 60 percent, from 900,000 workers in 1950 to 365,000 in 1970 (Statistics Norway, 1980, Table 17). The manufacturing sector absorbed part of the newly available labor, while the remainder found employment in the service sector. At the same time, urbanization increased rapidly due to internal (rural-to-urban) migration (immigration to Norway remained negligible throughout our sample period), while rural areas faced substantial population losses from the 1950s onward (Hansen, 1989). By 1970, approximately two-thirds of Norway’s population lived in urban areas.

How did the adoption of milking machines contribute to the structural transformation in Norway after WWII? In the early 20th century, dairying was the largest activity in Norway’s agricultural sector.¹³ On dairy farms, the main task of women, in addition to housework, was milking cows while men worked outdoors and typically complemented their farming

¹⁰Our finding that displaced rural women moved to cities to find better-paid employment is consistent with the view that women were, on average, less productive in agricultural work than men, and it also suggests that a big push was needed since moving to cities comes with high economic and social costs (e.g., Lagakos, 2020; Nakamura et al., 2021; Lagakos and Shu, 2023).

¹¹About 40 percent of the population worked in the primary sector during the 1920s (Mitchell, 1998).

¹²After WWII, Norway joined Bretton Woods, the General Agreement on Tariffs and Trade (GATT), the IMF, the World Bank, NATO, and the United Nations. The annual compound growth rate was approximately 4 percent (Grytten, 2020, Table 1). Norway’s economic success has been partly attributed to the “Nordic model,” which involves a strong role of the public sector (Acemoglu et al., 2021).

¹³Farming in Norway was traditionally based on family farms and milk production. Family farms were, and still are, the most common type of farm in Norway and other parts of Europe. Typically, parents, their children, and extended family members worked on the farm, together with seasonal and permanently hired workers. The most important farm products in Norway were milk, products derived from milk, and meat associated with milk production (Espeli et al., 2006).

employment with other seasonal work in the rural sector; for example, in fisheries, timber industries, or in the construction sector (Almås, 2020). This division of labor was deeply rooted in farming communities: “Dairying was defined as women’s work, to the point that the very idea of men performing it was regarded as laughable, or even heretical” (Osterud, 2014, p.667). Besides milking cows and other indoor work, women also worked on the fields alongside men during haymaking and other seasonal harvesting activities. This traditional gender division of farm tasks is well documented in Norway and the other Nordic countries (e.g., Almås and Haugen, 1991; Sommestad, 1994; Kaarlenkaski, 2018).

Milking cows remained women’s main chore on dairy farms until the adoption of milking machines. While the first milking machines were patented in the United States in the late 19th century, widespread adoption across Europe and the United States only took place after WWII (e.g., Bateman, 1969; Bieleman, 2005; Settele, 2018).¹⁴ Norway was no exception to this pattern, as Figure 1 illustrates. Although there was a slow uptake in the 1930s, the adoption of milking machines on Norwegian farms only widely took place after WWII. The most important factor behind this take-off is that, in 1951, Norway lifted all import restrictions on agricultural equipment (Espeli, 1990).

The widespread adoption of milking machines after WWII had a profound impact on dairy farming (Bieleman, 2005).¹⁵ Compared to hand milking, a milking machine could milk a substantially larger number of cows. For example, in 1964, a single person in a milking parlor with eight workstations could milk 30 cows per hour with a milking machine. Without such a machine, one person could hand-milk only seven or eight cows per hour, with decreasing productivity as fatigue accumulated (Settele, 2018). In contrast to other farm equipment and machinery, milking machines were affordable and profitable even for small farms as soon as the 1950s because they were used indoors in cowsheds, without requiring expansion or further investment, and because the machines themselves were relatively inexpensive. For a farmer in 1950, the price of a milking machine was about the same as half a year’s wages for a male servant. In contrast, it was five times more costly to buy a tractor.¹⁶

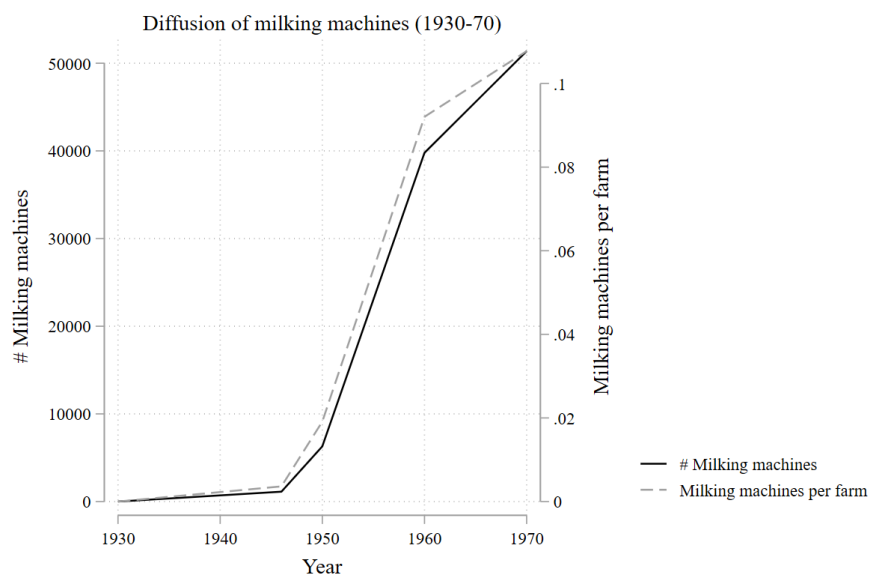
Who was displaced by the adoption of milking machines? The traditional division of labor on dairy farms as explained above indicates that milking machines automated hand

¹⁴The reasons for this delayed adoption are manifold. Bateman (1969, p.211), for example, describes how farmers hesitated to adopt milking machines because they were fire hazards and often injured cows.

¹⁵With the adoption of milking machines, milk yield per cow increased in Norway from around 2,000 kilograms in 1950 to more than 4,000 kilograms in 1969 (see Appendix Figure 2). A similar pattern is also observed in the other Nordic countries or in the Netherlands (Bieleman, 2005).

¹⁶According to Almås (personal communication) the price of a milking machine was ca. NOK 2,000 in 1950, while a standard tractor produced in the United States cost about NOK 10,000. To put this in perspective, the price of a milking machine corresponded to a male servant’s half-year wage with board—NOK 1,840 in 1952/53 (Statistical Yearbook 1955, Table 250)—and roughly to a female servant’s yearly wage.

Figure 1



NOTE.— This figure shows the evolution of milking machines (left vertical axis) and milking machines per farm (right vertical axis) in Norway between 1930 and 1970. Source: Census of Agriculture (own calculations).

milking, a task typically performed by women. Specifically, young women aged around 16-25 commonly worked as milkmaids on farms before getting married (see, e.g., [Almås \(2002\)](#)). After the widespread adoption of milking machines, the demand for these milking services disappeared. Hence, when dairy farms shifted to milking cows mechanically, this process almost exclusively displaced female workers, in particular milkmaids and servants ([Thorsen, 1986](#); [Brandth, 2002](#)). [Almås et al. \(1983\)](#) describe the adoption of milking machines as “the masculinization of Norwegian agriculture.” Hiring female labor for milking cows was no longer needed, and men now took over the milking process using the new technology.¹⁷

Milking machines were part of the general mechanization of agriculture after WWII that pushed labor off the farms. The opportunities to remain in rural areas, however, differed according to gender. Men had a comparative advantage over the existing rural jobs. Specifically, a large share of jobs in rural areas consisted of seasonal work on farms, in construction, and in fisheries, which were usually carried out by male crofters.¹⁸ While the mechanization of farms reduced men’s opportunities to take on seasonal work on farms, they were still in

¹⁷This process not only affected hired female servants and milkmaids but also farmers’ wives and daughters, as a large part of the farm work was now taken over by men (see [Almås \(2002\)](#) and Appendix Figure 3).

¹⁸Crofters comprised a large share of the rural population in Norway. They typically rented small landholdings that were not large enough to feed their families.

high demand for these other seasonal jobs, especially during the post-WWII boom years. These alternative rural jobs offered high returns to the skills men had already acquired as part-time farm workers. For women, the situation differed as they did not have access to these existing jobs in rural areas. As a consequence, women displaced from farms left the countryside in the hope of finding new jobs in the cities (Almås et al., 1983; Brandth, 2002). As our empirical analysis will show, an overwhelming proportion of the displaced female workers found employment in high-skill occupations.

Overall, the historical narrative suggests that the rapid mechanization of agriculture after WWII pushed labor off the farms, and that women were generally more affected by the modernization process. Affected men continued to have employment opportunities in the rural areas, while displaced women had a comparative advantage in urban employment. Hence, we expect different long-term effects from the adoption of milking machines for women and men in relation to the decision to migrate to cities, future income, employment, and corresponding human capital investments. The next section formalizes these predictions.

3 Model

We build a simple model that captures gender differences in (a) task division in agriculture, (b) displacement effect of automation, and (c) rural-to-urban mobility following the adoption of a labor-saving technology. We combine the key ideas of comparative advantage to explain rural-to-urban migration (Roy, 1951), with a task-based production function that allows for the gender division of labor and labor-saving technological change (Zeira, 1998; Autor et al., 2003; Acemoglu and Autor, 2011). The model helps to identify the compliers of our quasi-experiment and formulates the hypotheses that we bring to the data.

Consider an economy with a large number of municipalities divided into two areas: rural and urban. Municipalities in rural areas are mostly specialized in the primary sector (R) while urban areas are specialized in the manufacturing and services sectors (U). Men and women inelastically supply one unit of labor. Each individual i is endowed with two skills, $\alpha_R(i)$ and $\alpha_U(i)$. These skills represent efficiency units for labor in the rural and urban sector, respectively. In our setting, $\alpha_U(i)$ represents skills demanding more general human capital for occupations in the cities. The skill pair $(\alpha_R(i), \alpha_U(i))$ is equally distributed by gender. We define an individual i 's comparative advantage in the urban sector as $\alpha_U(i)/\alpha_R(i)$. Individuals maximize their consumption. To do so, they face the choice of supplying their labor to either the urban or rural sector. To gain insights for our empirical analysis, we focus on the decisions of individuals in rural areas, for whom supplying labor to the urban sector requires moving to a city. This entails moving costs c , which we assume to be a fraction of

their earnings (Nakamura et al., 2021).¹⁹ This could be thought of as the economic cost of moving to a new locality, the foregone social ties and rural insurance networks (Munshi and Rosenzweig, 2016), but also as the educational investments necessary to secure employment in, for example, the city’s service sector.

The rural sector produces one final good Y_R by combining two tasks, y_1 and y_2 . For simplicity, we assume a constant returns to scale Cobb-Douglas technology:

$$Y_R = y_1^{1-\beta} y_2^\beta . \quad (1)$$

Two factors of production are used in the rural sector: labor L_R and capital M . To capture the gender division of labor in traditional agriculture, we assume that task y_1 uses female labor, and task y_2 uses male labor. In our setting, task y_1 can be interpreted as milking cows, and task y_2 as work traditionally done by men, e.g., cultivating fields, seasonal work in construction or fisheries. To capture the displacement effects of milking machines, assume that capital (milking machines) M and female labor are perfect substitutes. Formally, the production function of each task is:

$$y_1 = A_R L_R^f + M \quad \text{and} \quad y_2 = A_R L_R^m , \quad (2)$$

where $L_R^f = \int_{i \in \mathcal{F}_R} \alpha_R(i) di$ and $L_R^m = \int_{i \in \mathcal{M}_R} \alpha_R(i) di$ are female and male labor in rural areas, and \mathcal{F}_R and \mathcal{M}_R denote the set of female and male workers in the rural sector.

This task-based production function encompasses the canonical labor-augmenting technological change (A_R) and labor-saving technological change. Specifically, the machines used in the first task, M , are supplied perfectly elastically at market price $\mu > 1$, which falls exogenously due to technological advances. Hence, the declining price of the machines is the labor-saving technological change in our model.

The urban sector produces one final good Y_U using labor L_U as the only factor of production, irrespective of gender. Formally, the production function is:

$$Y_U = A_U L_U , \quad \text{where} \quad L_U = \int_{i \in \mathcal{S}_U} \alpha_U(i) di \quad (3)$$

and \mathcal{S}_U denotes the set of female and male workers employed in the urban sector. Labor markets are perfectly competitive and the economy is small, so the prices of the rural (P_R)

¹⁹Although we do not directly observe moving cost, our empirical analysis provides important insights on it. First, we show that migration patterns did not differ across more and less dairy-intensive municipalities in the pre-milking machine era. Second, by using fixed effects for municipalities and county-by-birth cohorts, we account for time-invariant *municipality-specific* and time varying *county-specific* moving costs that may have affected women’s decisions to migrate and their long-run income gains.

and urban (P_U) goods are taken as given. This implies that the wage per efficiency unit of labor in the urban sector is $W_U = A_U P_U$.

Three main conditions govern the remainder of the equilibrium. The first is the perfect substitutability of female labor and machines in the rural sector. This implies that the wage per efficiency unit of female labor in the rural sector is pinned down by the labor-augmenting technological change, A_R , and by the labor-saving technological change, captured by the price of machines μ :

$$W_R^f = A_R \mu \quad (4)$$

The second condition is the Cobb-Douglas production technology in the rural sector, which implies that machines used in task y_1 and male labor used in task y_2 are q-complements. Hence, the wage per efficiency unit of male labor in the rural sector is negatively associated with the price of machines:

$$W_R^m = A_R P_R^{\frac{1}{\beta}} \beta \left(\frac{1 - \beta}{\mu} \right)^{\frac{1-\beta}{\beta}}. \quad (5)$$

The third condition is worker self-selection among rural and urban areas. The labor earnings for worker i are $W_R^f \cdot \alpha_R(i)$ for women in the rural sector, $W_R^m \cdot \alpha_R(i)$ for men in the rural sector, and $W_U \cdot \alpha_U(i)$ for women and men in the urban sector. Taking into account the cost of moving, this implies that the marginal female worker, i^* , is indifferent between remaining in a rural area and moving to an urban area if $W_R^f \cdot \alpha_R(i^*) = (1 - c) \cdot W_U \cdot \alpha_U(i^*)$ and the marginal male worker j^* is indifferent if $W_R^m \cdot \alpha_R(j^*) = (1 - c) \cdot W_U \cdot \alpha_U(j^*)$. It is useful to re-define these indifference conditions as a function of the relative earnings in the urban vs. rural sector of female, η_i^f , and of male, η_i^m , workers:

$$\eta_i^f := \frac{W_U}{W_R^f} \cdot \frac{\alpha_U(i)}{\alpha_R(i)} \quad \text{and} \quad \eta_i^m := \frac{W_U}{W_R^m} \cdot \frac{\alpha_U(i)}{\alpha_R(i)}.$$

The indifference condition is then $\eta_{i^*}^f = \eta_{j^*}^m = \frac{1}{1-c}$. Note that this differs from the optimal allocation of workers, which is achieved when the marginal female worker is \tilde{i} and the marginal male worker is \tilde{j} with $\eta_{\tilde{i}}^f = \eta_{\tilde{j}}^m = 1$.

The model's equilibrium is illustrated in Figure 2, Panel A. Female workers with a higher comparative advantage in the urban sector have higher relative earnings in that sector.²⁰ All women with a comparative advantage above \tilde{i} would earn a higher salary in the urban sector.

²⁰For simplicity, the figure η_i^f takes a linear form by assuming that $\alpha_U(i)$ and $\alpha_R(i)$ are uniformly distributed, but that different skill distributions can lead to different shapes. The only necessary assumption is that η_i^f is upward-sloping, i.e., that $\frac{\alpha_U(i)}{\alpha_R(i)}$ reflects a comparative advantage in the urban sector.

However, the moving cost implies that all women with a comparative advantage below i^* will remain employed in the rural sector, and that only women with a comparative advantage above i^* will relocate to the cities and be employed in the urban sector. Hence, all women between \tilde{i} and i^* will be “misallocated” and their earnings would increase if they moved to a city. An analogous argument applies for men.

Let us now consider the situation at the time of the mechanization of agriculture and derive predictions for our empirical analysis. As explained above, the adoption of milking machines automated tasks typically performed by women in rural areas. In our model, this labor-saving technological change is captured by a decline in the price of the machines, M , from μ to μ' . This quasi-experiment is illustrated in Figure 2, Panels B and C.

