Financial Depth, Income Inequality, and Economic Transition*

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Abstract: This paper examines the evolving finance-inequality nexus during the process of economic transition. We estimate the varying marginal effects of financial depth on income inequality in every state of the transition process. Using China as an example of transition economies, we establish the causal effects of financial depth on urban income inequality and examine the estimation biases when the evolving relationship is not appropriately characterized. Along the transition process of the Chinese economy, we identify a robustly asymmetric and roughly inverted-L shaped relationship between financial depth and urban inequality. We find that financial depth alone accounts for 11%-28% of the overall variations of urban income inequality and the marginal impacts of financial depth change with the degree of credit constraint, the fraction of state ownership, and the level of economic development.

Key Words: Financial Depth; Income Inequality; Economic Transition

JEL Codes: D31, G20, O11, C14

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1 Introduction

We empirically revisit the finance-inequality nexus. Different from most prior studies, the current paper pays particular attention to the evolving marginal impacts of financial depth on income distribution along the process of economic transition. To materialize this perspective, we concentrate on the transition practice of the Chinese economy during 1981-2016 and explore its unique economic features to build the causal effects of financial depth on income inequality. Our work is motivated by three observations.

First, both financial depth and income distribution evolve along the process of economic transition. Numerous studies have integrated them into general equilibrium growth theories to explore how their relationship alters with the changing economic reforms or different stages of development (*e.g.*, Greenwood and Jovanovic, 1990; Galor and Zeira, 1993; Banerjee and Newman, 1993; Buera and Shin, 2013; Alvarez-Cuadrado and Japaridze, 2017; Ghossoub and Reed, 2017). Intuitively, economic transition induces variations of the finance-inequality nexus over time and across regions, giving rise to the changing role of finance. Although frequently discussed in both theory and practice, how finance-inequality nexus evolves during economic transition has not been explicitly or fully addressed in empirical analysis. The changing nexus cannot be characterized by either a linear (Das and Mohapatra, 2003; Beck *et al.*, 2007; Beck *et al.*, 2010; Ayyagari *et al.*, 2013; Madsen *et al.*, 2018) or a quadratic form (Clarke *et al.*, 2006; Liu *et al.*, 2017; Baiardi and Morana, 2016 and 2018) of financial development in regressions with fixed coefficients and an invariant model structure. As we will show later (in section 4.3.4), this leads to model misspecification and identification problems, giving rise to biased estimations and inference about the finance-inequality nexus.[1]

Second, cross-country studies dominate the prevailing analysis of finance-inequality nexus. This situation is mainly driven by the demand for a broad view on the average effects of financial development. However, a large cross-country dimension amplifies the problem of measuring variables consistently (Levine and Zervos, 1993; Frazer, 2005; Demirguc-Kunt and Levine, 2009). It complicates the issue of endogeneity due to omitted institutional and regulatory factors (D'Onofrio *et al.,* 2019) and also limits the amount of determinants of income distribution that should be controlled for due to data availability. All of them bring about extra issues on econometric estimations and economic interpretations. Moreover, a 'one size fits all' model may not work across countries (Ayyagari *et al.*, 2013; Rewilak, 2013) and renders policy suggestions difficult to accommodate various country-specific situations.

[1] Existing studies have found implicit evidence for the identification problem in both cross-country and within-country cases (*e.g.*, Clarke *et al.*, 2006; Liu *et al.*, 2017). For example, the coefficient of financial development is statistically significant when it enters the regression alone. But the significance disappears when both the level and squared terms of finance enter the regression, despite their joint significance.

Third, it is not fully understood what channels work with financial depth to impact income distribution. Although some candidate variables have been discussed in theory, their practical effects are an empirical issue. Some studies interacted channel variables with finance to examine their influence on the finance-inequality relationship. Such a linear interactive term neither allows the changing strength of the interaction nor deals with the possibility of a nonlinear correlation properly.

In this paper, we attempt to fill the above gap by providing new and robust estimates of the causal effects of financial depth on income inequality in every state of the transition process using provincial data within one country, *i.e.*, China. Since economic transition involves constant changes of economic structure and various reforms in different stages, the impact of financial depth on income distribution should be time-varying and region-dependent from a general equilibrium perspective. A qualified empirical model is expected to address the implied unknown forms of nonlinearity in both variables and parameters (Anand and Kanbur, 1993a and 1993b). In the current study, we extend a recently developed partially linear semi-parametric model to address the above issues. The nonparametric component in the model endows us with the flexibility to explore fully the direct impacts of the unknown-form financial depth on income inequality along economic transition. Our estimations deal with the changing model structure by generating observation-specific coefficients for the endogenously determined financial depth.

China is close to an ideal testing ground to our research question. On the one hand, the Chinese economy is moving from a planned to a market-oriented economy. The sample period analyzed in this paper spans from 1981 through 2016 which is one of the most remarkable periods of structural economic transformation in human history. The transition process brings about significant changes of income distribution, domestically and internationally (Ding and He, 2018; Darvas, 2019). However, there has been little systematic study of the finance-inequality nexus in China. On the other hand, China features numerous provinces that differ significantly in terms of culture, endowment, development stages, and strategies but follow the same statistical variable definitions. Due to regional segmentation (Boyreau-Debray and Wei, 2004) and local developmentalism (Li and Zhou, 2005), an inter-provincial study within China is similar to an international one: one has the reasonable amount of observations with significant variations of each variable. Due to the regulation of the National Bureau of Statics, variables in different provinces follow consistent definitions, mitigating the measurement problem. Compared to cross-country studies, more income determinants can be incorporated into the model that provides a more credible base for analyzing the finance-inequality relationship (Besley and Burgess, 2003; Rewilak, 2013).

Specifically, this paper exploits cross-region and over-time variations of 30 provinces during 1981-2016 to identify the effects of financial depth on urban income inequality and disentangle the channels through which financial deepening operates on income distribution during economic transition. As further elaborated in section 2.2, we confine our focus to the income distribution of urban households due to the data limitation in the rural area and, more importantly, due to our research desire to uncover the effects of financial depth on income distribution within an economic environment in which market forces play a role.

To reveal the causal effects, we employ the control function approach that works through instrumental variables (IVs). Our method allows us to test directly the endogeneity of financial depth. Specifically, we use (i) the entry behavior of modern foreign banks in each province during 1842 (the end of the First Opium War) and 1949 (when the P.R. China was established) and (ii) the competitive behavior of provinces due to local developmentalism to help construct the IV for financial depth. The results are remarkably similar despite separate sources of IV construction and they do not appear to be driven by the simultaneity bias.

Our major findings are briefly summarized here. First, there is a highly non-linear and roughly inverted-L shaped relationship between financial depth and urban income inequality. The pattern is asymmetric with a long left tail during the transition of the Chinese economy. Second, parametric models fail to reveal the asymmetric pattern and produce biased estimates for both the level and marginal effects of financial depth. Third, our finding is robust to alternative measures of income inequality, financial depth, and instrumental variables and also robust to the inclusion of a time trend and a dynamic model specification. Financial depth alone accounts for 11% to 28% of the total variations of urban income inequality during China's transition process. Fourth, despite the changing pattern and strength during the transition process, we find that the degree of credit constraint, the fraction of state ownership, and the level of economic development are plausible channels through which financial depth can help reduce inequality.