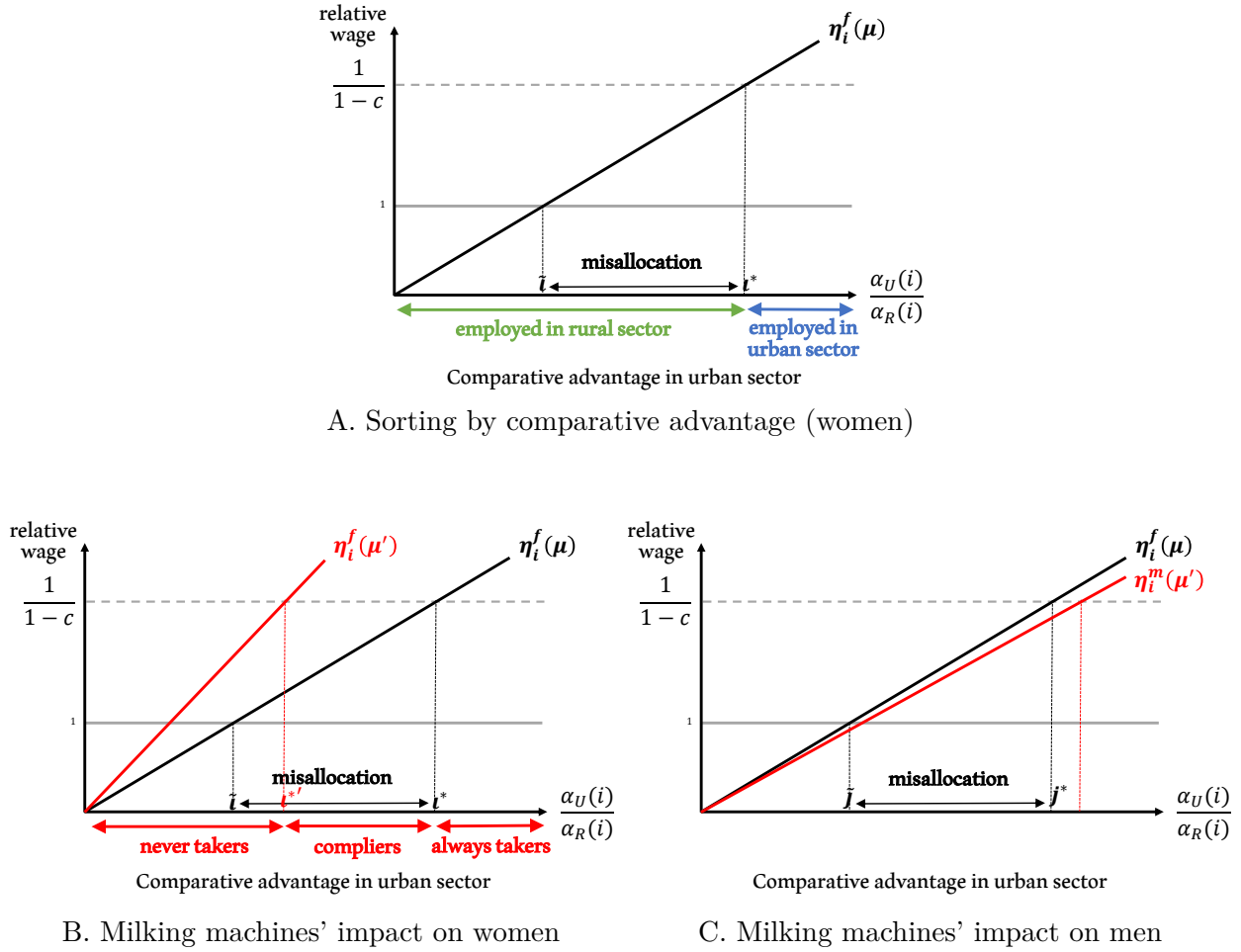
The *first prediction* is that the adoption of milking machines will displace women from agricultural jobs in the rural sector and push them out of the countryside to find employment in the urban sector. It is immediately clear from equation (4) that a decline in the price of machines reduces the female wage in rural areas.²¹ This is illustrated by the relative earnings curve shifting up (red line) in Figure 2, Panel B. Since female and male workers are bound to a task in the rural sector, this does not generate any re-sorting of female workers across tasks in the rural sector. Instead, the Roy framework with respect to rural and urban skills, implies that female workers’ decisions to migrate to urban areas will respond elastically to relative wage levels in the rural and urban sectors. Specifically, all women with a comparative advantage between $i^{*'} and i^* will be displaced by milking machines from agricultural jobs in the rural sector and migrate to find employment in the urban sector.$

The model also allows us to identify the compliers. Based on the terminology of Angrist (2004), female workers to the left of $i^{*'}$ in Figure 2, Panel B are “never-takers.” They have such a strong comparative advantage in the rural sector that they will not migrate to urban areas, even after the adoption of milking machines. Female workers between $i^{*'}$ and i^* are “compliers.” They will migrate to urban areas if and only if their municipality adopts milking machines. Finally, female workers to the right of i^* are “always-takers”. They have such a strong comparative advantage in the urban sector that they will move, even if their municipality does not adopt milking machines.

The *second prediction* is that, on average, displaced women will experience long-run income gains. This prediction emanates from the fact that the first women displaced by milking machines are those with the highest comparative advantage in the urban sector. These women are misallocated workers, in the sense that their earnings would be higher in the urban sector to begin with, but they remain in rural areas only due to the moving cost. In Figure 2, this is illustrated by the fact that the displaced women (between $i^{*'}$ and i^*) are

²¹That is, $\partial W_R^f / \partial \mu = A_R > 0$, and hence, $\partial \eta^f / \partial \mu = -(A_U P_U / A_R \mu^2) \cdot (\alpha_U(i) / \alpha_R(i)) < 0$.

Figure 2



NOTE.— This figure shows the model's equilibrium (Panel A) and comparative statics for the effects of the adoption of milking machines on women (Panel B) and men (Panel C). For illustrative purposes, we assume that $\alpha_U(i)$ and $\alpha_R(i)$ are uniformly distributed.

in the region of misallocated workers (between \tilde{i} and i^*). A depression in female rural wages, such as the one induced by the automation of milking tasks, can break up this allocative inefficiency and induce long-run income gains to the displaced female workers who relocate to cities. This result hinges on the assumption that the cost of moving is large enough such that a substantial share of the compliers are misallocated in rural areas prior to the technology shock. Recent evidence supports this assumption, showing that barriers to migration and moving costs are substantial in rural settings similar to our case study (see e.g., Nakamura et al. (2021) and Munshi and Rosenzweig (2016)).

The *third prediction* is that rural municipalities with farming conditions better suited for

dairy production will adopt milking machines to a greater extent, and hence, will experience more drastic displacement effects. Let this economy be a collection of rural municipalities $j \in J$, which operate with the production functions in equations (1) and (2), but are heterogeneous with respect to $\beta(j)$, the factor share of different farming tasks. A small $\beta(j)$ represents a task- y_1 -intensive municipality—in our setting, municipalities better suited for dairy production. Although all municipalities face the same price of milking machines, μ , the degree to which municipalities adopt this technology depends on $\beta(j)$. To see this, it is useful to define the input demand in rural municipalities as $\theta(j) = (A_R L_R^f(j) + M(j)) / (A_R L_R^m(j))$. In other words, $\theta(j)$ captures how much a rural municipality j demands milking machines and/or female labor (i.e., task- y_1 input) relative to male labor (i.e., task- y_2 input). Assuming that each municipality satisfies productive efficiency,

$$\partial Y_R(j) / \partial L_R^f(j) = W_R^f(j), \quad \partial Y_R(j) / \partial M(j) = \mu, \quad \text{and} \quad \partial Y_R(j) / \partial L_R^m(j) = W_R^m(j),$$

implies that the input demand in rural municipalities is $\theta(j) = [P_R(1 - \beta(j)) / \mu]^{\frac{1}{\beta(j)}}$. The partial derivative of $\ln \theta(j)$ with respect to μ and $\beta(j)$ is:

$$\frac{\partial \ln \theta(j)}{\partial \mu} = \frac{-1}{\mu \beta(j)} < 0 \quad \text{and} \quad \frac{\partial^2 \ln \theta(j)}{\partial \mu \partial \beta(j)} = \frac{1}{\mu \beta(j)^2} > 0. \quad (6)$$

Equation (6) shows that as the price of milking machines declines, the demand for milking machines and/or female labor (i.e., for task- y_1 input) increases. As shown above, this increased input demand will be met entirely by an influx of milking machines, as female wages in the rural sector will fall and marginal female workers will reallocate their labor input to the urban sector. In addition, the cross-partial derivative shows that the aforementioned influx of milking machines, and hence, the first-order displacement effect of milking machines on female labor, will be relatively larger in municipalities with a large $1 - \beta(j)$. We adopt this theoretical insight into our estimation strategy. Specifically, we capture municipality-level heterogeneity in dairy production prior to the diffusion of milking machines by the number of milk cows per farm in 1930 (see Section 5).

The *fourth prediction* is that the adoption of milking machines after a fall in their price from μ to μ' will increase the wage per efficiency unit of male labor in the rural sector.²² From equation (5), we see that $\partial W_R^m / \partial \mu = -P_R A_R [(1 - \beta) / \mu]^{\frac{1}{\beta}}$. This different effect for men is illustrated in Figure 2, Panel C. Note that the effect of the decline in the price of milking machines on men's relative earnings η_i^m is smaller in magnitude than the effect on

²²This is consistent with the evidence in Section 2 that the rapid mechanization of farming led to the masculinization of agriculture in Norway.

women’s relative earnings η_i^f and goes in the opposite direction.²³ Hence, this labor-saving technological change in relation to men triggers neither a displacement effect nor migration to cities, and as a result, the potential long-run income gains from moving to a city are not realized. Men with a comparative advantage between \tilde{j} and j^* remain where they are.

In the remaining part of the paper, we bring these predictions to the data and evaluate how women who were born in rural areas when Norwegian farms introduced milking machines performed later in life.

4 Data

In this section, we describe our primary sources: (i) linked individual-level administrative datasets from the Norwegian Registry Data maintained by Statistics Norway, and (ii) municipality-level data on the adoption of milking machines from the census statistics on Norwegian farms. Other secondary datasets are introduced in the relevant sections of the empirical analysis below.

In our analysis, we focus on adult outcomes of women from rural municipalities who, at ages 16-25, would have traditionally been hired by farms to perform hand milking (see Section 2). Our main sample includes circa 380,000 women born in rural municipalities with at least one farm in 1929,²⁴ who were aged 16-25 in 1930, 1940, 1950, 1960, or 1970 (agricultural census years).²⁵ In extended specifications, we also consider the corresponding cohorts of men in our main sample. We refer readers to Appendix Table 1 for detailed summary statistics.

4.1 Registry data

Our individual-level data draw on the administrative registries provided by Statistics Norway. For our analysis, we use the linked central population register covering the full Norwegian population from 1960 to 2019, the full count population censuses of 1960, 1970, and 1980, the education register, and the tax and earnings register. These registers provide information on place of birth and residence, occupation, earnings, educational attainment, and personal

²³The effect for men is smaller than for women because $\partial W_R^f / \partial \mu$ is larger in magnitude than $\partial W_R^m / \partial \mu$, as long as $\mu > P_R(1 - \beta)$. This condition is satisfied when milking machines are first introduced, as the pre-adoption price of new technologies, here μ_0 , tends to infinity.

²⁴We classify municipalities as rural if they report no urban population and at least one farm in the Census of Agriculture 1929.

²⁵Specifically, we consider women turning 16 to 25 in each agricultural census year, who might have been 15 at the start of the year. For the 1946 agricultural census, we consider women aged 16-25 in 1940 instead of in 1946 in order to avoid overlapping cohorts in 1946 and 1950.

identifiers that make it possible to follow men and women over time.

From the central population register, we use the municipality of birth to build our sample of young rural women and to measure women’s exposure to the adoption of milking machines. We measure exposure at the age of 16-25, when they would have traditionally been hired as milkmaids.²⁶ The central population registry also includes personal identifiers, which we use to follow women over time. Importantly, these unique identifiers allow us to link all women, notwithstanding changes in their last name after marriage. This adds to the credibility of our data over other historical studies using automated linking methods to create historical panel data without unique identifiers. The unique personal identifier also enables matching to registers on tax and earnings, education, and full count censuses.

We supplement this data with full count population censuses from 1960, 1970, and 1980. The censuses are used to identify each individual’s occupation and to evaluate the displacement effect of milking machines out of agriculture for young women later in life. To do this, we classify occupations into farming and non-farming activities and evaluate how the diffusion of milking machines when a woman was aged 16-25 affected her occupation after age 25, as reported in the subsequent census.²⁷ The occupations registered in the censuses are self-reported and cover almost the entire population. On average, 9 percent of the women in our sample worked in agriculture after the age of 25. We also use the decennial occupation data to examine effects on the occupations’ skill content. More specifically, we use the classification of occupations matched with skill content from O*Net to group occupations outside agriculture into high-, medium-, and low-skilled jobs (Autor, 2019). Around 12.5 and 18 percent of the women in our sample who were not employed in farming performed high- and medium-skill jobs after the age of 25.

The full count population censuses also report the municipality of residence of each individual. This, together with the municipality of birth, allows us to examine long-distance, rural-to-urban migration patterns.²⁸ We evaluate the extent to which the diffusion of milking machines when a woman was aged 16-25 affected her decision to migrate. About one quarter of the women in our sample moved to a city.

In addition, we measure earnings by linking individuals to the tax registry maintained

²⁶In other words, we use the municipality of birth as a proxy for the municipality of residence at age 16-25. This assignment also avoids capturing the effect of endogenous migration decisions.

²⁷Specifically, for women aged 16-25 in 1930, 1940, and 1950, we look at their occupation in the 1960 Census; for women aged 16-25 in 1960, we look at their occupation in the 1970 Census; and for women aged 16-25 in 1970, we look at their occupation in the 1980 Census. When a woman’s occupation is missing in a given census, we look at their reported occupation in a later census.

²⁸We define rural-to-urban migration as moving to an urban area outside one’s county (*fylke*) of birth. We also construct measures of migration to any city, to a town with higher education institutions, and migration outside and within an one’s county of birth.

by Statistics Norway, which has been available since 1967. We use gross earnings to evaluate both the short- and long-term effects of the adoption of milking machines on women’s income, as well as their labor force participation. For short-term effects, we follow the year-by-year income trajectory of women turning 16 in 1970—the first cohort in our sample for which yearly income data is available from the start of their working life. For long-term effects, we consider our main sample, measure their income later in life, and construct income percentile ranks based on all individuals (i.e., men and women) born in the same year. Specifically, we construct income percentile ranks based on gross earnings at the age of 45. Because the tax registry only starts in 1967, we use gross earnings at age 52 for women aged 16-25 in 1940 and pre-tax earnings at age 62 for women aged 16-25 in 1930. Appendix Figure 4 shows that there is a high correlation between income percentile ranks at ages 45, 52, and 62. Similarly, several studies show that income rank is less sensitive to the age at which income is measured than the income in levels (e.g., [Chetty and Hendren, 2018](#)). The average adult earnings are approximately 65,000 Norwegian kroner (NOK) for women in our sample. For female labor force participation (FLFP), we consider an adult woman as working if she reports positive earnings at age 45. Since this excludes the earliest cohorts (women aged 16-25 in 1930 and 1940), Appendix Table 13 considers alternative FLFP definitions using occupation data from the Census records.

Finally, we measure educational attainment using the educational database provided by Statistics Norway. This data is based on educational attainment reports submitted directly by the educational institutions to Statistics Norway every year since 1970. This minimizes any measurement error from misreporting. As measures of educational attainment, we use whether individuals completed at least upper-secondary education or hold a bachelor’s degree or higher. On average, 10 percent of the women in our sample attained undergraduate education or higher (see Appendix Figure 5).

4.2 Agriculture censuses

We combine our individual-level data with aggregated municipality-level census statistics on Norwegian farms. These agricultural censuses were collected on a decennial basis,²⁹ cover our entire study period from 1930 to 1970, and report detailed statistics on the number of farms, agricultural machinery, equipment, crops, and livestock in each municipality. However, there is no information on agricultural output. For our analysis, we use the number of milking machines per farm in each municipality in each census year as measure of local technology adoption. Over our study period, an average rural municipality had seven milking machines

²⁹Except in 1940 were the agricultural census was delayed to 1946 because of WWII.

per 100 farms, although as discussed above, there is a considerable heterogeneity across time and space (see Figure 1 and Appendix Figure 6). In addition, we use information on the number of dairy cows per farm in each municipality in 1930 to capture the intensity of (formal and informal) female labor engaged in milking cows prior to the introduction of milking machines. The agricultural censuses also report information that is useful to construct control variables that capture initial municipality-specific characteristics that could also have affected the diffusion of milking machines over time, such as the agricultural intensity and the farm size distribution. The selection of the controls are based on a Lasso procedure, which we describe in the next section.

5 Empirical strategy

Our goal is to estimate the causal effect of the adoption of milking machines on various individual outcomes of interest, including displacement from farming, migration, income, and labor force participation. We use an instrumental-variable approach that exploits plausibly exogenous variation in the local uptake of milking machines. We do so by constructing an exposure measure to milking machines, which combines changes in the nationwide adoption of milking machines (Figure 1) with local differences in the importance of dairy farming across municipalities in the pre-milking machines era (Figure 3).³⁰

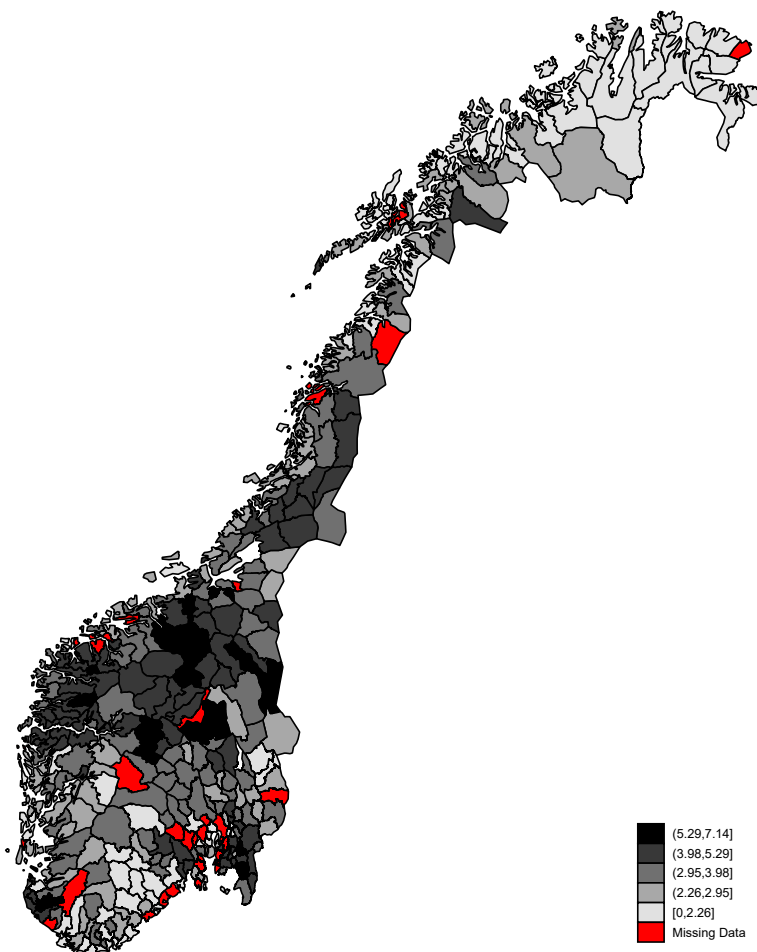
Formally, we define our local milking machine exposure measure, $E_{j,d(c)}$, as:

$$E_{j,d(c)} = \frac{\bar{M}_{d(c)}}{\bar{F}_{d(c)}} \times \frac{C_{j,1930}}{F_{j,1930}}, \quad (7)$$

which consists of two components: The first component is the total number of milking machines in Norway, $\bar{M}_{d(c)}$, normalized by the total number of farms in Norway, $\bar{F}_{d(c)}$, at the census year $d(c)$ when birth cohort c was aged 16-25; the ages at which women were traditionally hired as milkmaids. This component can be interpreted as the national “shift” in the adoption of milking machines. It captures the cohort variation generated by the diffusion of milking machines in Norway, which took off after 1951 when Norway lifted all import restrictions on agricultural equipment (Espeli, 1990). The second component captures the intensity of (*formal and informal*) female labor engaged in milking cows in municipality j in 1930, before the first milking machines were adopted in Norway. Specifically, $C_{j,1930}$ denotes the number of milk cows in municipality j in 1930 and $F_{j,1930}$ the number of farms in

³⁰Conceptually, our approach of capturing the local impact of a technology shock is similar to studies evaluating the effects of trade liberalization or immigration restrictions on local economies (e.g., Kovak, 2013; Dix-Carneiro and Kovak, 2017; Abramitzky et al., 2023).

Figure 3: Milk cows per farm in 1930



NOTE.— This figure shows the distribution of the number of milk cows per farm across Norwegian municipalities in 1930. Source: Population Census of 1930 (own calculations).

municipality j in 1930. Because milking machines automated cow milking, a task previously performed by milkmaids, the number of milk cows per farm captures the treatment intensity at the municipality level.³¹ Importantly, this component is a proxy for the local “share” of women employed as milkmaids, including women who were hired without a formal contract (e.g., family members). For robustness, we show that results are very similar when using the share of female labor *formally* hired as milkmaids in 1930 instead of the number of milk cows per farm in 1930.³²

³¹Although we use the nationwide roll-out of milking machines, the municipality-level differences in milk cows per farm in 1930 generate local variation in exposure to this technology shock.

³²Our preferred specification considers the number of milk cows per farm and not the share of milkmaids

The first stage uses the exposure measure defined in equation (7) to capture exogenous variation in the number of milking machines per farm adopted at each municipality over time. The first-stage equation is outlined as follows:

$$M_{j,d(c)} = \alpha_j + \beta_c + \tau E_{j,d(c)} + \sum_t \mathbf{1}[c = t] \times \mathbf{X}'_j \theta_t + e_{j,c}, \quad (8)$$

where $M_{j,c}$ is the number of milking machines per farm in municipality j at the census year $d(c)$; and α_j and β_c are fixed effects for municipalities and birth cohorts.³³ The set of controls, X'_j , includes two measures of agricultural intensity in 1930 (the share of improved farmland and the number of farms per capita) and a measure of the farm size distribution in 1930 (the ratio of large to small farms), both interacted by birth cohort fixed effects. We select these flexible trends based on a Lasso procedure, which we present in Appendix Table 2.³⁴

The corresponding second-stage equation is:

$$Y_{i,j,c} = \alpha_j + \beta_c + \gamma \hat{M}_{j,d(c)} + \sum_t \mathbf{1}[c = t] \times \mathbf{X}'_j \theta_t + \epsilon_{i,j,c}, \quad (9)$$

where Y_{ijc} denotes the outcome of interest for woman i born in year c in municipality j ; α_j and β_c are fixed effects for municipalities and birth cohorts; and $\hat{M}_{j,d(c)}$ is the instrumented number of milking machines per farm in municipality j at the time when birth cohort c was aged 16-25. Standard errors are clustered at the municipality level to account for correlations within a municipality in a given year and over time. We also show that our results are robust when accounting for different degrees of spatial correlation using Conley standard errors (Conley, 1999) with different distance cutoffs. Throughout our analysis, we keep municipality borders constant based on the “kommuner” classification of 1980. We also flexibly account for county-specific trends by adding county-by-birth cohort fixed effects to estimating equations (8) and (9).

because, in addition to capturing informal labor, this measure is picked by our Lasso procedure as a more important determinant of milking machine adoption.

³³It is not necessary to add the share of milkmaids in municipality j in 1930 to equation (8), as the municipality fixed effects capture the direct effect.

³⁴Our estimation strategy shares similar features with the classic shift-share instrumental variables approach (Bartik, 1991). Our exposure measure uses cows per farm as “shares” and the nationwide increase in milking machines per farm as “shifters” to instrument the uptake of milking machines per farm at the municipality level. Moreover, the use of a Lasso method to select relevant control variables was inspired by suggestions for shift-share designs in Goldsmith-Pinkham et al. (2020). However, in contrast to the typical shift-share approach, we have a clear zero date that we use to validate our research design (see Section 5.1). See Adao et al. (2019) for further discussions of shift-share designs.

5.1 Threats to identification

The two-stage least squares (TSLS) estimate of γ measures the casual impact of the introduction of milking machines under the assumption that our instrument is relevant and satisfies the exclusion restriction. We follow several strategies to substantiate the validity of our instrument. First, our local milking machine exposure measure, $E_{j,d(c)}$, is exogenous to changes in women’s outcomes during periods of rapid technological change because it combines a nationwide “shift” with a local treatment intensity measured before the first milking machines made their way into Norway. Second, we use a Lasso procedure to select the relevant control variables that might be correlated with both the endogenous regressor and the outcome variables (see Appendix Table 2). Specifically, we use Lasso to assess whether our measure of technology adoption, $M_{j,d(c)}$, is correlated with any other initial (year 1930) municipality characteristics that might generate differential trends in outcomes across municipalities. Besides the number of milk cows per farm, the only other controls selected by the Lasso procedure are farms per capita, the share of improved farmland, and the ratio of large to small farms.³⁵ Moreover, we also show that the number of milk cows per farm is not positively correlated with municipality wealth and wages in 1930 (see Appendix Figure 10).³⁶ The selected controls are interacted with birth cohort fixed effects (see equations (8) and (9)). These flexible trends’ specifications capture the possibility that cohorts in rural municipalities before the arrival of milking machines were on a different trajectory of structural transformation. Third, to further account for time-varying unobservables that may violate the exclusion restriction, we flexibly account for county-specific cohort trends by including county-by-birth cohort fixed effects. Fourth, we contrast the results with young rural men (Section 6.4) and conduct a series of robustness checks to further address potential concerns over omitted variable bias.

Moreover, although the exclusion restriction is impossible to test directly, we can show that the outcomes of women in rural municipalities more (or less) affected by the adoption of milking machines evolved similarly in the pre-milking machine era. This is accomplished by using the following event-study specification:

$$Y_{i,j,c} = \alpha_j + \beta_c + \sum_{t=1930}^{1970} \gamma_t \mathbf{1}[d(c) = t] \times \frac{C_{j,1930}}{F_{j,1930}} + \epsilon_{i,j,c} , \quad (10)$$

³⁵All other controls included in Appendix Table 2—the share of milkmaids, the share of female employment in agriculture, the female labor force participation rate, the female net-migration rate, population density, an indicator for early adoption of tractors, the share of female population between, respectively, 15 and 19, 20 and 39, 40 and 59, 60 and over, the capital labor ratio, the municipality area, the ratio of large to small farms, male and female income, and male and female wealth—are not selected by the Lasso procedure.

³⁶In addition, Appendix Figure 11 shows that the farm size distribution did not change overtime, and hence, was probably unresponsive to the adoption of milking machines.

where we regress various outcomes of interest, Y_{ijc} , on the number of milk cows per farm in 1930, $\frac{C_{j,1930}}{F_{j,1930}}$ (i.e., the treatment intensity), interacted by a set of indicator variables, $\mathbf{1}[d(c) = t]$, for birth cohorts, c , who entered the labor market at different decades, $d(c)$. We also include municipality (α_j) and cohort (β_c) fixed effects. We refer to the 1930s as the pre-treatment cohorts, use the 1940s as the reference cohorts, and the 1950s, 1960s, and 1970s as the post-treatment cohorts. The set of γ_t coefficients captures how the relationship between women’s long-term outcomes and the treatment intensity differs across cohorts.

Figure 4 presents estimates of γ_t based on equation (10), along with the national roll-out of milking machines in Norway over time (gray line). Panel (a) considers milking machines per farm as the dependent variable. Hence, it can be interpreted as the first stage of our analysis, showing how the treatment intensity relates to the adoption of milking machines. The estimated γ_t -coefficients reveal that rural municipalities with more milk cows in the pre-milking machines era had a higher uptake of milking machines per farm in the 1950s, 1960s, and 1970s.³⁷ This finding supports the relevance of our instrument and is in line with the historical narrative and with the model’s third prediction.

Panels (b) to (g) consider our main long-term outcomes of interest. These event-study specifications allow us to evaluate whether the outcomes of the pre-treatment cohorts with different treatment intensities follow parallel trends before the uptake of milking machines. All figures show quantitatively negligible differences in the outcomes for the pre-treatment cohorts. The number of milk cows in the pre-milking machines era predicts a similar share of women working in agriculture as adults and migrating from their birthplace into cities in the 1930s and 1940s. Similarly, before the mass adoption of milking machines, there are no differential effects on women’s income rank at age 45, the share taking on high skill jobs outside agriculture, or on educational attainment.

We provide additional evidence to support the parallel trends assumption. We conduct a placebo experiment in which we ask what would have happened in dairy-intensive municipalities if the substantial increase in milking machines between 1950 and 1960 had occurred between 1900 and 1910.³⁸ Reassuringly, there are no signs of pre-trends in the relevant outcomes, which are summarized in Appendix Table 3. The point estimates are all very small, close to zero, and statistically insignificant suggesting that agricultural employment, moving costs, and female labor force participation were not already on a decline in dairy-

³⁷Since there were no milking machines in Norway in 1930, the estimated coefficient for the pre-treatment cohort is zero.

³⁸The data for our placebo experiment is the historical complete count census records of Norway in 1900 and 1910 provided by the Norwegian Historical Data Centre (University of Tromsø) and the [Minnesota Population Center](#) (2020). The data contain detailed information about individuals’ occupations, their municipality of birth, and residence.

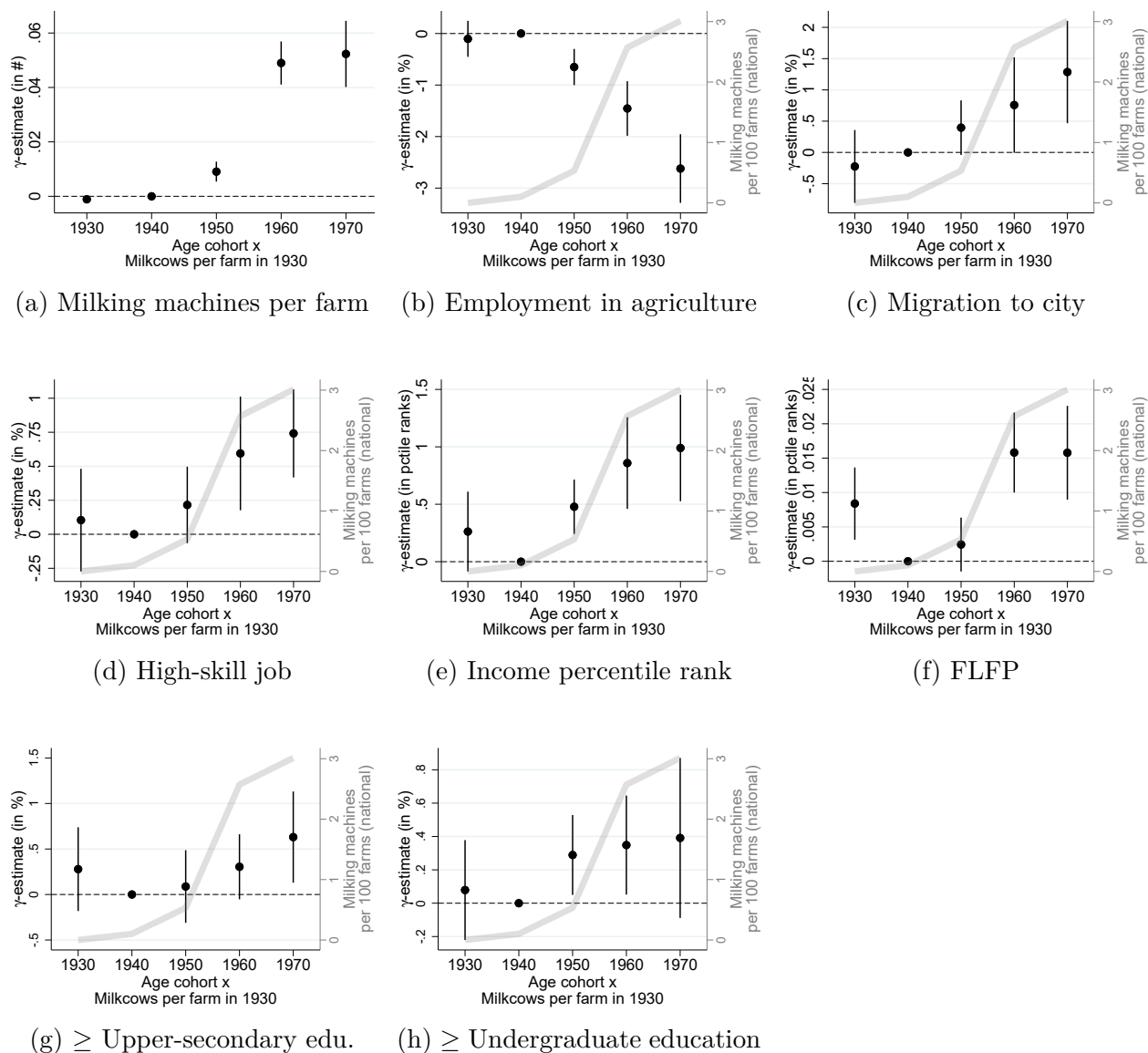


Figure 4: Cohort-specific relationship between long-term outcomes and the pre-milking machines dairy intensity.

NOTE.— This figure plots estimates and confidence intervals of γ from equation (10) on women's outcomes as adults (after age 25). Dots show the estimated cohort-specific effect of the municipality-level milkcows per farm in 1930 (left y-axis). Lines indicate the number of milking machines per 100 farms in Norway (right axis). The x-axis is the decade at which cohorts were aged 16–25, the age when women were commonly hired as milkmaids. The sample is women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in 1930–1970. Panel (d) restricts the sample to women employed in non-agricultural occupations as adults. Income and FLEP is measured at age 45 for cohorts aged 16–25 in 1950, 1960, and 1970, and at age 52 and 62 for cohorts aged 16–25 in 1940 and 1930, respectively.

intensive municipalities at the beginning of the 20th century.³⁹ Overall, this suggests that our main results do not capture substantial pre-trends in dairy-intensive municipalities before the widespread adoption of milking machines after WWII. Coupled with the Lasso procedure and the county-by-birth cohort fixed effects, our estimation strategy should effectively identify the local labor push effect as a result of the diffusion of milking machines.

Finally, Panels (b)-(h) of Figure 4 reveal a completely different pattern for the post-treatment cohorts. In dairy-intensive municipalities, women were more likely to work outside the agriculture sector and migrated to cities in the 1950s, 1960s, and 1970s. They also worked in higher-skilled jobs, earned higher incomes, were more likely to participate in the labor force, and invested more in their education. Because milking machines automated hand milking after the 1950s, these results provide some preliminary evidence that milking machines triggered a process of structural change that, in the long-term, benefited women exposed to this technology shock. In the next section, we show that these “reduced form” effects indeed reflect the local adoption of milking machines.

6 Empirical results

We begin our empirical analysis in Section 6.1 by examining the *short-term* effects of the introduction of milking machines on young rural women. Section 6.2 shows the *long-term* effects for women who lived in *rural* municipalities at the age of 16–25 in 1930–1970. This sample contains the group of *compliers* that we can identify using our estimation strategy. According to the predictions of our model, these women are expected to be displaced by milking machines, migrate, invest in their education, and take up jobs outside agricultural sector. Section 6.3 discusses the underlying mechanisms behind these results. We conclude the empirical analysis by contrasting the results with young rural men in Section 6.4.