To the best of our knowledge, our work is the first one that accounts explicitly for economic transition and explores, in every state of the transition process, the nonlinear finance-inequality nexus in the developing world. This paper contributes to the literature along multiple dimensions. First, using manually collected grouped income data for urban households, we construct different measures of income inequality (three Gini coefficients and one Theil index) for 30 Chinese provinces in the past three decades to explore fully variations of income distribution across regions and over time. Second, we characterize the economic transition using a partially linear semi-parametric model and quantify the causal effects of financial depth on inequality using different IVs for financial depth. We show that parametric estimations face serious model misspecifications and produce biased predictions due to the inappropriate consideration of economic transition. Our work identifies the highly non-linear effects of financial deepening and provides a test for the competing theories.[2] Third, we quantify the importance of financial depth in explaining the variations of the urban income inequality during economic transition. Relative to other factors, financial deepening plays a non-negligible role in driving income distribution, lending support to theoretical studies. Fourth, by allowing for bivariate and non-linear correlations, we extend the model to identify possible channels through which financial depth operates on income distribution. These factors facilitate policy evaluations and design of the effects of financial development.

Finally, some cross-country studies also mentioned nonlinear relationships. Among these studies, Clarke *et al.* (2006) pointed out the necessity of paying attention to the process of economic development, as different mechanisms may dominate in different periods and across different regions. Kim and Lin (2011) analyzed the threshold effects of financial development on income inequality across countries. Liu *et al.* (2017) investigated similar effects across Chinese provinces in the form of a quadratic term and the threshold effects. Madsen *et al.* (2018) found that the relationship between inequality and growth varies with the stage of financial development. Compared to cross-country studies, our work benefits from the consistent variable measurement and institutional factors within a single country. Moreover, our paper explores the nonlinear relationship that differs from previous studies. As China's reform features gradualism, it leads to a gradually varying finance-inequality nexus across regions and over time. In parametric regressions (with threshold effects, squared terms, interactive terms, etc.) it can be difficult to capture the fully-fledged nonlinearity along the transition path.[3] Our method, however, allows us to focus on the smooth transition of the marginal impacts of financial depth. It also reveals the evolving strength of the working channels through which finance impacts income inequality during economic transition.

The remainder of this paper is organized as follows. Section 2 describes the model specifications and the variable definitions. Section 3 introduces the estimation strategies. Section 4 discusses the estimation results and the robustness checks and section 5 examines the working channels. Section 6 summarizes the paper, with discussions on policy implications.

[2] Theory makes mixed predictions about the finance-inequality linkage. Some studies argue for an inverted-U shaped relationship; income inequality widens in the early state and declines as financial structure matures (Greenwood and Jovanovic, 1990). Some studies argue for a negative relationship because a better functioning financial system benefits the poor by facilitating their human capital investment and improving their wage returns (Banerjee and Newman, 1993; Galor and Zeira, 1993). Others have claimed the possibility of a positive relationship; more developed financial sectors still prefer to lend more to the rich who are able to provide collateral (Rajan and Zingales, 2003; Townsend and Ueda, 2006; Claessens and Perotti, 2007). See the recent summary by Baiardi and Morana (2018).

[3] Although the panel threshold regression allows possible nonlinearity arising from different stages of financial development, it presupposes that the finance-inequality nexus is piecewise-linear and monotonic below and above the threshold(s). As in the case of quadratic terms, it faces a misspecification problem. Moreover, it is difficult to explore the working channels of finance through such a specification.

Details on data collection, variable construction, and supplementary results are collected and put into the online Appendices A-D.

2 Model and Variables

2.1 Model Specifications

Given our research interest in the finance-inequality linkage, we specify a partially linear model, as follows:

$$y_{it} = m(x_{it-1}) + \omega_{it-1}^{'}\phi + \alpha_i + \gamma_t + u_{it} \tag{1}$$

where y denotes a measure of income inequality; $m(\cdot)$ is an unknown function of financial depth (x); ω is a vector of control variables; and u is a random disturbance term. Equation (1) is a two-way fixed effects model with α and γ representing provincial- and time-specific effects, respectively. The nonparametric component $m(\cdot)$ can take any functional form between finance and inequality and allows for unknown forms of nonlinearity in both variables and coefficients to incorporate the impacts of economic transition flexibly. In addition to the strategy introduced in section 3 (*i.e.*, control function instrumental variable estimations), we lag all explanatory variables (x and ω) by one period to further alleviate the possible endogeneity problem. We are interested in the estimated pattern of m and its gradient $\beta(x_{it-1}) = \frac{\partial y_{it}}{\partial x_{it-1}} = \frac{\partial m(x_{it-1})}{\partial x_{it-1}}$. The former represents the fitted value of the unknown functional form m, *i.e.*, the pattern of income inequality when financial depth varies. The latter governs the slope of the fitted $m(x_{it-1})$, describing the marginal impacts of financial depth on income inequality with other variables being accounted for.

2.2 Income Inequality

Income inequality can be measured by different ways. One popular and feasible measure is the Gini coefficient ($Gini$), which varies between 0 and 1, with a larger value indicating a higher level of inequality. Gini coefficients can be calculated either from survey data or grouped income data. The former type of data features a rich set of household information but lacks a long time horizon and national coverage (Piketty and Saez, 2014). Given our research interests over a relatively long time horizon of economic transition, we calculate annual Gini coefficients of urban households for 30 Chinese provinces using manually-collected grouped disposable income data during the period 1981-2016.[4] With different functional

[4] China has three types of provincial administrative units: municipalities, autonomous regions and provinces. In this study we use "province" to represent all three types.

forms of the Lorenz curve, we adopt three approaches to calculate Gini coefficients: the area approach ($Gini1$), the polynomial approach ($Gini2$), and the World Bank approach ($Gini3$). Appendix A details the calculation process and the assumptions made by each approach on the specification of the Lorenz curve.

Another popular measure regarding the dispersion of income is the Theil index, which is sensitive to transfers of income from poor to rich. Essentially the Theil index calculates the average of the logarithms of the reciprocals of income shares weighted by income. As introduced in Appendix A, we calculate the annual Theil index for each province during the sample period using the grouped disposable income and population data.

In this paper, we focus our attention on income inequality among urban households of each province. Data availability is one reason: more than 70% of the observations are missing in the rural area. With rural households incorporated, the resulting sample will lose reasonable representativeness and hinder the accuracy and reliability of estimations. More importantly, if we bring in rural households, we have to deal with the urban-rural income gap, rural inequality, and related issues properly. All of them are important issues for the overall income distribution in China but their determinants are dominated by institutional and political factors, such as the Hukou (household registration) system and differentiated industrial policies, other than finance and other market forces. Given our interest to explore the finance-inequality linkage and to reveal the varying effects of financial depth over time and across regions, an environment including rural areas becomes less tempting within the current framework.