6.1 Contemporaneous income effects

It has been documented elsewhere that, in the short run, labor automation brings economic hardship to displaced workers (e.g., [Acemoglu and Restrepo, 2020](#)). The historical narrative suggests that the adoption of milking machines in Norway had similar short-term negative effects on young rural women who, as a result, lost their jobs as milkmaids. The displacement costs were substantial. For example, during the 1950s, the foregone income of not working as milkmaids was around NOK 3,100 per year for women. This would cover around one-quarter

³⁹Since we always include fixed effects for municipalities and county-by-birth cohort, our empirical analysis already accounts for time-invariant *municipality-specific* and *time varying county-specific* moving costs.

of the expenditure of a working-class household with two children in a Norwegian city.⁴⁰

To measure the short-term effects of the adoption of milking machines, we use yearly income data from Norway’s tax registry. Since the earliest tax registry data is from 1967, the short-term analysis is restricted by construction to the group of compliers in 1970. Specifically, we focus on women who turned 16 in 1970, which allows us to evaluate the short-term income responses from the start of their working life. Importantly, the Census of Agriculture 1970 reports a large-scale uptake of milking machines.⁴¹ Hence, the evolution of the incomes of these young women in the years following 1970 provides a good illustration of the short-run effects of the adoption of this new technology. If the adoption of milking machines triggered negative short-term effects, we would expect young women’s incomes to evolve differently in municipalities with a high and low adoption of milking machines. We estimate the differential evolution of young women’s incomes as follows:

$$Y_{i,j,t} = \alpha_j + \delta_t + \sum_{t=1971}^{2000} \gamma_t \mathbf{1}[t - 1970] \times M_j^{high} + u_{i,j,t}, \quad (11)$$

where Y_{ijt} is the income in year $t \in \{1970, \dots, 1995\}$ of a woman i who turned 16 in 1970 and who was born in rural municipality j measured in logarithmic units as $\log(1+\text{income})$. We also include fixed effects for municipality (α_j) and year (δ_t) in equation (11). The variable of interest is the interaction between M_j^{high} , an indicator variable equal to one if the number of milking machines per farm in municipality j in 1970 was above the 1970 median, and $\mathbf{1}[t - 1970]$, a set of dummy variables for the number of years since 1970—when the relevant uptake of milking machines took place for the women in this sample. The γ_t coefficients capture the differential evolution of incomes after 1970 for young women in municipalities with above- vs. below-median adoption of milking machines.

Figure 5 displays the estimated γ_t coefficients from equation (11) using a panel of 8,935 women over 25 years (1970-1995). In the short run, the adoption of milking machines entails substantial negative effects on young women’s incomes: In the first four years, incomes declined by 18-35% for women from municipalities with above-median adoption relative to women from municipalities with below-median adoption.⁴² This is consistent with an adverse income effect of being displaced from milkmaid jobs.⁴³

⁴⁰For more details, see Statistical Yearbook of Norway 1955, Tables 237 and 250.

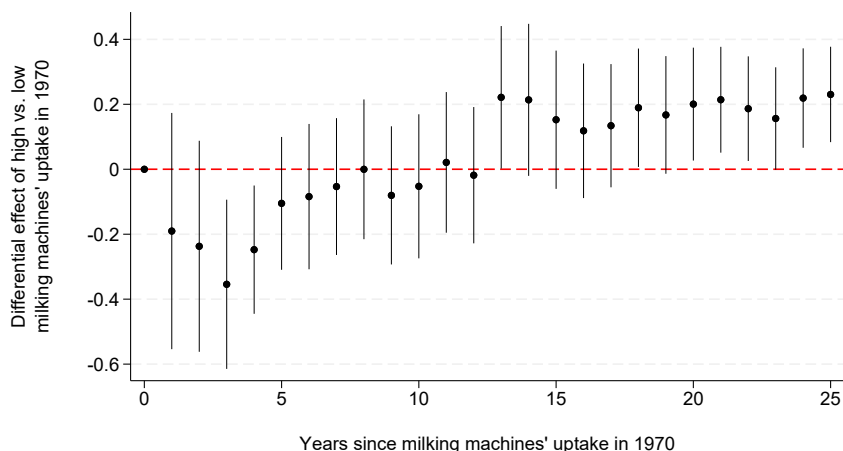
⁴¹The number of milking machines increased from 40,000 in 1960 to 50,000 in 1970 (Figure 1).

⁴²The omitted category is 1970, so Figure 5 shows the differential evolution of incomes in high vs. low adoption municipalities relative to the 1970 differences. The difference is statistically significant at the 1% and 5% levels in the third and fourth year, respectively.

⁴³Appendix Figure 7 shows that the probability of reporting a zero income (i.e., of being unemployed or at school) after three years increased by 2 percentage points for women from municipalities with above- vs. below-median adoption. In addition, the figure shows that these negative short-term effects are robust

In Appendix Table 4, we also use the 1960 Census to show similar negative effects for earlier cohorts. We document a negative association between the uptake of milking machines in 1960 and the share of household members who were employed in 1960.⁴⁴ That said, there is also a positive association between the adoption of milking machines and contemporaneous student activity. This suggests that young women stayed longer at school as a result of reduced earning opportunities when milking machines replaced milkmaid work.

Figure 5: Year-by-year evolution of young women’s incomes after 1970, by milking machines’ uptake in 1970



NOTE.— This figure plots estimates of γ_t from Equation (11) and 95% confidence intervals. The sample is a panel of 8,935 women and their incomes over 25 years (1970–1995). It is restricted to women born in rural municipalities who turned 16 in 1970. Standard errors are clustered by municipality.

Finally, Figure 5 shows that the negative short-term effects on young women’s incomes are short-lived. Five years after the 1970s roll-out, we observe no significant income differences between women who, in 1970, resided in municipalities with different adoption rates. After twelve years, the negative income effects are reversed, and women originally from municipalities with a high uptake of milking machines consistently receive around 20% higher incomes. This provides some initial evidence that the diffusion of milking machines, despite its initial negative income effects, increased the long-term earning opportunities for affected young women. Below, we study these long-term effects in detail and show that they are

to using the inverse hyperbolic transformation for women’s incomes, to including individual fixed effects in equation (11), and to comparing the evolution of incomes after 1970 for women from municipalities with above- vs. below-median milk cows per farm in 1930.

⁴⁴We consider the share of employed household members to measure negative short-term effects at the household level. This complements the estimates of equation (11), which capture negative short-term effects at the individual level for affected women (individual income data have only been available since 1967).

associated with a structural change process that transformed women’s work.

6.2 Main results: long-term effects

We begin our long-term analysis by assessing whether the diffusion of milking machines pushed young female workers out of agriculture and triggered rural-to-urban migration, two crucial elements of structural change. We also evaluate whether affected women were more likely to work and had higher incomes as middle-aged adults.

Panel A of Table 1 presents our main results. The estimating equation is (9) and the estimation method is TSLS. The number of milking machines per farm is instrumented by the local exposure to milking machines as outlined in equations (7) and (8). Both measures are standardized. Hence, the parameter of interest, $\hat{\gamma}^{TSLS}$, can be interpreted as the effect of one standard deviation increase in milking machines per farm. For each outcome, we report two specifications. The first includes only fixed effects for municipalities and birth cohorts. The second, our baseline, adds the controls selected by the Lasso procedure and county-by-birth cohorts fixed effects.⁴⁵ In addition, we also control for flexible trends by the 1930s municipality-level capital intensity in agricultural production (proxied by an indicator for the early adoption of tractors) and female incomes. For comparison, Table 1 also reports the corresponding reduced form effects (Panel B) and the OLS estimates (Panel C).

In columns (1)-(2), we present compelling evidence that women who were more affected by the diffusion of milking machines at the age of 16-25—the ages at which they would have traditionally been hired as milkmaids—were less likely to be engaged in agriculture as middle-aged adults.⁴⁶ The TSLS estimate is negative and statistically significant at the 1-percent level. Consistent with the evidence presented in Panel (a) of Figure 4, the corresponding first-stage coefficient, is positive and statistically significant at the 1-percent level (see Appendix Table 5). There is also no sign of a weak instrument (the Kleibergen-Paap F-Statistic of instrument strength is far above the rule of thumb cutoff of 10). Overall, this suggests that our TSLS estimate effectively captures a local displacement effect as a result of the adoption of milking machines. The displacement effect is also quantitatively sizable. The point estimate in column (2) implies that a one-standard-deviation increase in milking machines per farm decreases a woman’s likelihood of working in agriculture after the adoption of milking machines by around 4.4 percentage points, or 48 percent of the sample mean, which is an economically sizable effect.

⁴⁵We do not report results with these controls in levels (i.e., not interacted with flexible trends) as the municipality fixed effects already absorb any cross-sectional differences across municipalities.

⁴⁶About 30 percent of the women in our sample do not report any occupation in the following census. Results are robust to excluding them from the analysis (see Appendix Table 6).

Table 1: The diffusion of milking machines and women's long-term outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment in agriculture			Migration to city	Income pctlile rank			FLFP
Panel A. IV								
Milking machines per farm	-0.041*** (0.005)	-0.044*** (0.005)	0.021*** (0.007)	0.030*** (0.006)	1.529*** (0.337)	1.887*** (0.303)	0.040*** (0.009)	0.038*** (0.007)
Panel B. Reduced form								
Milkcows per farm 1930 × National m.m. per farm	-0.035*** (0.005)	-0.039*** (0.004)	0.018*** (0.006)	0.027*** (0.006)	1.281*** (0.319)	1.693*** (0.263)	0.031*** (0.007)	0.032*** (0.005)
Panel C. OLS								
Milking machines per farm	-0.018*** (0.003)	-0.016*** (0.002)	0.010*** (0.003)	0.008*** (0.003)	0.846*** (0.149)	0.636*** (0.136)	0.021*** (0.003)	0.011*** (0.003)
Observations	379,366	379,366	379,366	379,366	342,952	342,952	271,590	271,590
F-stat first stage	97.553	105.402	97.553	105.402	95.212	101.254	78.611	81.846
Mean dep. variable	0.091	0.091	0.257	0.257	34.125	34.125	0.781	0.781
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes
County-by-by-year FE	no	yes	no	yes	no	yes	no	yes
Flexible trends	no	yes	no	yes	no	yes	no	yes

NOTE.— This table shows IV, reduced-form, and OLS estimates based on equations (8) and (9). Income is measured at age 45 for cohorts aged 16–25 in 1950, 1960, and 1970 and at age 52 and 62 for the cohorts aged 16–25 in 1940 and 1930, respectively. Female labor force participation (FLFP) is an indicator variable equal to one if the woman reported a positive income at age 45. The sample includes women born in rural municipalities with at least one farm in 1930, who were aged 16–25 in the census years 1930–1970. In cols. 7–8, the sample is restricted to cohorts for which we know their income at age 45. Independent variables are normalized to have a mean of zero and an SD of one. Flexible trends are selected with a LASSO procedure (see Appendix Table 2) and include two municipality-level measures of agricultural intensity in 1930 (i.e., the share of improved farmland and farms p.c.) × birth cohort FE; the municipality-level farm-size distribution in 1930 (i.e., the ratio of large—above 200 decares—to small farms—below 5 decares) × birth cohort FE; a municipality-level measure of capital intensity in 1930 (i.e., an indicator for early tractor adoption) × birth cohort FE; and the municipality-level female income in 1930 × birth cohort FE. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

In columns (3)-(4), we show that municipalities with a higher uptake of milking machines also experienced a substantial out-migration of young female workers. The TSLS estimate is positive and statistically significant at the 1-percent level. A one-standard-deviation increase in milking machines per farm increased the likelihood of a potentially displaced woman to migrate out of their county of birth and into a city by 3 percentage points, or about 12 percent of the sample mean. Altogether, our results suggest that the diffusion of milking machines reduced female employment in agriculture and increased urbanization by pushing young affected women out of their rural homes and into cities.

Next, columns (5)-(6) examine the effect of the adoption of milking machines on women’s income rank as middle-aged adults.⁴⁷ In line with the evidence presented in Section 6.1, we find that in the longer term, women from more dairy-intensive municipalities ended up at a higher echelon of the income distribution. The TSLS estimate is between 1.5-1.8 and statistically significant at the 1-percent level. In other words, we find that for a one-standard-deviation increase in milking machines per farm women climbed up the income distribution by almost two percentiles. Importantly, women more exposed to milking machines at the age of 16-25 improved their income rank as middle-aged adults, not only because they were more likely to participate in the labor force (extensive margin), as columns (7)-(8) show, but also because they had a higher income (measured in logs) at the age of 40-45 (Appendix Table 7). These results are most likely driven by women who left their birthplace and moved to cities (Appendix Table 8).⁴⁸

One general observation is that the TSLS and reduced form estimates reported in Table 1 are quantitatively similar when adding the controls selected by the Lasso procedure and county-by-birth cohort fixed effects (if anything, there are somewhat larger in absolute terms). As expected, the OLS estimates (Panel C) are substantially smaller (in absolute terms) than the TSLS estimates. The IV results are *local average treatment effects* (LATE) as they measure the effect of the compliers, who have higher economic returns to moving to cities than the average rural population—the average treatment effect (ATE) (Imbens and Angrist, 1994). From our model, we expect heterogeneity in returns from leaving the farming sector and moving, and the positive selection for the compliers is following the predicted from our Roy model (Panel B of Figure 2). Moreover, the reduced form estimates or intention to treat estimates (Panel B)—the relation to the IV is that the IV is the reduced form

⁴⁷To do so, we construct income percentile ranks based on the income at age 45 of all individuals (i.e., women and men) born in the same year. The results remain unchanged if we construct income percentile ranks based on women only or when excluding the earlier cohorts from the sample since their adult income is measured at ages 52 and 62 respectively (see Section 4.1 for details).

⁴⁸Because of data limitations (income for the tax registry is only available from 1967), the results in Appendix Tables 7 and 8 are only based on women aged 16-25 in 1950, 1960, and 1970.

weighted by the compliers or the first stage—are consistent with the event study estimates presented in Figure 4 suggesting that young rural women in dairying municipalities were indeed affected by the roll-out of milking machines after WWII.

These results are also robust to modifications of our exposure measure to milking machines (Appendix Table 10). For this exercise, we replaced the number of milk cows per farm by the share of women employed as milkmaids in 1930 to proxy dairy-farming suitability prior to the diffusion of milking machines.⁴⁹ They are also not confounded by local access to hydroelectric power—the main mode of electricity production in Norway during our study period (Appendix Table 12).⁵⁰ Moreover, standard errors are similar when we account for spatial dependence in the error term using Conley (1999) standard errors with different distance cutoffs (Appendix Figure 9).⁵¹

Overall, our results indicate that the diffusion of milking machines transformed women’s work after WWII by breaking up allocative inefficiencies across sectors. It increased the labor force participation and incomes of displaced young women as middle-aged adults.⁵²

6.3 Long-term mechanisms: educational investments

We now turn our attention to the underlying mechanisms behind these results. We examine educational investments as a possible channel through which the automation of hand milking, despite its negative income effects in the short term, resulted in income gains in the long term for affected young women.

These results are presented in columns (1)-(3) of Table 2. Estimates are obtained from estimating equation (9) including our baseline controls. The TSLS estimates confirm our hypothesis that displaced young women invested more in human capital. Specifically, column (1) shows that affected women experienced substantial occupational upgrading into occupations requiring high skills. This sample only consists of women who *did not work* in the agricultural sector as middle-aged adults. The TSLS estimate is statistically significant at the 1-percent level. A one-standard-deviation increase in milking machines per farm resulted in a 1.1 percentage point higher likelihood of working as a middle-aged adult in a high-skill occupation, or about 9 percent of the sample mean. Columns (2)-(3) show that

⁴⁹Although the share of milkmaids is a less exogenous proxy of dairy-farming suitability than our baseline measure and does not capture unpaid labor, their use can also be motivated by our model’s third prediction.

⁵⁰Most hydroelectric power plants were built in the period 1900–1920. By 1920, plants were distributed all over Norway; see Leknes and Modalsli (2020, Figures 1 and 2).

⁵¹Furthermore, Appendix Table 11 compares estimates across municipalities that had no milking machines by 1950 vs. had adopted them by 1950. Estimates across these stratified samples are very similar, suggesting that the treatment effect did not vary substantially over time.

⁵²Our findings also imply that a general increase in the rural-urban wage gap after WWII alone cannot explain these patterns.

women exposed to milking machines at the age of 16-25 were more likely to have at least (i) upper secondary education and (ii) an undergraduate degree. Both estimates are statistically significant at the 1-percent level. For example, a one-standard-deviation increase in milking machines per farm increased the likelihood of women completing at least upper secondary education by 1.5 percentage points, or 9 percent of the sample mean—a quantitatively sizable effect. This is consistent with the historical narrative that, after WWII, better-educated young rural women took up white-collar jobs in the cities. The results also suggest that human capital investments played a major role in the occupational upgrading experienced by Norwegian women after the automation of hand milking.

Next, we delve deeper into this mechanism by examining the relationship between local (above primary) schooling infrastructure and rural out-migration triggered by the diffusion of milking machines. Because the reinstatement of displaced women into high-skill jobs in urban areas required further investment in formal education, we expect migration decisions to depend on the local schooling infrastructure. First, we expect displaced young women to migrate to towns with higher-education institutions. Second, we expect less out-migration from affected rural areas with high schools. We examine these hypotheses using data from Machin et al. (2012) on Norway’s local schooling infrastructure.⁵³ The data lists whether a municipality had at least one high school (gymnasium) or higher-education institution (*Høyskole* or university) in 1963.

To test the first hypothesis, we present TSLS estimates of regressing the probability of migrating into a town with a higher-education institution on milking machines per farm. The estimating equation is (9) and includes the same set of controls as in Section 6.2. Column (4) of Table 2 shows that a one-standard-deviation increase in the number of milking machines per farm increased the likelihood of a potentially displaced woman moving to a town with a higher-education institution by 3.8 percentage points, or about 12 percent of the sample mean.⁵⁴ The point estimate is statistically significant at the 1-percent level.

To test the second hypothesis, we add an interaction term between the number of milking machines per farm, $M_{j,d(c)}$, and an indicator variable equal to one if a woman’s municipality of birth had a high-school in 1963, HS_j , to estimating equation (9). This interaction term is instrumented with our exposure measure in equation (7), $E_{j,d(c)}$, interacted with HS_j .⁵⁵ Columns (5)-(8) of Table 2 presents the second-stage estimates. The estimates show that the diffusion of milking machines pushed women out of rural areas into towns with higher-education institutions, cities, and outside their county of birth. These effects are stronger

⁵³The data is for 435 municipalities in 1960, which correspond to 421 municipalities using 1980 borders.

⁵⁴This effect is not only driven by the five towns had a university (Oslo, Bergen, Trondheim, Tromsø, and Ås). For example, in 1963 there were 28 different municipalities with a *Høyskole*.

⁵⁵The municipality fixed effects absorb the direct effect of a municipality having a high-school in 1963.

Table 2: The diffusion of milking machines, educational investments, and migration decisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
		High-skill occupation	Upper-sec. education	≥ Undergrad. education	Town with higher-edu. institution	Town with higher-edu. institution	Any city	Outside county	Inside county
Milking machines per farm	0.011*** (0.003)	0.015*** (0.005)	0.015*** (0.004)	0.038*** (0.008)	0.041*** (0.008)	0.035*** (0.008)	0.041*** (0.008)	-0.005 (0.007)	
Milking machines per farm × mun. has high school in 1963	-0.022*** (0.006)	-0.024*** (0.006)	-0.017*** (0.006)	0.006 (0.005)	
Observations	344,658	376,594	376,594	351,691	351,691	367,394	367,394	367,394	
F-stat first stage (1)	104.343	105.487	105.487	99.334	104.251	105.767	105.767	105.767	
F-stat first stage (2)	287.966	291.610	291.610	291.610	
Mean dep. variable	0.125	0.168	0.108	0.329	0.329	0.377	0.403	0.287	
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes	
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes	
County-by-year FE	yes	yes	yes	yes	yes	yes	yes	yes	
Flexible trends	yes	yes	yes	yes	yes	yes	yes	yes	

NOTE.— This table shows IV estimates based on Equations (8) and (9). Interactions in cols. 5-8 capture the differential effect of the diffusion of milking machines in municipalities with at least one high-school (gymnasium) in 1963, and are instrumented with our exposure measure (Equation (7)) × a dummy for municipalities with at least one high-school in 1963. The sample includes women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in 1930–1970. Col. 1 restricts the sample to women employed outside of agriculture after age 25; Cols. 4–8. exclude municipalities with no information on the school structure. Independent variables are normalized to have a mean of zero and an SD of one. Flexible trends include municipality-level measures of: agricultural intensity in 1930 (i.e., the share of improved farmland and farms p.c.) × birth cohort FE; ratio of large-to-small farms in 1930 × birth cohort FE; capital intensity in 1930 (i.e., early-tractor adoption) × birth cohort FE; and female income in 1930 × birth cohort FE. Sanderson-Windmeijer F-stats are reported for each instrument's first stage in cols. 5-8. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

in municipalities lacking schooling infrastructure (reference group) than in municipalities that have a high-school. We find no effects on migration decisions that are not part of a structural transformation process, i.e., short-distance migration (inside the county).⁵⁶ These results reveal that women’s decision to move was partly driven by the desire to acquire more education to access high-skill employment. Importantly, they also suggest that the long-term effects of mechanization are not institution-independent, as the lack of local schooling infrastructure seems to exacerbate the out-migration of displaced workers.

Importantly, our results are not simply a byproduct of education reforms. The Folk School Law (1936) and the Primary School Reform (1959) were the two major social-democratic reforms of Norway’s schooling system during our sample period.⁵⁷ The Folk School Law aimed to equalize access to primary schooling across rural and urban areas (Rust, 1989) and was fully implemented in every municipality by 1941.⁵⁸ Hence, this reform occurred before the widespread adoption of milking machines after WWII. The Primary School Reform, on the other hand, increased compulsory education from 7 to 9 years and was implemented by different municipalities at different points in time from 1960 to 1972 (Black et al., 2005).⁵⁹ Although the roll-out of this reform was concomitant with the large scale adoption of milking machines, the two processes were orthogonal. Appendix Figure 8 shows that municipalities with a large-scale adoption of milking machines by 1960 did not implement the Primary School Reform earlier than municipalities with few or no milking machines (Panel A). A local polynomial regression of the first cohort affected by the reform in each municipality on our treatment-intensity measure confirms that the roll-out of the reform was statistically independent from the diffusion of milking machines (Panel B).⁶⁰ Furthermore, Appendix Table 9 shows that our main results are robust to controlling for the roll-out of the Primary Education Reform.⁶¹

⁵⁶The Sanderson-Windmeijer (SW) first-stage F-statistics in columns (5)-(8) indicate that the instrumental variable estimates are not substantially biased (Sanderson and Windmeijer, 2016).

⁵⁷Municipalities were given five and 12 years, respectively, to implement the two reforms.

⁵⁸By 1941, every rural municipality had fully implemented the increase in the number of weeks of instruction (from 15 to 16 and 18 weeks in the first three and last four grades), the reduction of class sizes (from 35 to 30), and the curricula changes embedded in the Folk School Law reform.

⁵⁹In addition, access to schools improved and the curriculum was reformed.

⁶⁰The figure uses data from Black et al. (2005). Panel A plots our treatment-intensity measure in 1960 (right) and the first cohort affected by the reform (left) in each municipality, sorted by the reform implementation date. Panel B displays a Kernel-weighted local polynomial showing that, on average, the 1953-54 cohort was the first affected by the reform independently of a municipality’s milking-machine adoption rate.

⁶¹To do so, we include a reform indicator in estimating equation (9) equal to one if municipality m had fully implemented the Primary School Reform when cohort c attended school.

6.4 Gender effects

Finally, we show that the introduction of milking machines had opposite effects on men and women, narrowing the long-term gender gap in income and labor force participation.

To do so, we extend our analysis along two dimensions: First, we extend our sample with the corresponding cohorts of men born in rural municipalities aged 16-25 in the census years 1930-1970. To estimate the gender-specific effects of the adoption of milking machines, we modify our baseline estimating equation (9) by interacting the number of milking machines per farm, $M_{j,d(c)}$, with an indicator for men. This interaction term captures the differential effect of the adoption of milking machines on men and women. As before, we instrument $M_{j,d(c)}$ with our milking machine exposure measure of exposure ($E_{j,d(c)}$), and $M_{j,d(c)} \times men_i$ with our measure of exposure interacted with an indicator for men. Our modified specification includes a gender dummy, the baseline controls and their interactions by gender.

Table 3: The diffusion of milking machines, results for both sexes

	(1) Employment in agriculture	(2) Migration to city	(3) Income ptcle rank	(4) Labor force participation
Milking machines per farm (γ_1)	-0.044*** (0.005)	0.031*** (0.006)	1.892*** (0.305)	0.038*** (0.007)
Milking machines per farm \times Man (γ_2)	0.015** (0.006)	-0.010* (0.005)	-1.861*** (0.387)	-0.032*** (0.006)
Observations	726,537	726,537	687,621	549,058
Effect for men ($\gamma_1 + \gamma_2$)	-0.029	0.021	0.031	0.006
p-value	0.001	0.001	0.934	0.011
Sanderson-Windmeijer F-stat (1)	105.84	105.84	105.23	.
Sanderson-Windmeijer F-stat (2)	122.29	122.29	103.79	84.75
Man FE	yes	yes	yes	yes
Municipality \times Man FE	yes	yes	yes	yes
Birth year \times Man FE	yes	yes	yes	yes
County \times byear \times Man FE	yes	yes	yes	yes
Flexible trends \times Man FE	yes	yes	yes	yes

NOTE.— This table shows IV estimates for the effect of the diffusion of milking machines on women’s and men’s long-term outcomes. The number of milking machines per farm is normalized to have a mean of zero and an SD of one. Interactions capture the gender differential effect of the diffusion of milking machines. IV estimates are based on Equations (8) and (9), where the interactions are instrumented with our measure of exposure (Equation (7)) \times an indicator variable for men. The sample includes men and women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1930–1970. Dependent variables are defined as in Table 1. Flexible trends include municipality-level measures of: agricultural intensity in 1930 (i.e., the share of improved farmland and farms p.c.) \times birth cohort FE; ratio of large-to-small farms in 1930 \times birth cohort FE; capital intensity in 1930 (i.e., early-tractor adoption) \times birth cohort FE; and female income in 1930 \times birth cohort FE. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

Table 3 presents the results. Two important patterns emerge. First, our previous esti-

mates for the long-term effect of the diffusion of milking machines on young rural women are robust to include men in the analysis. Specifically, the estimates on the number of milking machines per farm in this extended specification also show that, after the adoption of milking machines, young women in dairy intensive municipalities were displaced from farming (column 1), migrated to cities (column 2), climbed up the income distribution (column 3), and were more likely to participate in the labor force (column 4). The magnitude of all estimates is similar to that in our baseline specification (Table 1). Second, we find that the adoption of milking machines had opposing effects on men, reducing long-term gender differences in income and labor force participation. Relative to women in the same cohort, men were more likely to remain in farming after the diffusion of milking machines (column 1) and were less likely to emigrate from rural areas (column 2). Importantly, income differences between these men and women were reduced by about 2 percentile ranks (column 3), and differences in labor force participation rates dropped by almost 4 percentage points.⁶² Overall, these results provide compelling evidence that the adoption of milking machines had fundamentally different consequences for young rural men and women in Norway.

7 Conclusion

In this paper, we focused on one of the most important automation processes in agriculture, the mechanization of milking cows—a task that provided jobs for hundreds of thousands of young rural women—to study the economic consequences of gender-biased technological change. Our focus was on Norway, which provides an ideal setting in which to evaluate the short-term and long-term effects of the roll-out of milking machines at the micro-level.

Combining the Norwegian individual-level registry data with municipality-level statistics on the uptake of milking machines from the agricultural census, we show that the introduction of milking machines had different consequences for young men and women in rural areas. Affected young women were pushed out of agriculture and moved to the cities, where they invested more in their education and eventually earned higher incomes as middle-aged adults. On the other hand, the corresponding cohorts of affected men were not displaced by the adoption of milking machines and remained largely in rural areas. This contributed to reducing gender gaps in labor force participation and income, and to the transformation of women’s work in the 20th century. More generally, our results suggest that technological change can resolve the misallocation of workers across sectors thereby improving their economic status in the long-run.

⁶²We also report the Sanderson-Windmeijer (SW) first-stage F-statistics in Table 3. These are well above the rule-of-thumb level of 10.

These findings have some parallels to today’s debate about the economic consequences of labor competing against more and more sophisticated technologies, such as industrial robots and artificial intelligence. The net effect of automating tasks depends on whether the displacement effect outweighs productivity gains and the reinstatement effect of creating new labor-intensive tasks (e.g., [Acemoglu and Restrepo, 2018, 2019](#)). In our case, the creation of new jobs in the manufacturing and service sectors appears to be the dominant force. As in other European countries after WWII, Norway’s economy was in a transition phase with remarkable growth rates, especially in the manufacturing and service industries. Despite the fact that milking machines immediately displaced young female agricultural workers, in the long run they benefited (on average) from being pushed off the farms because the Norwegian economy provided new job opportunities for women in cities. However, it should be clear from this discussion that the effects of automation are not institution independent, and that the introduction of gender-biased labor-saving technologies in agriculture might not benefit displaced workers. The effects will likely depend on their comparative advantage, local schooling infrastructure, and gender-specific job opportunities in rural and urban areas.

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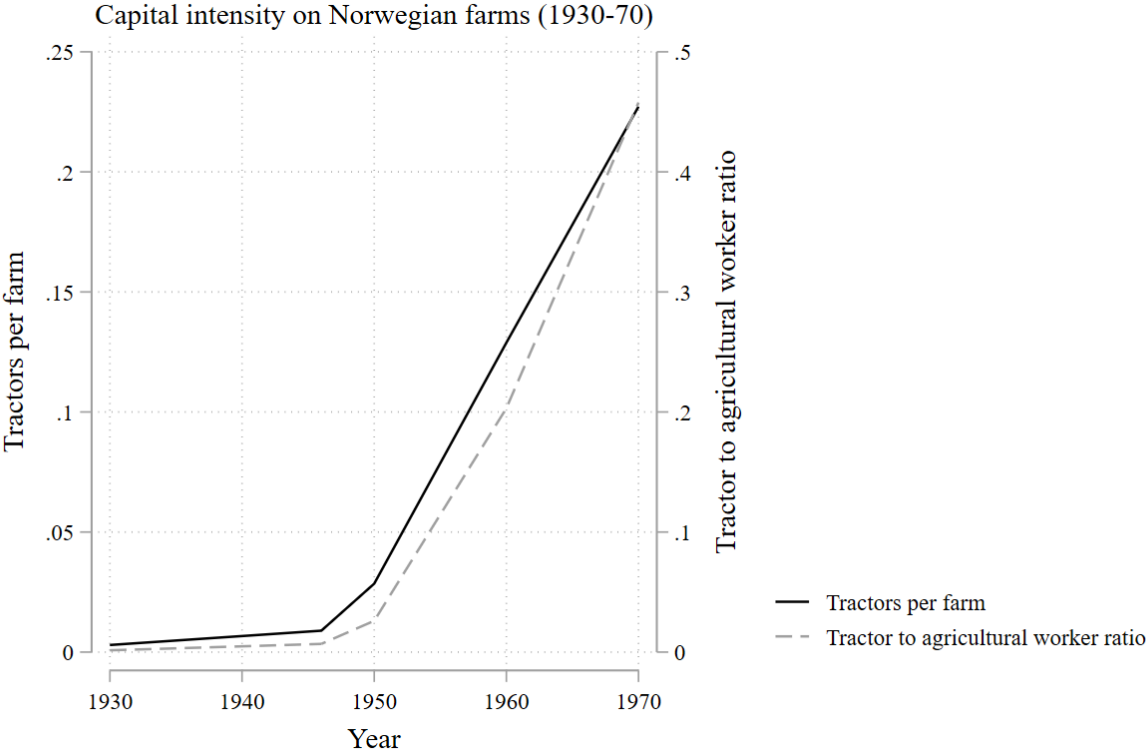
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Online appendix. Figures and tables

Figure 1: Capital intensity in agriculture (1930–1970)



NOTE.— This figure shows the evolution of tractors per farm (left vertical axis) and the ratio of tractor to agricultural worker (right vertical axis) in Norway between 1930 and 1970. Source: Census of Agriculture (own calculations).

Figure 2: Milk yields per cow (1927/28–1969)

Tabell 8. Mjølkekemengd pr. ku og egg pr. høne. Kilo. Heile landet *Milk yield per cow and eggs per hen. Kilos. The whole country*

Husdyrprodukt <i>Livestock product</i>	1927-28	1930	1935	1939-40	1949-50	1954-55	1959-60	1964	1969
Mjølke pr. ku <i>Milk per cow</i> ..	1 534 ¹⁾	1 620	1 698	1 761	2 092	2 314	2 681	3 139	4 027
Egg pr. høne <i>Eggs per hen</i> ..	6,3	7,3	8,1	9,0	9,2	9,9

1) 1925.

NOTE.— This figure shows the evolution of milk yields per cow from 1927-28 to 1969.
Source: Central Bureau of Statistics of Norway (1974, Table 8).