2.3 Financial Depth

The key explanatory variable in equation (1) is financial depth. Financial development is a multi-dimensional concept. In an influential survey, Levine (2005) summarizes five broad functions of the financial system to ease information, enforcement, and transaction costs that eventually influence savings and investment decisions.[5] He also raises an important qualification in the survey: it is difficult to measure financial development and to link empirical constructs with theoretical concepts. Leading indicators of financial development used in the (international) studies include (i) the liquid liabilities of financial intermediaries divided by GDP (King and Levine, 1993), (ii) the degree of public ownership of banks (La Porta *et al.*, 1999), (iii) the bank assets divided by GDP (Clarke *et al.*, 2006), and (iv) bank

[5] According to Levine (2005), financial systems (i) produce information ex ante about possible investments and allocate capital, (ii) monitor investments and exert corporate governance after providing finance, (iii) facilitate the trading, diversification, and management of risk, (iv) mobilize and pool savings, and (v) ease the exchange of goods and services.

credit to the private sector (Beck *et al.*, 2000). In this paper, we do not aim to innovate in the measurement of financial development as most of the above indicators are appropriate in cross-country studies. Considering the cross-region analysis within a country and the data limitation, we focus our attention on the perspective of financial deepening. We resort to the regional bank loans that closely reflect local savings and investment decisions to measure regional aggregate depth of the financial system or regional size of the financial sector (Levine, 2005). Specifically, financial depth is defined as the year-end loans divided by provincial GDP; *i.e.*, the unit of bank credit corresponding to one unit of output. As detailed in Appendix B, the difference between FD1 and FD2 is that the former includes loans denominated in both Renminbi (RMB) and other currencies, whereas the latter includes only RMB-denominated loans.

2.4 Control Variables

In addition to financial depth, we follow the literature and incorporate other factors in the vector ω as control variables.[6] Table 1 summarizes all control variables that we have considered and Table 2 provides the descriptive statistics. Among these variables, the first is real GDP per capita in natural log and its squared term, controlling for the direct effects of economic development on income distribution. During the process of economic transition, industrialization and urbanization have been discussed frequently as important driving forces behind income distribution; we use the ratio of the value added in the secondary and tertiary industries to GDP as a measure of sectoral structure (industrialization) and use the ratio of the year-end population living in urban areas to total population as a measure of urbanization.

Government expenditure constitutes a factor that may affect income distribution. We use the GDP fraction of government expenditure to measure government size. A similar role is played by the state owned enterprises (SOEs), which may lead to more evenly distributed income across people; we use the percentage of workers employed by the SOEs to measure economic ownership.

Other institutional and demographic factors are also considered. Population size (in log) is incorporated to control for the effects of population growth on income distribution. In addition to its size, population may differ across regions in other aspects. (i) Ethnic, linguistic, or religious fractionalization may affect income distribution because people may be reluctant to location redistribution when diversity is greater. In the context of different provinces in China, we use the fraction of minority population (all nationalities other than

[6] Representative studies include Clarke *et al.* (2006), Claessens and Perotti (2007), Cai *et al.* (2010), Piketty and Saez (2014), Zhou (2014), and Darvas (2019), among others.

'Han') in each province to characterize fractionalization. (ii) Workers' status in the labor market (being either employed or unemployed) directly affects their income; we use the urban unemployment rate to measure labor market conditions in each province. (iii) Education contributes to the accumulation of human capital which in turn changes income distribution. We calculate the average years of education in each province and use its natural log to measure the degree of education and human capital accumulation.

Price fluctuations also affect income distribution because inflation hurts the poor relatively more than it hurts the rich. We use the consumer price index (CPI) to calculate the inflation rate and control for its effects. In addition, housing price movements significantly affect agents' credit demand and income flow; we incorporate the logarithm of the average selling price of commercialized buildings to measure the effects of housing price movements.

Technical progress increases the demand for skilled workers relative to unskilled workers, accounting for skill premium and changing income distribution. We collect the transaction value of technical contracts and use its ratio to GDP to measure technical progress and the degree of innovation in each province.

In addition to the above closed-economy factors, open-economy factors are also considered. Trade openness describes the external connection an economy has through international trade and affects the economic development and income distribution simultaneously. It is measured by the GDP fraction of trade volume (exports plus imports). Foreign direct investment (FDI), through the channel of international finance, can come in with different types of production technology, boosting the demand for either skilled or unskilled workers and affecting inequality. We include the ratio of FDI to GDP to capture its effects.

Analysis in this paper will be based on annual provincial panel data within China. Therefore some factors explored in the literature, which are not changing over time (*e.g.*, the initial levels of income distribution, schooling, and GDP) or varying across regions (*e.g.*, the status of property rights, civil liberty, country risk), are controlled for by the fixed effects α_i or γ_t in equation (1), along with other unobservable heterogeneity that may arise.

3 Estimation Strategy

3.1 Estimation Procedure

Given our interests in the finance-inequality dynamics during economic transition, a proper estimation technique should be flexible enough to deal with the unknown-form nonlinearity of model specifications and coefficients and permit possible variations of this relationship over time and across regions. Simple parametric regressions typically fail to reach the above targets (Frazer, 2005; Townsend and Ueda, 2006). In this paper, we resort to a semi-parametric estimation that features a partially linear model specification. The non-parametric component is able to capture the nonlinear finance-inequality relationship of any type. Using notations in equation (1), it means that we will not impose any restrictions on the specification of m. Our empirical model will allow us to estimate $m(x_{it-1})$ and gradient $\beta(x_{it-1}) = \frac{\partial m(x_{it-1})}{\partial x_{it-1}}$ for each observation of financial depth during the transition process.

Another advantage of our estimation procedure lies in the fact that the endogeneity of financial depth can be tested directly.[7] Solving endogeneity issues used to be challenging in nonparametric (semi-parametric) estimations. We adopt the strategy of Ozabaci *et al.* (2014) and extend it to the panel data setup to identify the non-linear causal effects of financial depth on income distribution. Control variables discussed in section 2.4 are included parametrically to alleviate the 'curse of dimensionality', hence leading to a partially linear model. The estimation strategy includes the following three steps.

Step 1: let z_{it} denote a valid IV for financial depth x_{it} and run the following regression

$$x_{it} = f(z_{it}) + \omega_{it}^{'}\delta + \alpha_i + \gamma_t + v_{it} \tag{2}$$

where f is an unknown function of z; ω is the same vector of control variables as in (1); and α_i and γ_t represent the provincial- and time-specific effects. Equation (2) is estimated using the approach of B-spline. Specifically, z is expanded as cubic B-spline basis functions and each function is multiplied by a coefficient. That is, f is approximated by a linear combination of cubic B-spline basis functions.[8] By doing this, we are able to perform a joint test on the significance of the B-spline expansion coefficients in f and check the correlation between the IV and x_{it}. Estimation of equation (2) generates $\widehat{v}_{it}$, which is related to x_{it} but is orthogonal to z_{it}.

Step 2: add $\widehat{v}_{it-1}$ to equation (1) and run the following regression

$$y_{it} = m(x_{it-1}) + g(\widehat{v}_{it-1}) + \omega_{it-1}^{'}\phi + \alpha_i + \gamma_t + u_{it} \tag{3}$$

[7]The endogeneity of financial depth is justified in both theoretical and empirical studies. As explored in most general equilibrium theories (*e.g.*, Greenwood and Jovanovic, 1990; Galor and Zeira, 1993; Banerjee and Newman, 1993; Buera and Shin, 2013; Alvarez-Cuadrado and Japaridze, 2017; Ghossoub and Reed, 2017), financial development and income distribution are determined simultaneously in the process of economic growth. There is also a growing body of literature that explores the reverse causal impacts of inequality on financial development, in particular after the great recession. See, for example, the discussions in de Haan and Sturm (2017) and the references therein.

[8]Here we follow estimation specifications in Ozabaci *et al.* (2014). The number of knots is specified as $\lfloor 2N^{\frac{1}{5}} \rfloor$, where $\lfloor \cdot \rfloor$ denotes the integer part of $\cdot$ and N is the sample size. The knots are placed at evenly-spaced percentiles.

where m and g are unknown functions of x and $\widehat{v}$, respectively. Equation (3) is also estimated using the approach of B-spline by expanding m and g. The endogeneity of financial depth is indicated by the statistical significance of the coefficients in g, which can be tested directly. Due to the addition of g, equation (3) resolves the endogeneity problem and generates consistent estimates of $\widehat{m}$, $\widehat{\phi}$, $\widehat{\alpha}$, $\widehat{\gamma}$, and $\widehat{g}$ (*i.e.*, the control function approach).