Figure 3: Labor input on agricultural holdings (1928-29 to 1965-66)

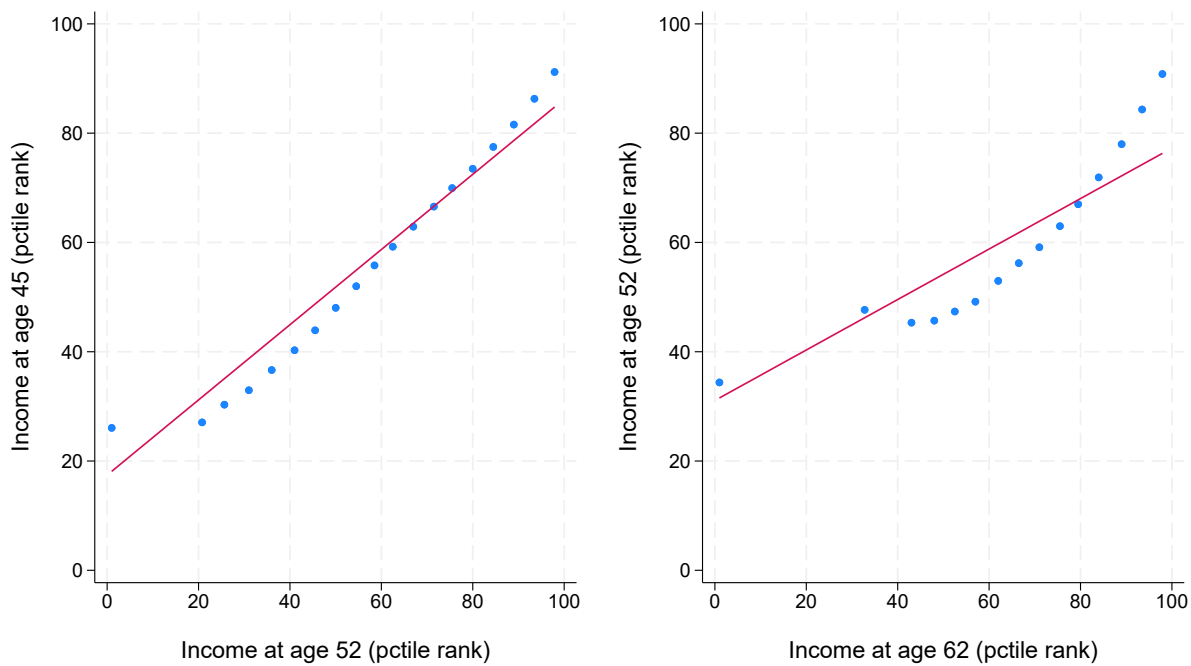
Tabell 78. Arbeidskraft på brukene. Årsverk.
Labour input on holdings. Man-years.

År Year	I alt Total		Brukere og ektemaker <i>Holders and their spouses</i>		Andre familiemedlemmer <i>Other family members</i>		Fremmed arbeidshjelp <i>Hired workers</i>	
	Menn Males	Kvinner Females	Menn Males	Kvinner Females	Menn Males	Kvinner Females	Menn Males	Kvinner Females
	Årsverk i alt ¹ <i>Total man-years¹</i>							
1928—29	257 513	311 742	124 390	172 265	86 945	92 872	46 178	46 605
1938—39	276 266	313 037	131 151	174 301	91 134	92 745	53 981	45 991
1948—49	236 959	277 001	132 950	177 600	67 729	75 791	36 280	23 610
1951—52	213 200	258 800	131 600	179 100	55 000	62 900	26 600	16 800
1953—54	195 400	241 800	125 600	175 200	48 400	53 300	21 400	13 300
1955—56	191 100	232 300	123 400	170 800	47 900	49 400	19 800	12 100
1958—59	178 621	205 850	117 295	159 437	38 694	36 612	22 632	9 801
1961—62	164 031	196 925	108 126	158 541	37 456	31 142	18 449	7 242
1965—66	141 787	169 764	99 383	142 516	28 718	22 304	13 686	4 944
	Av dette i jordbruket ² <i>Of which in agriculture²</i>							
1958—59	159 522	69 808	106 420	45 254	36 291	18 765	16 811	5 789
1961—62	147 714	66 224	98 599	45 804	35 285	16 118	13 830	4 302

Noter ¹ Medregnet arbeid i egen skog og husarbeid. ² Ikke medregnet skogs- og husarbeid.
 Notes ¹ Including forestry and household work. ² Excluding forestry and household work.

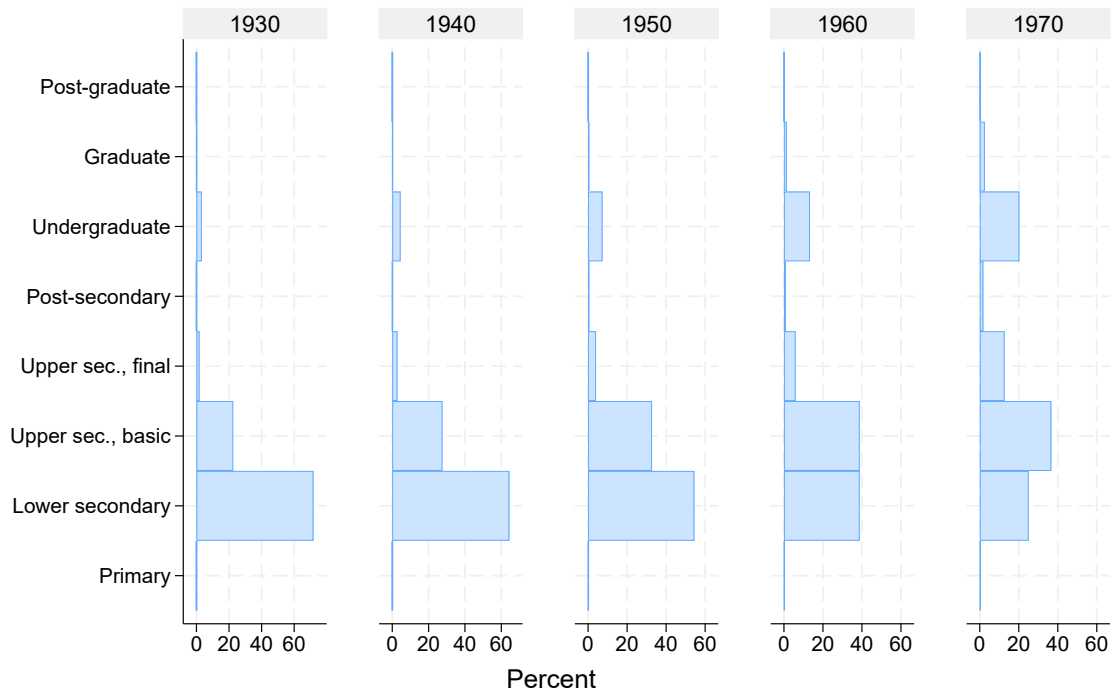
NOTE.— This figure shows the labor input on farms by gender and by type of worker (holders and spouses, other family members, and hired workers) for the years 1928-29 to 1965-66. Source: Central Bureau of Statistics of Norway (1968, Table 78).

Figure 4: Comparison of income ranks based on income at ages 45, 52, and 62



Note: Income ranks calculated over birth-year cohorts for all women in our baseline sample with income data at ages 45, 52, and 62.

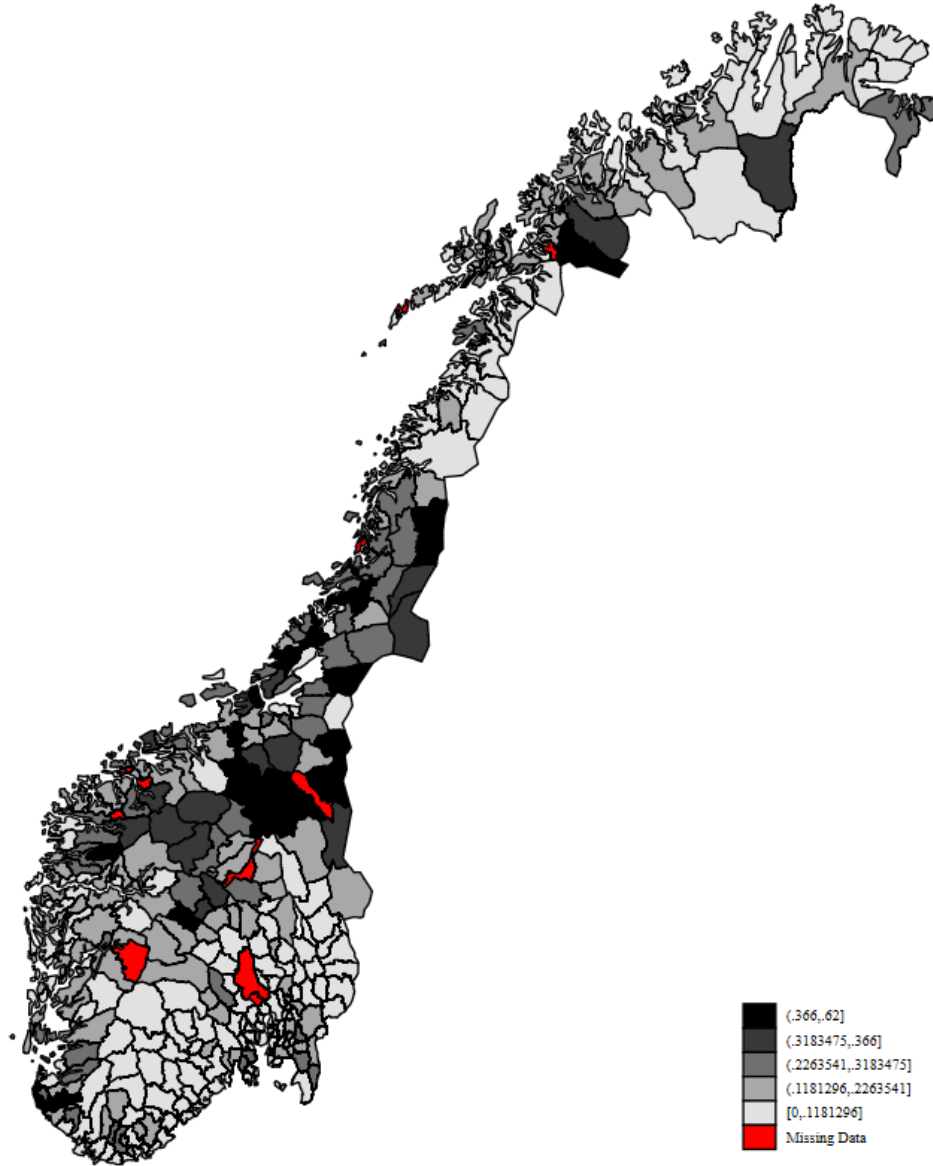
Figure 5: Education distribution over time (1930–1970)



Sample: This figure plots the education distribution of rural women aged 16–25 in 1930, 1940, 1950, 1960, and 1970.

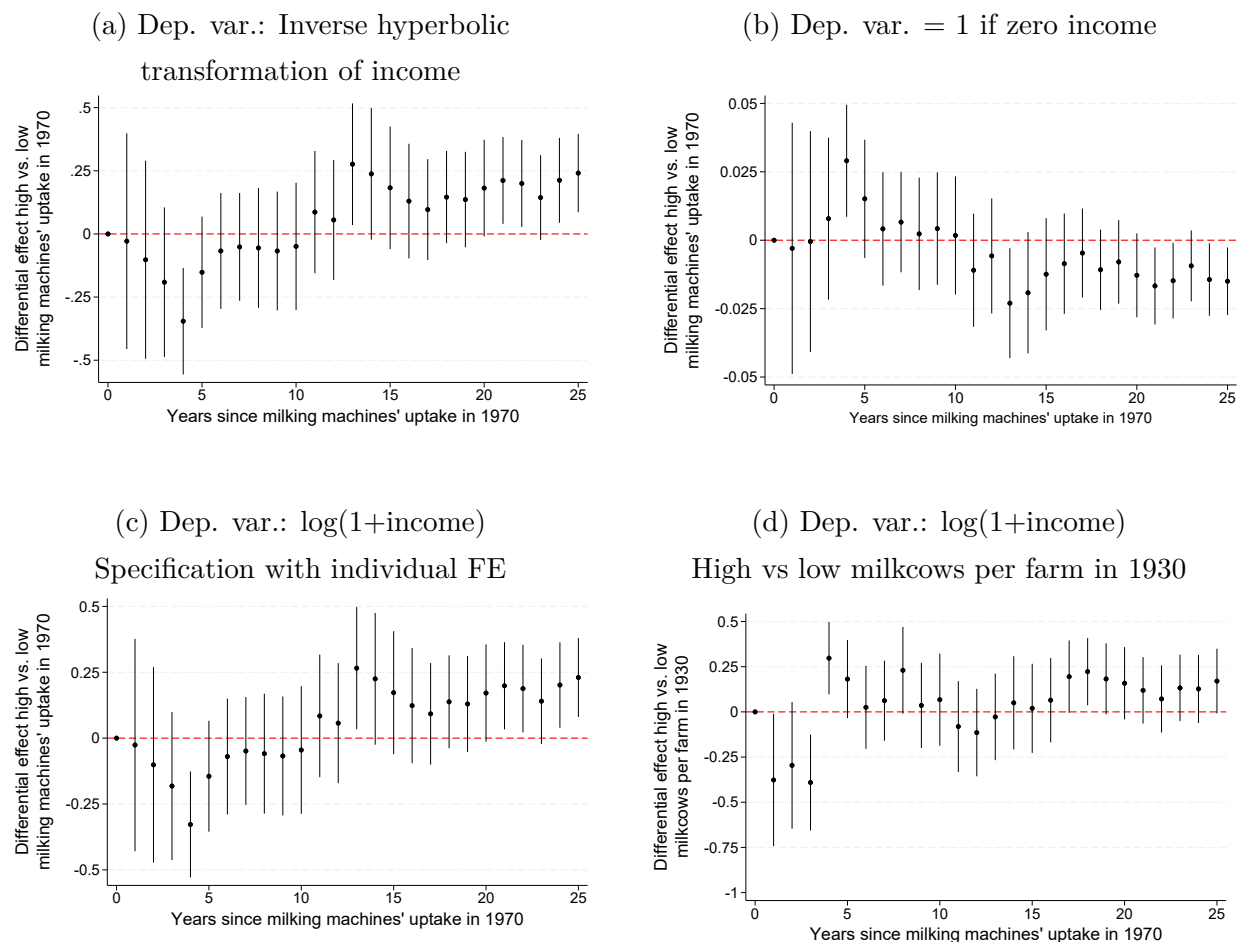
Figure 6

Milking machines per farm in 1969



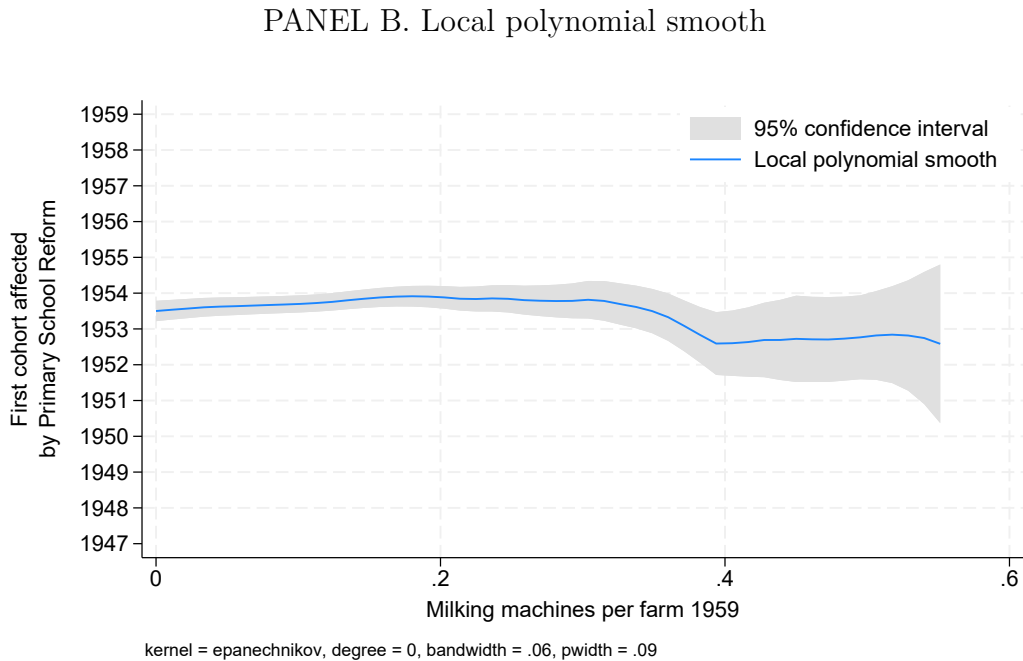
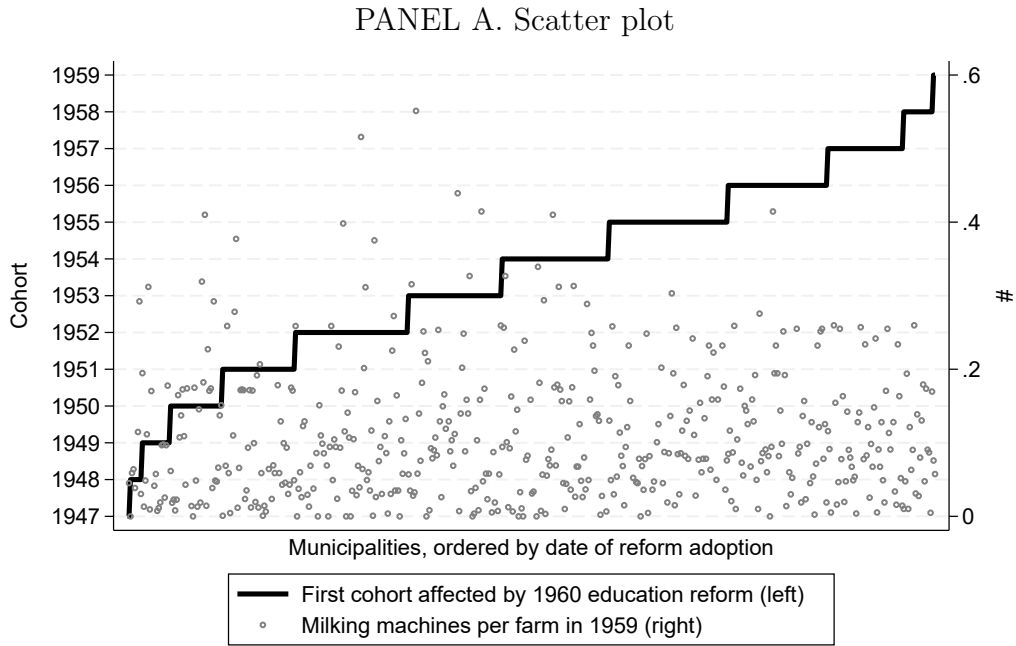
NOTE.— This figure shows the distribution of milking machines per farm in 1969 across Norwegian municipalities. A darker color refers to higher values of milking machines per farm. Red polygons denote missing observations. Source: Census of Agriculture (own calculations).