Step 3: define the *net Gini (or net Theil)* $\widetilde{y}_{it}$ as

$$\widetilde{y}_{it} = y_{it} - \widehat{g}(\widehat{v}_{it-1}) - \omega'_{it-1}\widehat{\phi} - \widehat{\alpha}_i - \widehat{\gamma}_t \tag{4}$$

and run the following nonparametric regression

$$\widetilde{y}_{it} = m(x_{it-1}) + \varepsilon_{it} \tag{5}$$

By subtracting all explanatory variables other than financial depth from Gini (Theil), the resulting *net Gini (or net Theil)* $\widetilde{y}_{it}$, by construction, is affected only by financial depth plus some random noise. A local linear estimation with a Gaussian kernel is then applied, along with Hurvich *et al.*'s (1998) AIC approach for bandwidth selection. Equation (5) produces an estimated relationship both between $\widetilde{y}_{it}$ and x_{it-1} and between $\widetilde{\beta}_{it-1}$ $\left(\equiv \frac{\partial \widetilde{y}_{it}}{\partial x_{it-1}}\right)$ and x_{it-1}. The former delivers the empirical finance-inequality linkage and the latter concerns the marginal impacts. We also calculate the 95% confidence interval for the fitted net Gini (or net Theil) and gradients according to the asymptotic property derived in Ozabaci *et al.* (2014).[9]

3.2 Instrumental Variables

Given our panel data setup, a qualified instrumental variable z should vary in both time and regional dimensions. We use two separate methods to construct our IV. The first one relies on the entry behavior of modern foreign banks in each province during 1842-1949; the second one focuses on the competitive behavior among provinces due to local developmentalism.

For the first one, we use $entry_i$ — the number of modern foreign banks that entered province i between the First Opium War (1840-1842) and 1949, when the the P.R. China was established — to construct the IV for financial depth in province i. Before the First Opium

[9] Our analysis in section 4 could have been performed based on estimations in step 2, which also deliver consistent estimates. We move to step 3 for two reasons. First, as shown in Ozabaci *et al.* (2014), a non-parametric regression improves upon the efficiency, hence the accuracy of our analysis. Second, the B-spline approach in step 2 complicates the calculation of the standard errors of the non-parametric component $m(\cdot)$. With step 3 we can significantly reduce the computational burden.

War, China was relatively closed under the governance of the Qing dynasty. The financial sector only consisted of domestic native banks. The First Opium War opened China's door to the outside world and modern foreign banks began to enter. The first entry took place in 1845 in Guangdong province, where the financial system was relatively well-developed. This was then followed by entries in other provinces with a relatively mature financial sector. The more entries that happened in a province, the more advanced was the financial system in that province. Moreover, if the financial sector in one province was well-developed in the past, there is a high chance that this province has a well-established financial industry nowadays. This close relationship can be explained by institutional, cultural, and other factors (*e.g.*, Chen *et al.*, 2020). Therefore, the number of foreign bank entries, $entry_i$, is expected to be positively correlated with the current degree of financial development.

As for the exogeneity of $entry_i$, when to enter which province mainly serves the military and political purposes of foreign investors from different countries *back then*, largely exogenous to the *current* income distribution of that province. A legitimate concern may arise, however. There may be some factors that shaped foreign bank entry in the 19th century also affecting the current income distributions, particularly those time-invariant factors including the geographic location. We make various efforts to address this issue. First, we refine our model specification to mitigate this concern. A panel data model with two-way fixed effects is specified in equation (1) to directly address the effects of time-invariant variables and alleviate the endogeneity issue. Time-varying variables related to geographic locations, such as trade openness and FDI, are also incorporated as part of the control variables in ω to minimize the non-finance channels through which $entry_i$ affects income distribution. Second, following Henderson *et al.* (HPP, 2013), we add the constructed IV into the initial regression mode (*i.e.*, equation 1) and check its statistical significance. The idea of this HPP test is that a valid IV should not be related to the error term (*i.e.*, affecting income inequality through other channels) and it should be insignificant when put into the initial model. Third, as introduced below, we also consider alternative ways to construct the IV. If the IV from an alternative set of information produces similar results, then they do not appear to be driven by simultaneity bias.

The alternative set of information comes from the competitive behavior among Chinese provinces. In the literature, it is related to the political tournament effects (Chen *et al.*, 2005; Li and Zhou, 2005), the prevailing local developmentalism (Su *et al.*, 2012), and regional segmentation in China (Boyreau-Debray and Wei, 2004). Specifically, we use $x_{-i,t-s}$, the s-period lagged degree of financial depth of all provinces other than province i, to instrument financial depth in province i. We argue that $x_{-i,t-s}$ is related to financial depth x_{it} but exogenous to income inequality y_{it}.

On the one hand, competition across provinces leads to a negative correlation between financial depth within and outside of a province. At any point of time, the total amount of financial resources (*e.g.*, bank credit, deposits, FDI, and preferential policy) is fixed on the national level. If one province exhibits better and/or faster financial development, more financial resources will be attracted into this province. *With other control variables taken into account*, a higher degree of financial depth in one province is accompanied by a lower degree of financial depth outside of this province. This argument is tested and verified by our data (see the discussion in section 4.2 and Figure 1).[10]

On the other hand, the competitive behavior of provinces also justify the exogeneity of the IV. Due to the tournament effects among provinces for GDP growth, political career paths, foreign investment, and central government support, etc., financial activities in any other province $j(\neq i)$ serve certainly their local economic development and will not aim to improve province i's income distribution. This argument for local developmentalism is consistent with the empirical finding that Chinese provinces feature regional segmentation (Boyreau-Debray and Wei, 2004). Therefore, financial development outside of province i is essentially exogenous to the income distribution within province i.

Despite these arguments, a similar concern may still arise for $x_{-i,t}$ on its exogeneity as in the case of $entry_i$. We lag this IV by s periods to further strengthen its exogeneity. As robustness checks, we compare results based on different IVs and discuss the extent to which the results may change in section 4.3.1.

In the following baseline estimations, we combine $entry_i$ with $x_{-i,t-s}$ to construct the IV for financial depth in province i, *i.e.*, $z_{it} = x_{-i,t-s}/entry_i$. By construction, the extended IV z incorporates information of both foreign bank entry and provincial tournament effects and it is negatively correlated with financial depth. In the robustness analysis, we will examine the model's performance when the entry behavior of modern foreign banks and the competing behavior of provinces are used separately as instruments.

[10] One may argue that the competition among provinces appears within the same country and financial deepening takes place simultaneously across all regions following national events/policies. It is noted, however, that the above negative comovement between financial depth within and outside of a province is conditional on the time- and individual-fixed effects and the variations of all control variables. As shown in equation (2) and Figure 1, we only claim a negative correlation between x_{it} and $x_{-i,t-s}$ given all other variables.

4 Empirical Analysis

4.1 Data

This paper uses a provincial-level panel data set. The sample spans from 1981 to 2016 with annual frequency for 30 provincial regions, with some observations missing in the early years.[11] Our major data source is the provincial Statistical Yearbook from 1982-2017 for 31 Chinese provincial regions. Other data sources include the China Compendium of Statistics 1949-2008 and various issues of the China Statistics Yearbook from 1982-2017. Data for modern foreign banks come from Lin *et al.* (2019) and resources therein.

We begin our analysis in the early 1980s for two major reasons. First, China's reform began at the end of 1970s. Before that, the Chinese economy was better characterized by a planned economy: income distribution was not affected much by market factors, and China did not have a market-based financial system. Second, the provincial Statistical Yearbook was not published regularly until 1981 or later in most provinces. Therefore, data earlier than 1980 are mostly unavailable from public data sources.

Following the variable definitions in section 2, significant efforts were made to construct all the variables needed. Appendices A, B, and C detail the procedure and methodology we adopted to construct the measure of inequality, financial depth, and control variables. The tedious data work laid the foundation for the following estimations and analyses.

4.2 Baseline Estimations

We begin discussing the empirical results in this section. First of all, we perform a baseline estimation with (i) the Gini coefficients based on the World Bank approach ($y = Gini3$), (ii) the financial depth based on total year-end loans ($x = FD1$), (iii) the instrumental variable lagged by order 0 ($z_{it} = x_{-i,t}/entry_i$), and (iv) the removal of 1% extreme observations from both tails of financial depth.[12]

Following section 3.1, we first run the three-step procedure without considering any control variables in ω. Panel 1 of Figure 1 illustrates graphically the estimation result of step 1 in equation (2). The horizontal axis is the IV, z_{it}, and the vertical axis is the fraction of financial depth explained by the IV, $\hat{f}(z_{it})$. With a two-way fixed effects panel data model considered, a clearly negative relationship appears between the IV and financial depth, confirming our previous argument of local developmentalism. We then perform a joint test on the significance of the expansion coefficients in f. The resulting F statistic reported in

[11] Chongqing and Sichuan are combined for consistent measurement of variables.

[12] Other levels of winsorization, *e.g.*, 0.5% and 1.5%, produce similar results.

column 1 of Table 3 is 6.3796 with a probability of 0.0000, excluding the case of an irrelevant IV. When we put the IV into equation (1) following Henderson *et al.* (2013), the HPP test statistic is 1.0778 with a probability of 0.3767, rejecting the existence of non-finance channels through which the IV affects income distribution. These two tests, combined together, lend empirical support to the validity of the constructed IV. Column 1 also reports the F test on the joint significance of the expansion coefficients in g from step 2. The probability of 0.0000 suggests strongly the endogeneity of financial depth, justifying the necessity of using an IV.

Due to the adoption of semi-parametric methods, we obtain $\widetilde{m}$ and $\widetilde{\beta}$ for each observation of x_{it} during the process of economic transition. Main results are reported in graphical forms supplemented by tables. Panel 1 of Figure 2 shows the estimation results from step 3, the estimated relationship of net Gini and financial depth. The black and solid line represents the fitted $\widetilde{m}$, while the red and dotted lines indicate its 95% confidence intervals. First, our estimations clearly identify a highly non-linear relationship between financial depth and income inequality along the transition process. When the level of financial depth is low, income inequality widens with the degree of financial depth. After a certain threshold, further financial deepening begins reducing income inequality. This finding shows the existence of a roughly inverted-U shaped pattern, more precisely, a roughly inverted-L shaped pattern during the process of economic transition, consistent with the prediction of Greenwood and Jovanovic (1990). Second, the pattern is not symmetric: it is left-skewed with a long left tail. Over a relatively long process, income inequality increases with financial depth. Once the turning point is passed, the curve declines faster, and inequality decreases with further financial deepening. Third, financial depth accounts for a significant fraction of the variations of urban Gini. From panel 1 in Figure 2, the fitted net Gini, *i.e.*, the fraction of Gini explained solely by financial depth, ranges from -0.0049 to 0.0340.[13] We calculated the average Gini across provinces during the sample period, and the result ranges from 0.12 to 0.32. This suggests that financial depth alone explains approximately (0.0340+0.0049)/(0.32-0.12)=19.45% of the total variations of urban income inequality during the sample period.[14]

Next, we take into account all control variables discussed in section 2.4. Panel 2 of Figure 1 illustrates graphically the relationship between the IV and financial depth estimated from

[13] The Gini coefficients always take positive values. Here the net Gini represents Gini minus its second-stage predictions $\widehat{Gini}$ excluding financial depth in order to isolate the impact of financial depth in graphical form. See equation (4) for definitions. The pattern and range of the fitted net Gini indicate how and to what extent financial depth alone impacts income inequality.

[14] In an important work, Cai *et al.* (2010) compiled a data set using Urban Household Income and Expenditure Survey (UHIES) during 1992-2003. After decomposing the overall urban inequality into the inequality explained by observable individual differences and residual inequality, they found that the former explained less than 40% of the overall variations of urban inequality. Although our work employs a different data set, compared to the 40% contributed by all observable factors, the 19.45% of the variations of urban income inequality suggest a non-negligible role of financial depth relative to other factors.

step 1 in equation (2). With additional control variables considered in ω, a similarly negative pattern arises. When we perform tests of IV on the joint significance of the expansion coefficients in f, column 2 in Table 2 reports an F statistic of 5.1114, with a probability of 0.0000, suggesting a strong relationship between financial depth and the IV. Column 2 also reports the HPP test statistic of 1.4515, with a probability of 0.1548, lending support to the validity of the IV. The bottom F test on the joint significance of the expansion coefficients in g again detects the endogeneity of financial depth. However, a problem arises due to the statistical insignificance of most of the control variables in column 2. Usually, insignificant control variables do not affect the estimation and inference of key explanatory variables. But in the current three-step procedure, the insignificance of most regressors in step 2 implies a poor goodness of fit. One regressor may either be inherently irrelevant to income distribution or be correlated with other control variables and lead to joint insignificance. Either case will distort the calculation of the net Gini used in step 3 (see equation 4). In other words, those insignificant regressors contaminate the fitted net Gini and undermine the reliability of estimations in step 3. Therefore, we have to perform a careful variable selection process according to certain criteria to solve this issue. The criterion we adopt here is the Akaike information criterion (AIC): we carefully compare various combinations of control variables and stick with the one that best explain income inequality, *i.e.*, the one that minimizes AIC.[15] This process allows us to end up with a specification with seven regressors in step 2. Column 3 in Table 2 reports the estimated coefficients of these variables.

Panel 2 of Figure 2 plots the fitted net Gini from step 3 after performing the variable selection process. Compared to panel 1, the inverted-L shaped pattern with asymmetric left skewness looks very similar, although the right tail becomes steeper, indicating a more apparent role of financial depth toward reducing inequality. The fitted net Gini ranges from -0.0061 to 0.0236 and financial depth alone accounts for about 14.81% of the total Gini variations in urban areas.

4.3 Robustness

The previous section confirms the qualitative and quantitative importance of financial depth and identifies an asymmetric and roughly inverted-L shaped relationship between financial depth and urban inequality. Are they robust to alternative variable definitions and model specifications? Can similar results be delivered by parametric models as in prior

[15] Variable selection is a well-discussed issue in empirical works. Here both forwards and backward selections have been explored. Moreover, we also tried using the criterion of R^2 and LASSO type of variable selection method. The final results are similar, with some of the surviving variables still statistically insignificant.

studies? We perform various checks below before making further analysis.