Figure 7: Robustness checks for contemporaneous effects



NOTE.— This figure plots estimates and 95% confidence intervals of γ_t from alternative specifications of Equation (11). Panel (a) uses the inverse hyperbolic transformation of income as the dependent variable. Panel (b) uses an indicator for zero income as the dependent variable. Panel (c) adds individual fixed effects to Equation (11) (instead of the municipality fixed effects) and uses the baseline dependant variable, $\log(1+\text{income})$. Panel (d) compares the evolution of young women's incomes after 1970 in municipalities with above- vs. below-median milkcows per farm in 1930 and uses the baseline dependant variable, $\log(1+\text{income})$. As before, the sample is a panel of 8,935 women and their incomes over 25 years (1970–1995). It is restricted to women born in rural municipalities who turned 16 in 1970. Standard errors are clustered by municipality.

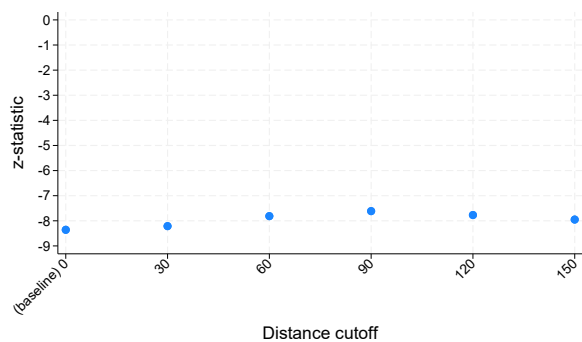
Figure 8: The roll-out of the Primary School Reform and the diffusion of milking machines across municipalities



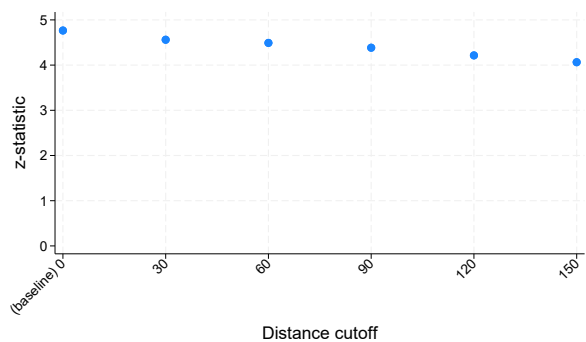
NOTE.— The sample consists of 497 municipalities based on their 1960 borders, with at least one farm in 1929. Data on the first cohort affected by the Primary School Reform in each municipality is from [Black et al. \(2005\)](#).

Figure 9: Conley Standard Errors with different distance cutoffs

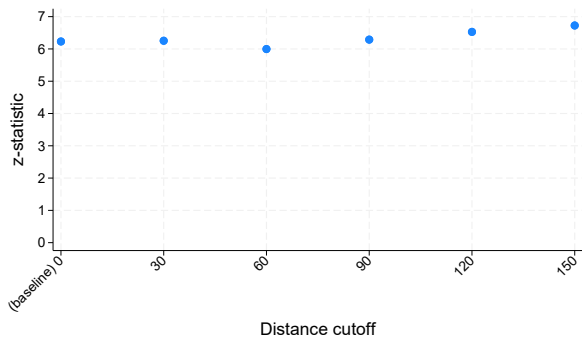
(a) Employment in agriculture (Table 1, col. 2)



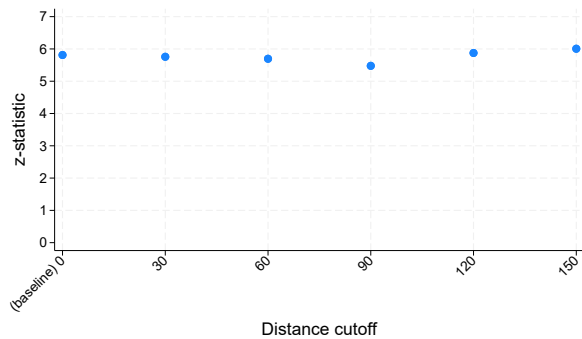
(b) Migration to city (Table 1, col. 4)



(c) Income percentile rank (Table 1, col. 6)

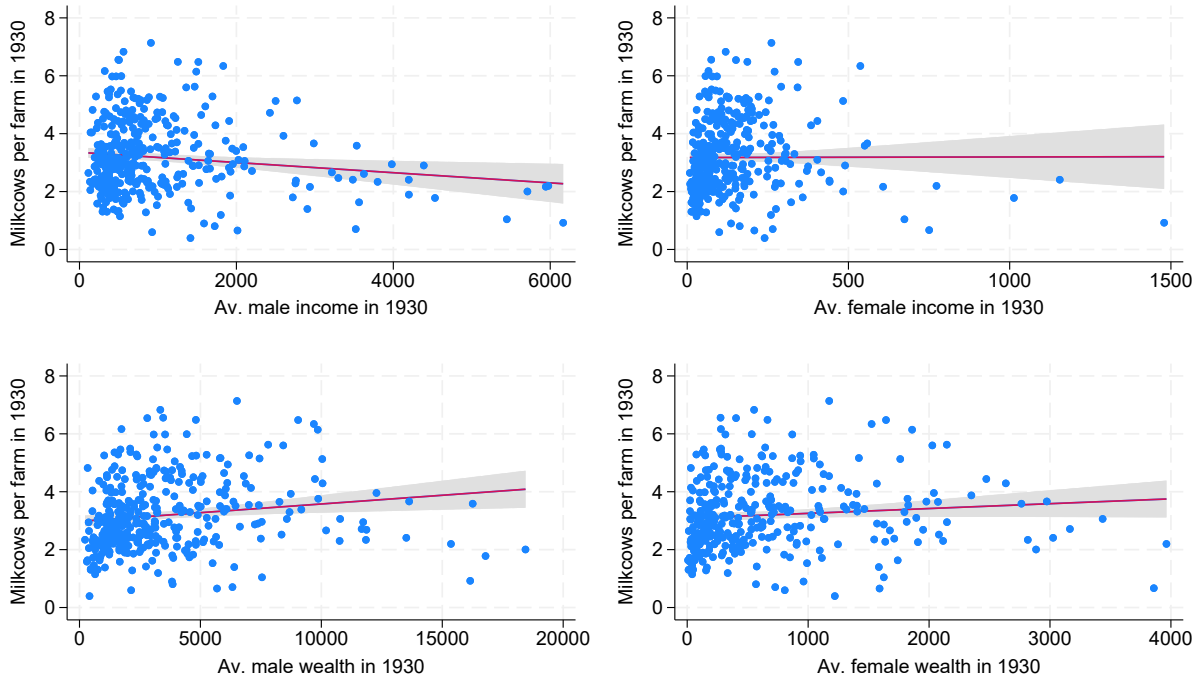


(d) FLFP (Table 1, col. 8)



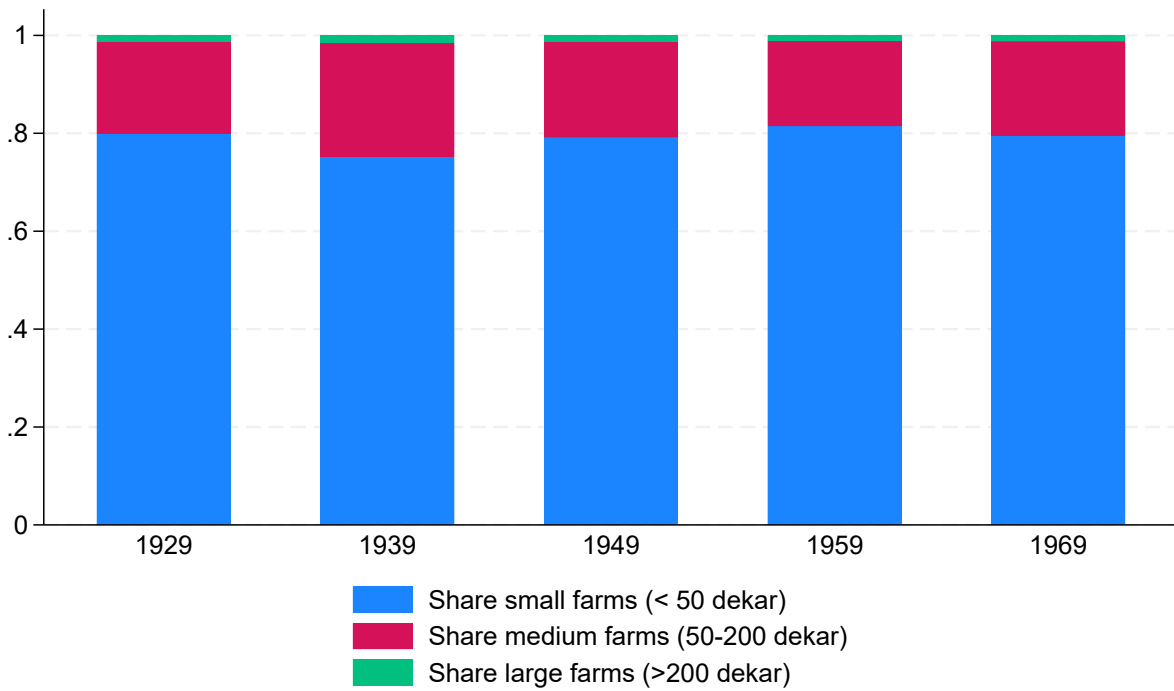
NOTE.— This figure shows spatially-adjusted z-statistics for the effect of milking machines per farm in our baseline IV specifications with the full set of FE and controls and the full sample; see Table 1 for further details. The baseline cutoff is the point at which the spatial error correlation is assumed to be 0; calculated using [acreg Colella et al. \(2019\)](#).

Figure 10: Milk cows per farm, income, and wealth by 1930



Note: Income and wealth data based on F.O.B. 1930 data digitized from Statistics Norway archives. The figure excludes outlier municipalities with male and female incomes above, respectively, 10,000 and 2,000 NOK, and with male and female wealth above, respectively, 20,000 and 5,000.

Figure 11: Farm size distribution over time (1929–1969)



Note: This figure plots the distribution of farms by size (below 50 dekar, 50-200 dekar, and above 200 dekar).
Source: Census of Agriculture (own calculations).

Table 1: Summary statistics for women in baseline sample

	Mean	Standard deviation	Observations
Technology diffusion in municipality of birth:			
Milking machines per farm	0.067	0.102	379,366
Milking machines per farm (cohort 16-25 in 1930)	0.000	0.000	45,127
Milking machines per farm (cohort 16-25 in 1940)	0.003	0.008	78,663
Milking machines per farm (cohort 16-25 in 1950)	0.018	0.035	77,920
Milking machines per farm (cohort 16-25 in 1960)	0.110	0.097	80,105
Milking machines per farm (cohort 16-25 in 1970)	0.153	0.124	97,551
Milk cows per farm in 1930	3.084	1.238	379,366
Share milkmaids in 1930	0.018	0.017	379,366
Outcomes for all women:			
Employment in agriculture (after age 25)	0.091	0.288	379,366
Migration anywhere (ever)	0.689	0.463	379,366
Migration to city (ever)	0.257	0.437	379,366
Migration to town with higher-edu. institution (ever)	0.331	0.471	355,527
Migration outside county of birth (ever)	0.398	0.490	379,366
Migration inside county of birth (ever)	0.291	0.454	379,366
Income at age 45 [†] in NOK	65015.878	82474.057	342,792
Female labor force participation (age 45)	0.781	0.413	271,450
Upper secondary education or more	0.168	0.374	376,594
Undergraduate education or more	0.108	0.310	376,594
Outcomes for women in non-agriculture occupation:			
High-skill occupation	0.125	0.330	344,658
Mid-skill occupation	0.183	0.387	344,658
Low-skill occupation	0.343	0.475	344,658
Municipality-level controls:			
Share improved farmland in 1929	0.703	0.241	379,366
Farms p.c. in 1930	0.132	0.037	379,366
Early-tractor adoption by 1930 (0/1)	0.455	0.498	379,366
Ratio large to small farms (in 1929)	0.119	0.239	379,366
Ratio large to small farms (contemporaneous)	0.067	0.252	378,018
Hydropower potential	0.433	0.779	364,780
Hydropower status in 1900-1910	0.072	0.258	366,641

NOTE.— This table shows summary statistics for our baseline sample: women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1930–70. [†]Income is measured at age 45 for cohorts aged 16–25 in 1950, 1960, and 1970 and at age 52 and 62 for the cohorts aged 16–25 in 1940 and 1930, respectively.

Table 2: Determinants of milking machine diffusion (1929–69)

	(1)	(2)	(3)	(4)
	Milking machines per farm			
Milkcows per farm in 1930	0.032*** (0.003)	X	0.032*** (0.003)	X
Share milkmaids in 1930	-0.312 (0.223)		-0.318 (0.228)	
Share females in agriculture in 1930	-0.014 (0.126)		-0.014 (0.128)	
Female labor force participation in 1930	0.120* (0.066)		0.121* (0.068)	
Female net-migration rate in 1930	-0.025 (0.021)		-0.025 (0.021)	
Population density in 1930	0.259*** (0.075)		0.259*** (0.077)	
Farms per capita in 1930	0.415*** (0.072)	X	0.417*** (0.074)	X
Share improved farmland in 1930	0.067*** (0.011)	X	0.067*** (0.011)	X
Tractor dummy in 1930	-0.008 (0.006)		-0.008 (0.006)	
Share females age 15-19 in 1930	-0.434** (0.200)		-0.413** (0.205)	
Share females age 20-39 in 1930	-0.210* (0.121)		-0.204 (0.124)	
Share females age 40-59 in 1930	-0.168 (0.130)		-0.166 (0.133)	
Share females 60+ in 1930	-0.172 (0.120)		-0.167 (0.122)	
Capital-labor ratio in 1930	0.517 (1.074)		0.534 (1.096)	
Land area in 1930	0.000 (0.000)		0.000 (0.000)	
Ratio large to small farms in 1930	0.019** (0.009)	X	0.019** (0.009)	X
Avg. income males in 1930	-0.000 (0.000)		-0.000 (0.000)	
Avg. income females in 1930	0.000* (0.000)		0.000* (0.000)	
Avg. wealth males in 1930	-0.000 (0.000)		-0.000 (0.000)	
Avg. wealth males in 1930	-0.000 (0.000)		-0.000 (0.000)	
Method	OLS	LASSO	OLS	LASSO
Observations	1,449	1,449	1,449	1,449
R-squared	0.612		0.705	
County FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
County-Year FE	no	no	yes	yes

NOTE.— Column (1) regresses milking machines per farm on municipality characteristics in 1930 and fixed effects for census year and county. Column (2) shows the selected controls by the Lasso procedure. The Lasso procedure partials out county and census year fixed effects prior to control selection. Columns (3) and (4) show the corresponding results including county-by-census year fixed effects. Controls marked by "X" are selected by the Lasso procedure. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

Table 3: The diffusion of milking machines and women’s employment in agriculture and migration decisions—Placebo experiment 1900–1910

	(1)	(2)	(3)	(4)	(5)	(6)
	works in agriculture	works in agriculture	migrates to city	migrates to city	works at all (FLFP)	works at all (FLFP)
Panel A. IV						
Milking machines per farm	0.006 (0.006)	-0.002 (0.006)	-0.011 (0.007)	0.005 (0.008)	0.006 (0.007)	0.008 (0.008)
Panel B. Reduced form						
Milkcows per farm 1930 × National m.m. per farm	0.005 (0.005)	-0.001 (0.005)	-0.009 (0.006)	0.004 (0.006)	0.005 (0.006)	0.007 (0.007)
Panel C. OLS						
Milking machines per farm	-0.001 (0.004)	-0.002 (0.004)	-0.002 (0.004)	0.004 (0.004)	-0.002 (0.004)	-0.002 (0.004)
Observations	209,473	209,473	209,473	209,473	209,473	209,473
F-stat first stage	123.54	124.47	123.54	124.47	123.54	124.47
Mean(Y)	0.125	0.125	0.192	0.192	0.406	0.406
Municipality FE	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes
County-by-byear FE	no	yes	no	yes	no	yes
Flexible trends	no	yes	no	yes	no	yes

NOTE.— This table uses data from the 1900 and 1910 censuses to show the placebo effect of backdating the substantial adoption of milking machines between 1950 and 1960 to the beginning of the 20th century. It shows the placebo effect on whether a woman works in agriculture (Columns 1-2), who moved to the city (columns 3-4), and who worked at all (Columns 5-6). The sample includes women at age 16–25 and, as in the main analysis, looks at their outcomes 10 years later (i.e., at the age of 25–35 in the 1900 and 1910 censuses). All regressions include fixed effects for a woman’s municipality of birth and birth year. Columns (2), (4), and (6) also include county-by-birth year fixed effects, and the same set of controls selected with a LASSO procedure as in Table 1. Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the municipality level. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

Table 4: Short-run effects of the diffusion of milking machines, using 1960 Census data