4.3.1 Alternative Measures of Variables

Income Inequality

We use three alternative measures of income inequality, including two Gini coefficients based on the area approach ($Gini1$) and the polynomial approach ($Gini2$), and the Theil index, while keeping other settings unchanged in the baseline estimations.

Figure 3 shows the estimated relationship between financial depth and the net Gini (net Theil), with panels 1 to 3 adopting the inequality measure of $Gini1$, $Gini2$, and the Theil index, respectively. When we either change to alternatively calculated Gini coefficients or use the Theil index, the resulting curves look very similar: income inequality increases with financial depth in the early stage and then decreases with financial depth after a threshold value. The estimated pattern is still asymmetric, with a long left tail. With alternative inequality measures, financial depth alone explains 12.40% to 15.00% of the overall urban inequality.

Financial Depth

We use $FD2$ to replace $FD1$ in the baseline estimation. As the definition of $FD2$ excludes non-RMB-denominated loans from $FD1$, we would expect that the overall effects of finance will weaken, as $FD2$ only incorporates part of the total bank credit.

Results in Figure 4 agree with our conjecture. When removing non-RMB-denominated loans from the calculation of financial depth, the increasing and then decreasing pattern still arises. But the long left tail becomes more apparent due to the smaller range of $FD2$. Financial depth reduces inequality after a threshold value, confirming the robustness of the pattern. In this case financial depth alone explains 13.84% of the overall urban inequality.

Instrumental Variables

In this section, we discuss how and to what extent our results change with alternative IVs. First, we use a lagged IV. We lag the financial depth outside of province i by either one ($x_{-i,t-1}$) or two periods ($x_{-i,t-2}$) to augment $entry_i$ to construct the IV. These estimations are reported in the top two panels of Figure 5. In both panels, the estimated pattern is both qualitatively and quantitatively similar to what we had in Figure 2.

Second, we rely solely on the entry behavior of modern foreign banks in each province during 1842-1949. Since the $entry_i$ variable does not change over time, we augment this variable with an exogenous time trend, *i.e.*, $z_{it} = t \cdot entry_i$ to construct a valid IV for financial depth. Results are reported in the bottom left panel of Figure 5. Compared to the baseline results in Figure 2, the increasing trend before the turning point becomes more apparent. According to this figure, financial depth alone explains about 27.78% of the overall variations of urban Gini.

Third, we rely solely on the competitive behavior among provinces due to local developmentalism, $z_{it} = x_{-i,t}$. Results are reported in the bottom right panel of Figure 5. Compared to the baseline results in Figure 2, the familiar inverted-L shaped pattern arises again and the decreasing trend becomes more apparent on the right. According to this figure, financial depth alone explains about 13.55% of the overall variations of urban Gini.[16]

Through the above exercises, we find that the estimated relationship between financial depth and urban inequality is robust across alternatively constructed IVs. The quantitative fraction of Gini variations that financial depth accounts for changes with IVs but the inverted-L shaped pattern does not seem to be driven by the simultaneity bias. Through all cases, financial deepening alone explains 13.55% to 27.78% of the overall urban inequality, centering around the baseline estimation (14.81%).

4.3.2 Alternative Model Specifications

Linear Trend

In our baseline estimations, we include various control variables in addition to the financial depth to explain income distribution. One may find that some variables are growing over time. Our data show that six variables, including real GDP per capita and its squared term, population, years of education, industrialization, housing price, and urbanization, contain a linear time trend. One possibility we need to exclude is that the estimation results may be driven by a time trend, and not the variables discussed. To explore this possibility, we first add a linear trend directly into the baseline estimation of equation (1). The results are shown in panel 1 of Figure 6 and are very similar to the pattern in Figure 2. Adding a time trend does not alter our basic finding.

We then perform another experiment: we first take the log difference for real GDP per capita and its squared term, population, and housing price, and we then put the detrended variables and the remaining variables (*i.e.*, government size, minority, and trade openness) back into the estimations with a linear trend. The estimation results from the third step are reported in panel 2 of Figure 6. Compared to Figure 2, the pattern is qualitatively similar, with more apparent asymmetry and a shorter negatively sloped section. Even in this case, financial depth begins to reduce inequality after a turning point.

In both cases, the inclusion of a time trend does not qualitatively change the asymmetric and inverted-L shaped pattern. Financial deepening alone explains 14.81% and 23.43% of the overall urban inequality, respectively.

[16] In this case, we also experimented with lagged IVs and the results are similar.

Dynamic Model

In the baseline estimations, we use the lagged financial depth ($x_{i,t-1}$) as the explanatory variable, which accounts for some dynamic effects on income distribution. This may not be enough to address the long-run impacts. In this section, we put the lagged value of income inequality $y_{i,t-1}$ on the right-hand side of equation (1) and use a dynamic panel specification to characterize the long-run effects.

We follow the same procedure as in section 4.2 and consider all control variables that survive after the variable selection process. The estimation result is shown in Figure 7. Compared to Figure 2, the pattern looks very similar. With the dynamic specification, financial deepening alone explains 11.19% of the overall urban inequality.

4.3.3 City Provinces and Extreme Observations

One more concern arises routinely in the analysis using Chinese provincial data: the possible influence of city provinces, *i.e.*, Beijing, Tianjin, and Shanghai.[17] All of these three municipalities are provincial administrative regions. One may argue that the recorded variables for these regions may not characterize accurately the 'local' economies, because these regions are the gateway to the rest of China. Therefore, the estimations may be distorted. If we push this argument a bit further, one may consider that the potential outliers may occur in any specific province or year and not necessarily stay close to the tails of the FD distribution that could be taken care of by winsorization.

In the Appendix D, we argue that this concern may be unnecessary in our case. We further show that, by removing each time the observations of either one specific province or one specific year from the benchmark sample, the estimated pattern of $\widetilde{m}$ in Figures D1 through D5 remains similar. None of those cases delivers qualitatively different results compared to the baseline estimations.

4.3.4 Parametric Estimations

We have shown the robustness of the finance-inequality nexus in China: it is roughly inverted-L shaped and left-skewed. In our partially linear semi-parametric model, financial depth is identified as an endogenous variable, consistent with general equilibrium theories.

Can similar findings be delivered by a parametric model as specified in prior studies? Instead of examining the proper functional form of and condition for the turning point, most

[17] The fourth municipality, Chongqing, has been integrated into Sichuan province due to its short span of data series. See footnote 12.

existing studies have specified a quadratic form of financial development in their regression.[18] We perform the following experiments by replacing the nonparametric component $m(x_{it})$ in equation (1) with one of the following four parametric formulations:

$$\begin{aligned}
\text{Linear} &: \quad m(x_{it}) = \alpha_1 x_{it} \\
\text{Quadratic} &: \quad m(x_{it}) = \alpha_1 x_{it} + \alpha_2 x_{it}^2 \\
\text{Cubic} &: \quad m(x_{it}) = \alpha_1 x_{it} + \alpha_2 x_{it}^2 + \alpha_3 x_{it}^3 \\
\text{Quartic} &: \quad m(x_{it}) = \alpha_1 x_{it} + \alpha_2 x_{it}^2 + \alpha_3 x_{it}^3 + \alpha_4 x_{it}^4
\end{aligned}$$

Other settings are kept unchanged in the baseline model. We first perform a two-stage least squares estimation using the same z and its corresponding power forms as IVs for financial depth and its power forms. We perform the Hausman-Wu test for the endogeneity of finance and report the F statistic in the bottom of Table 4. It turns out that none of these four cases successfully identified financial depth as an endogenous variable. Because of that, we then perform the ordinary least squares estimations for each case and perform a joint significance test for finance, *i.e.*, $m(x_{it})$. The results are also reported in Table 4. Despite the joint significance of $m(x_{it})$, only the quadratic polynomial obtains individual significant terms due to the multicollinearity in the higher order polynomials.

In Figure 8, we plot the estimated m from these four parametric specifications along with our baseline semi-parametric specification. Panel 1 reports the estimations with the original scale. One can see that, compared to the 'true' pattern from the semi-parametric estimation, all parametric specifications over-estimate the magnitude of m, *i.e.*, the effects of financial depth are exaggerated seriously. If we ignore the scale and focus on the slope by stacking five curves together, panel 2 compares those results. The linear specification completely misses the negatively sloped section. The quadratic formulation catches the turning point at a wrong position, over-estimates the effects of financial depth before the turning point, and under-estimates its effects after the turning point due to its failure to capture the asymmetry. The cubic formulation does not improve the fitting compared to the quadratic formulation. The quartic formulation catches both the turning point and asymmetry, but the pattern before the turning point also deviates significantly from the semi-parametric model.

Overall, the above exercise shows that, if economic transition is not accounted for properly, the estimated role of financial depth is seriously biased and even misleading in terms of both level and marginal effects. A parametric specification with either a linear or a quadratic

[18] With a focus on the development-inequality relationship, Anand and Kanbur (1993a) found that estimation results were sensitive to different functional forms. Anand and Kanbur (1993b) further derived the appropriate functional forms for different inequality measures.

form of financial depth cannot identify endogeneity or detect the significance of finance. Most importantly, it provides a biased fit to the data: inferences from and policy suggestions based on these formulations are unreliable.

5 Working Channels

Analysis in section 4 shows that financial depth has an asymmetric and non-linear impact on income inequality. In this section, we examine the question of *through which channels* financial deepening comes to affect urban income distribution. In subsection 5.1, we first try to understand which part of the households, rich or poor, is affected more by financial depth along the transition process. This is then followed by an examination of whether some variables have interacted with financial depth to affect income distribution. In particular, we explore whether the impacts of financial depth are influenced by the degree of credit constraint, the fraction of state ownership, and the level of economic development.

This is performed separately. Each time, we pick one channel variable ω^1 and put it into step 3 with financial depth in the three-step procedure of section 3.1. In other words, we specify a bivariate nonparametric regression in step 3 and replace equation (5) with

$$\widetilde{y}_{it} = m(x_{it-1}, \omega^1_{it-1}) + \varepsilon_{it} \tag{6}$$

where $\widetilde{y}_{it}$ is calculated, as in equation (4), by subtracting from y_{it} the effects of all variables other than x_{it} and ω^1_{it} in order to isolate the impacts of finance and the channel variable in graphical form. Similar to parametric estimations focusing on the coefficients of interactive terms, we calculate and compare graphically the respective *marginal* effects of financial depth on income distribution ($\widetilde{\beta}_{it} \equiv \frac{\partial m(x_{it-1}, \omega^1_{it-1})}{\partial x_{it-1}}$), conditional on different levels of ω^1 (*i.e.*, 25 and 75 percentiles).[19] All results reported are based on the baseline setting after performing the variable selection processes in step 2.

5.1 Rich or Poor Households

Using the grouped income data introduced in section 4.1, we calculated two additional measures of inequality: P50P10 and P90P50. The former calculates the ratio of the average disposable income of the middle income group to that of the lowest income group (bottom 20 percentile) whereas the latter calculates the ratio of the average disposable income of the highest income group (top 20 percentile) to that of the middle income group. These two

[19] We also performed estimations for other percentiles (*e.g.*, 35 and 65 percentiles), the results are qualitatively similar.

measures are used to capture the relative distributions of the incomes of the poor and rich compared to the median income level. With these two measures, we re-estimate equation (1) using the baseline setting but replace the inequality measure with either P50P10 or P90P50.

Panel 1 (panel 2) of Figure 9 reports the relationship between financial depth and P50P10 (P90P50). Two key findings can be summarized following a careful comparison. First, in the early stage of financial deepening, both panels show an increasing trend and panel 2 exhibits a prolonged increase compared to panel 1. The increasing trend suggests an enlarged income gap between the rich and middle-income people and between the middle-income and the poor people simultaneously along the initial deepening of the financial system. However, compared to the income gap between the middle-income and the poor people in panel 1, the steady and prolonged increase in the income gap between the rich and the middle-income people in panel 2 drives more the left skewness observed in Figure 2. Second, both panels turn to a decreasing trend with the further deepening of the financial system, although the decreasing trend occurs earlier and is quantitatively more apparent in panel 1. Further financial depth begins reducing income inequality both between the rich and middle-income people and between the middle-income and the poor people. This process is disproportionate as the poor people catch up more quickly relative to the middle-income people.

Combining both panels, when the financial system is less developed, rich people benefit more (or lose less) from financial depth. Financial deepening raises the income of the rich people disproportionately and widens the overall inequality. When the financial system is more developed, poor households gradually benefit from financial deepening. The declining inequality is driven more by poverty alleviation, a finding consistent with Beck *et al.* (2007).

5.2 Credit Constraint: Housing Price

Which channel interacts with financial depth and affects income distribution? We first examine the effects of credit constraint. According to the China Household Finance Survey (CHFS, 2015), housing asset accounts for up to 69% of total assets of Chinese households. The preference for buying, rather than renting, a house is related closely to the Chinese culture. It causes the sensitive response of income, saving, and consumption to housing price fluctuations. This motivates us to use housing price variations to capture the changing credit constraint facing households. Due to different requirements on down payments and interest rates of housing mortgage loans, poor people may face a more binding credit constraint. Soaring housing prices magnify the constraint and affect income distribution.

We set $\omega^1 =$ housing price and perform the three-step estimation procedure with equation (6). Figure 10 reports the 95% confidence intervals of the estimated *marginal effects* of financial depth on income distribution conditional on a low or high level of housing price, *i.e.*, the 25th or 75th percentiles of housing prices in our sample, respectively. Here, we report only the confidence intervals of marginal effects $\tilde{\beta}$ to demonstrate the key information delivered by the figure. We find that the confidence bands for both the high and the low levels of housing price are above zero when finance is less developed. This suggests a positive marginal impact of financial depth on inequality in the early stage of development, consistent with previous findings.

The effects become different as finance deepens. In the case of a low housing price, the red and solid confidence band becomes extremely wide when finance reaches a certain point in Figure 10: the marginal effects of financial depth eventually disappear in this case. However, when housing price is high, the blue and dotted confidence band decreases gradually and eventually turns negative. In other words, when the housing price is relatively high, even though financial depth widens inequality in the early stage, it eventually starts reducing inequality after a threshold value with statistical significance. But this is not the case when the housing price is low. Intuitively, people rely more on financial intermediaries to ease their credit constraint when buying a more expensive house. Therefore, the role of financial depth in reducing income inequality becomes more evident in the case of housing booms, *i.e.*, when agents face a higher chance of credit constraint. Financial policy should be designed toward easing people's credit constraint to better improve income distribution.

5.3 Economic Ownership: SOEs

SOEs have played a pivotal role in the Chinese economy. Transition from a planned economy to a market-oriented one implies a declining role of SOEs and growing power of the market. After setting $\omega^1 = SOEs$ and estimating the bivariate nonparametric regression (6) conditional on two levels of SOEs at the 25th and 75th percentiles, respectively, we plot the 95% confidence intervals of the estimated *marginal effects* of financial depth on income distribution in Figure 11.