	(1)	(2)	(3)	(4)
	Household members in employment (share)	Household members in employment (share)	Student activity (0/1)	Student activity (0/1)
Milking machines per farm	-0.025* (0.015)	-0.030* (0.017)	0.078* (0.040)	0.132*** (0.040)
Observations	73,375	73,064	77,163	76,850
R-squared	0.038	0.040	0.163	0.168
Municipality FE	no	no	no	no
Birth year FE	yes	yes	yes	yes
County-by-year FE	no	yes	no	yes
Flexible trends	no	yes	no	yes
Mean dep. variable	0.466	0.466	0.156	0.155

NOTE.— This table shows the short-run effect of the diffusion of milking machines in 1960 on the share of individuals employed in each household (in Columns 1-2) and on an indicator of student activity (1 = yes; 0 otherwise) (in Columns 3-4), both measured in the 1960 Census. The sample is a cross-section of women aged 16–25 in 1960 born in rural municipalities with at least one farm in 1929. Estimates are based on $Y_{i,j,c} = \beta_c + \gamma M_{j,1960} + \sum_t \mathbf{1}[c = t] \times \mathbf{X}'_{j,c} \theta_t + \epsilon_{ijc}$, where i indexes women, j their municipality of birth, and c their birth cohort. The variable $M_{j,1960}$ is the number of milking machines per farm in 1960 in a woman's municipality of birth (j). The vector of flexible trends \mathbf{X} is defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

Table 5: First-stage estimates

	(1)	(2)	(3)
	<i>Dep. Var.: Milking machines per farm</i>		
Milkcows per farm 1930 \times National MM per farm	0.518*** (0.052)	0.512*** (0.054)	0.552*** (0.054)
Observations	379,366	379,366	379,366
F-statistic	97.553	90.750	105.402
Municipality FE	yes	yes	yes
Birth year FE	yes	yes	yes
County-by-year FE	no	yes	yes
Flexible trends	no	yes	yes

NOTE.— This table shows first-stage estimates from Equation (8). The sample includes women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1930–1970. All regressions include fixed effects for a woman’s birth municipality and birth year, county-by-birth year fixed effects, and flexible trends. Flexible trends include municipality-level measures of: agricultural intensity in 1930 (i.e., the share of improved farmland and farms p.c.) \times birth cohort FE; ratio of large-to-small farms in 1930 \times birth cohort FE; capital intensity in 1930 (i.e., early-tractor adoption) \times birth cohort FE; and female income in 1930 \times birth cohort FE. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6: Main results conditional on reporting an occupation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment in agriculture		Migration to city		Income pctile rank		FLFP	
Panel A. IV								
Milking machines per farm	-0.049*** (0.008)	-0.052*** (0.007)	0.027*** (0.007)	0.036*** (0.007)	2.133*** (0.358)	2.313*** (0.338)	0.051*** (0.009)	0.045*** (0.007)
Panel B. Reduced form								
Milkcows per farm 1930 × National m.m. per farm	-0.042*** (0.006)	-0.047*** (0.005)	0.023*** (0.006)	0.033*** (0.006)	1.815*** (0.348)	2.106*** (0.300)	0.040*** (0.008)	0.039*** (0.006)
Panel C. OLS								
Milking machines per farm	-0.020*** (0.003)	-0.017*** (0.003)	0.011*** (0.003)	0.010*** (0.003)	1.069*** (0.168)	0.829*** (0.152)	0.026*** (0.003)	0.015*** (0.003)
Observations	266,709	266,709	266,709	266,709	259,085	259,085	207,102	207,102
F-stat first stage	102.615	105.415	102.615	105.415	101.901	104.565	84.673	85.824
Mean dep var	0.130	0.130	0.276	0.276	38.422	38.422	0.831	0.831
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes
County-by-year FE	no	yes	no	yes	no	yes	no	yes
Flexible trends	no	yes	no	yes	no	yes	no	yes

NOTE.— This table shows IV, reduced-form, and OLS estimates for the effect of the diffusion of milking machines on women's long-term outcomes, conditional on reporting an occupation. The sample includes all women reporting an occupation who were born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1930–1970. Outcome variables and flexible trends are defined as in Table 1. Independent variables are normalized to have a mean of zero and an SD of one. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 7: The diffusion of milking machines and women’s income at ages 40–45

	(1) income>0 Age 40	(2) log(income+1) Age 40	(3) income>0 Age 45	(4) log(income+1) Age 45
Panel A. IV				
Milking machines per farm	0.027*** (0.008)	0.290*** (0.079)	0.024*** (0.006)	0.299*** (0.067)
Panel B. Reduced form				
Milkcows per farm 1930 × National MM per farm	0.021*** (0.006)	0.229*** (0.061)	0.019*** (0.005)	0.236*** (0.051)
Panel C. OLS				
Milking machines per farm	0.011*** (0.003)	0.115*** (0.028)	0.006** (0.002)	0.072*** (0.026)
Observations	233,777	233,777	233,777	233,777
F-stat first stage	68.500	68.500	68.500	68.500
Mean dep. variable	0.754	8.084	0.836	9.278
Municipality FE	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes
County-by-by-year FE	yes	yes	yes	yes
Flexible trends	yes	yes	yes	yes

NOTE.— This table shows IV, reduced-form, and OLS estimates for the effect of the diffusion of milking machines on women’s income at the age of 40–45, based on equations (9) and (9). The sample includes women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1950–1970, and whose income at ages 40 and 45 is listed in the tax registry (1967–2010). The dependent variable is a dummy variable equal to 1 if a woman reported any income at age 40 (Column 1) or 45 (Column 3), and log(income +1) at age 40 (Column 2) and at age 45 (Column 4). Independent variables are normalized to have a mean of zero and an SD of one. We include the full set of flexible trends, defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

Table 8: Decomposition of the income effect by mover status

	(1) income>0 Age 40	(2) ln(income+1) Age 40	(3) income>0 Age 45	(4) ln(income+1) Age 45
Stayers (omitted)	-	-	-	-
Migrates to rural	0.018*** (0.003)	0.233*** (0.037)	0.014*** (0.003)	0.236*** (0.031)
Migrates to urban	0.060*** (0.004)	0.795*** (0.045)	0.037*** (0.003)	0.627*** (0.038)
Observations	233,777	233,777	233,777	233,777
Mean dep. variable	0.754	8.084	0.836	9.278
Municipality FE	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes
County-by-year FE	yes	yes	yes	yes
Flexible trends	yes	yes	yes	yes

NOTE.— This table decomposes the income effect by mover status. The sample includes women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1950–1970, and whose income at ages 40 and 45 is listed in the tax registry (1967–2010). The dependent variable is a dummy variable equal to 1 if a woman reported any income at age 40 (Column 1) or 45 (Column 3), and $\log(\text{income} + 1)$ at age 40 (Column 2) and at age 45 (Column 4). The variable "Stayers" is the omitted category, "Migrate to rural" is a dummy variable equal to one if the woman moved from her birthplace to another rural municipality, and "Migrate to urban" is a dummy variable equal to one if the woman moved from her birthplace to an urban town. We include the full set of flexible trends, defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 9: Robustness to the roll-out of the Primary School Reform (1960-72)

	(1) Employment in agriculture	(2) Migration to city	(3) Income per capita	(4) FLFP	(5) Education ≥ upper-sec.	(6) Education ≥ undergrad.
Panel A. IV						
Milking machines per farm	-0.042*** (0.005)	0.029*** (0.006)	1.839*** (0.317)	0.038*** (0.007)	0.014*** (0.005)	0.013*** (0.004)
Primary School reform	-0.001 (0.004)	0.027*** (0.009)	0.347 (0.350)	0.003 (0.005)	0.020*** (0.007)	0.016** (0.007)
Panel B. Reduced form						
Milk cows per farm 1930 × National MM per farm	-0.038*** (0.004)	0.026*** (0.006)	1.655*** (0.279)	0.032*** (0.006)	0.013*** (0.004)	0.013*** (0.004)
Primary School reform	0.001 (0.004)	0.026*** (0.009)	0.266 (0.341)	0.001 (0.005)	0.020*** (0.007)	0.015** (0.007)
Panel C. OLS						
Milking machines per farm	-0.015*** (0.003)	0.008** (0.003)	0.648*** (0.148)	0.012*** (0.003)	0.007*** (0.003)	0.007*** (0.002)
Primary School reform	0.000 (0.004)	0.026*** (0.008)	0.300 (0.336)	0.002 (0.005)	0.020*** (0.007)	0.015** (0.007)
Observations	315,751	315,751	285,087	225,745	313,527	313,527
F-stat first stage	90.545	90.545	86.604	69.025	90.545	90.545
Mean dep. var.	0.086	0.257	34.170	0.781	0.166	0.106
Municipality FE	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes
County-by-year FE	yes	yes	yes	yes	yes	yes
Flexible trends	yes	yes	yes	yes	yes	yes

NOTE.— This table replicates the main results of Table 1 controlling for the Primary School Reform roll-out between 1960 and 1972. The variable $Primary\ School\ Reform_{jt}$ is an indicator equal to one if women born in cohort c studied after their municipality of birth j fully implemented the Primary School Reform, and equal to zero if they studied under the pre-reform system. The sample is smaller than in Tables 1 because we exclude municipalities where we have no information on when the reform was implemented. We include the full set of flexible trends, defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 10: IV and reduced-form results using milkmaid employment shares as alternative treatment-exposure measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment in agriculture		Migration to city		Income pctile rank		FLFP	
Panel A. IV								
Milking machines per farm	-0.058*** (0.012)	-0.085*** (0.024)	0.030*** (0.011)	0.045** (0.019)	2.641*** (0.652)	3.786*** (1.252)	0.048*** (0.016)	0.082*** (0.036)
Panel B. Reduced form								
Share milkmaids 1930 × National m.m. per farm	-0.017*** (0.003)	-0.016*** (0.002)	0.009*** (0.003)	0.009*** (0.003)	0.779*** (0.176)	0.723*** (0.151)	0.014*** (0.005)	0.015*** (0.004)
Observations	379,366	379,366	379,366	379,366	342,952	342,952	271,590	271,590
F-stat first stage	24.247	11.558	24.247	11.558	23.361	11.205	20.362	9.148
Mean dep. variable	0.091	0.091	0.257	0.257	34.125	34.125	0.781	0.781
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes
County-by-by-year FE	no	yes	no	yes	no	yes	no	yes
Flexible trends	no	yes	no	yes	no	yes	no	yes

NOTE.— This table shows IV and reduced-form estimates using the share of women employed as milkmaids in 1930 instead of the number of cows per farm in 1930 in the instrument. Specifically, the instrument is $\frac{M_{d(c)}}{F_{d(c)}} \times \frac{L_{j,1929}}{F_{j,1930}}$. As before, the first component is the national “shift” in the adoption of milking machines, i.e., the total number of milking machines in Norway, $\bar{M}_{d(c)}$, normalized by the total number of farms in Norway, $\bar{F}_{d(c)}$, at the census year $d(c)$ when birth cohort c was aged 16-25. The second component is the treatment intensity at the municipality level, i.e., the share of women employed as milkmaids. Specifically, $L_{j,1929}$ denotes the number of young women employed as milkmaids in municipality j in 1930 and $F_{j,1930}$ the total female population in municipality j in 1930. Dependent variables, samples, and flexible trends are defined as in Table 1. Independent variables are normalized to have a mean of zero and an SD of one. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 11: Comparing stratified samples

	(1)	(2)	(3)	(4)
	Employment in agriculture	Migration to city	Income pct rank	FLFP
<i>Panel A. Municipalities with >0 milking machines in 1950</i>				
Milkcows per farm 1930 × National m.m. per farm	-0.036*** (0.005)	0.027*** (0.007)	1.699*** (0.325)	0.031*** (0.007)
Observations	272,341	272,341	245,890	193,655
Mean dep. variable	0.091	0.257	34.440	0.783
<i>Panel B. Municipalities with no milking machines in 1950</i>				
Milkcows per farm 1930 × National m.m. per farm	-0.055*** (0.008)	0.018* (0.010)	1.381*** (0.487)	0.035*** (0.009)
Observations	107,024	107,024	96,901	77,795
Mean dep. variable	0.093	0.257	33.371	0.777
Municipality FE	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes
County-by-by-year FE	yes	yes	yes	yes
Flexible trends	yes	yes	yes	yes

NOTE.— This table shows reduced-form estimates on stratified samples. All samples include women born in rural municipalities with at least one farm in 1929, who were aged 16–25 in the census years 1930–1970. Panel A considers women in municipalities which had adopted milking machines in 1950 (switchers by 1950); Panel B considers women in municipalities which had not adopted milking machines in 1950 (non-switchers by 1950). Outcome variables and flexible trends are defined as in Table 1. Independent variables are normalized to have a mean of zero and an SD of one. Standard errors (in parentheses) clustered at the municipality level; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 12: Robustness controlling for access to hydroelectric power plants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment in agriculture		Migration to city		Income pctlile rank		FLFP	
Panel A. IV								
Milking machines per farm	-0.044*** (0.006)	-0.044*** (0.006)	0.029*** (0.007)	0.029*** (0.007)	1.897*** (0.317)	1.874*** (0.318)	0.041*** (0.007)	0.040*** (0.007)
Panel B. Reduced form								
Milkcows per farm 1930 × National m.m. per farm	-0.040*** (0.004)	-0.039*** (0.004)	0.027*** (0.006)	0.027*** (0.006)	1.700*** (0.259)	1.669*** (0.269)	0.034*** (0.005)	0.033*** (0.005)
Panel C. OLS								
Milking machines per farm		-0.016*** (0.002)		0.008** (0.003)		0.611*** (0.144)		0.012*** (0.003)
Observations	364,780	366,641	364,780	366,641	329,783	331,371	261,005	262,171
F-stat first stage	98.496	93.682	98.496	93.682	94.401	89.478	75.644	71.161
Mean dep. variable	0.092	0.091	0.258	0.258	34.169	34.159	0.781	0.781
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes
County-by-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Flexible trends	yes	yes	yes	yes	yes	yes	yes	yes
Hydropower instrument × byear FE	yes	no	yes	no	yes	no	yes	no
Hydropower 1900-10 status	no	yes	no	yes	no	yes	no	yes

NOTE. — This table shows IV estimates in extended specifications of equations (8) and (9) controlling for different measures of access to hydroelectric power plants. Odd columns control for the hydropower potential × birth year FE; Even columns control for the hydropower status between 1900 and 1910 (early adopters). Dependent variables, independent variables, flexible trends, and baseline sample are defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.

Table 13: Alternative definitions of female labor force participation (FLFP)

	Dep. var.: = 1 if > income in tax registry			Dep. var.: = 1 if occupation in Census (after 25) and > income in tax registry				
	at age 45 (baseline) (1)	(2)	(3)	at age 45, 52, 62 (4)	at age 45 (5)	at age 45, 52, 62 (6)	(7)	(8)
Panel A. IV								
Milking machines per farm	0.040*** (0.009)	0.038*** (0.007)	0.030*** (0.006)	0.030*** (0.005)	0.041*** (0.008)	0.043*** (0.007)	0.028*** (0.006)	0.032*** (0.006)
Panel B. Reduced form								
Milkcows per farm 1930 × National m.m. per farm	0.031*** (0.007)	0.032*** (0.005)	0.024*** (0.005)	0.026*** (0.004)	0.031*** (0.007)	0.036*** (0.006)	0.023*** (0.005)	0.028*** (0.005)
Panel C. OLS								
Milking machines per farm	0.021*** (0.003)	0.011*** (0.003)	0.017*** (0.002)	0.010*** (0.002)	0.022*** (0.003)	0.013*** (0.003)	0.017*** (0.002)	0.011*** (0.003)
Observations	271,590	271,590	310,460	310,460	271,590	271,590	310,460	310,460
F-stat first stage	78.611	81.846	92.346	95.781	78.611	81.846	92.346	95.781
Mean dep. variable	0.781	0.781	0.808	0.808	0.634	0.634	0.665	0.665
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
Birth year FE	yes	yes	yes	yes	yes	yes	yes	yes
County-by-year FE	no	yes	no	yes	no	yes	no	yes
Flexible trends	no	yes	no	yes	no	yes	no	yes

NOTE.— This table shows IV, reduced-form, and OLS estimates based on equations (8) and (9) for alternative definitions of female labor force participation. Our baseline measure (cols. 1-2) is an indicator variable equal to one if the woman reported a positive income at age 45. Because the income registry only starts in 1967, this measure excludes the cohorts aged 16-25 in 1940 and 1930. In cols. 3-4 we consider an indicator variable equal to one if the woman reported a positive income at age 45 (for cohorts aged 16-25 in 1950 to 1970), at age 52 (for cohorts aged 16-25 in 1940), and at age 62 (for cohorts aged 16-25 in 1930). In cols. 5-6, we consider an indicator variable equal to one if a woman reports a non-missing occupation in the Census conducted after age 25 and a positive income in the tax registry at age 45. In cols. 7-8, we consider an indicator variable equal to one if a woman reports a non-missing occupation in the Census conducted after age 25 and a positive income in the tax registry at age 45 (for cohorts aged 16-25 in 1950 to 1970), at age 52 (for cohorts aged 16-25 in 1940), and at age 62 (for cohorts aged 16-25 in 1930). Dependent, independent variables, and flexible trends are defined as in Table 1. Standard errors (in parentheses) clustered at the municipality level; *p<.05; **p<.01; ***p<.001.