In the early stage of financial depth, both confidence bands give a roughly positive marginal effect of finance on inequality: the positive relationship is consistent with Figure 2. More specifically, when the economy is dominated by SOEs, the blue and dotted confidence band fluctuates around the zero line before it becomes extremely wide. This pattern implies a limited and statistically insignificant role for the market-based financial sector to improve upon income distribution. However, when the proportion of SOEs drops to the 25th percentile, the red and solid confidence band tells a different story: financial depth still raises inequality in the early stage, but it eventually reverses the direction toward reducing inequality. This does not contradict what we observe in reality. Before 1998, SOEs accounted for a large fraction of the Chinese economy. Inequality widened with economic development and finance played a limited role. After 1998, the fraction of SOEs dropped dramatically. As the market economy has grown, the inequality-reducing role of finance has come in, so that inequality has levelled-off recently. This finding implies that financial policy can be more effective in reducing inequality when it is accompanied by deepening market reforms.

5.4 Economic Development: Real GDP per Capita

Economic development can affect income distribution directly; it can also work indirectly through financial depth (Beck *et al.*, 2007). We now explore the interactive effects of economic and financial development on income distribution. Letting ω^1= real GDP per capita in equation (6). Figure 12 illustrates the 95% confidence intervals of the estimated *marginal effects* of financial depth on income distribution conditional on two levels of real GDP per capita, the 25th and the 75th percentiles, respectively.

In both cases, the marginal effects are positive in the early stage; that is, the initial development of finance raises inequality. The effects differ significantly when financial system matures. When people are poor (red and solid confidence band), financial depth does not significantly reduce inequality regardless of how high the degree of financial depth is. Further deepening of finance can reduce inequality with certainty only when people become rich, as shown by the blue and dotted confidence band. This finding shows that financial depth cannot work mechanically without the support of economic development. A steady increase of household income, brought by decent economic growth, turns out to be extremely relevant to the proper functioning of financial depth on egalitarian income distribution.

6 Discussions and Concluding Remarks

By taking into account the effects of economic transition, we attempt to bridge the gap between the empirical studies on the finance-inequality nexus and the corresponding theoretical discussions. Through a partially linear semi-parametric model, we use a nonparametric component to characterize the evolving impacts of financial depth during the transition process. We further extend the model by employing a bivariate nonparametric model to analyze the non-linear interaction of financial depth and other variables through which finance exerts an indirect impact on income distribution.

Using China as an example of transition economies, we empirically re-examine the finance-inequality linkage and provide a test among competing theories. We establish the causal effects of financial depth on urban income distribution by addressing endogeneity via the control function approach. In particular, we make use of the entry behavior of modern foreign banks and the competitive behavior across provinces to construct instruments for financial depth. To facilitate policy making, the potential bias generated by parametric regression models is also discussed.

With the newly constructed measures of provincial income inequality during 1981-2016, we identified an asymmetric financial Kuznets curve in urban China, *i.e.*, a robust and roughly inverted-L shaped relationship between financial depth and income inequality, lending support to the predictions of Greenwood and Jovanovic (1990). Even though the exact turning point of financial depth changes with specific set of variables and model specifications, our estimations based on the partially linear model suggest that financial depth, after a prolonged process, will eventually bring down income inequality. Financial depth alone can explain 11% to 28% of the overall variations of urban income inequality during the transition process. In addition to the direct effects, our analysis suggests that financial policy-making will be more effective at enhancing egalitarian income distribution when it helps ease credit constraint, deepen market reforms, and promote economic development.

Our focus in this paper lies in the effects of financial depth on the distribution of income. An equally important issue, not explored in the current work, is the distribution of wealth. The accumulation of income flow and the initial stock of wealth both affect wealth distribution significantly over time. Our work is also silent on the effects of alternative dimensions of financial development (for example, financial access as discussed in Claessens and Perotti (2007)). Along the path of economic transition, a sub-national analysis of these important issues is left for future research.

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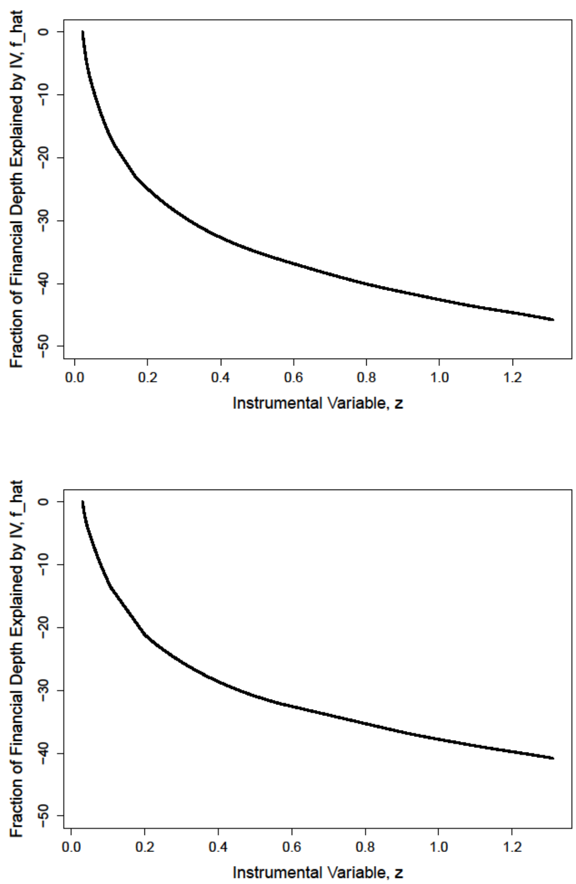
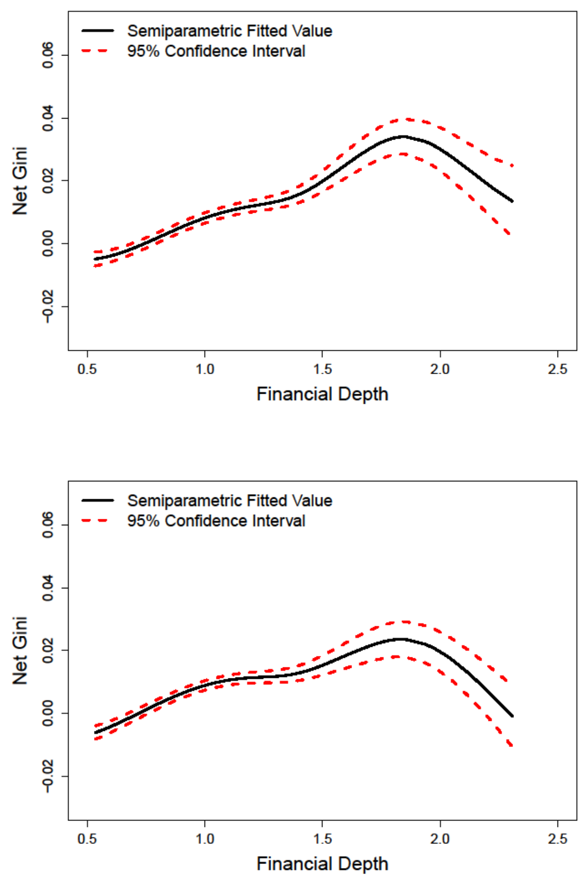
Figure 1: Relation between IV and Financial Depth



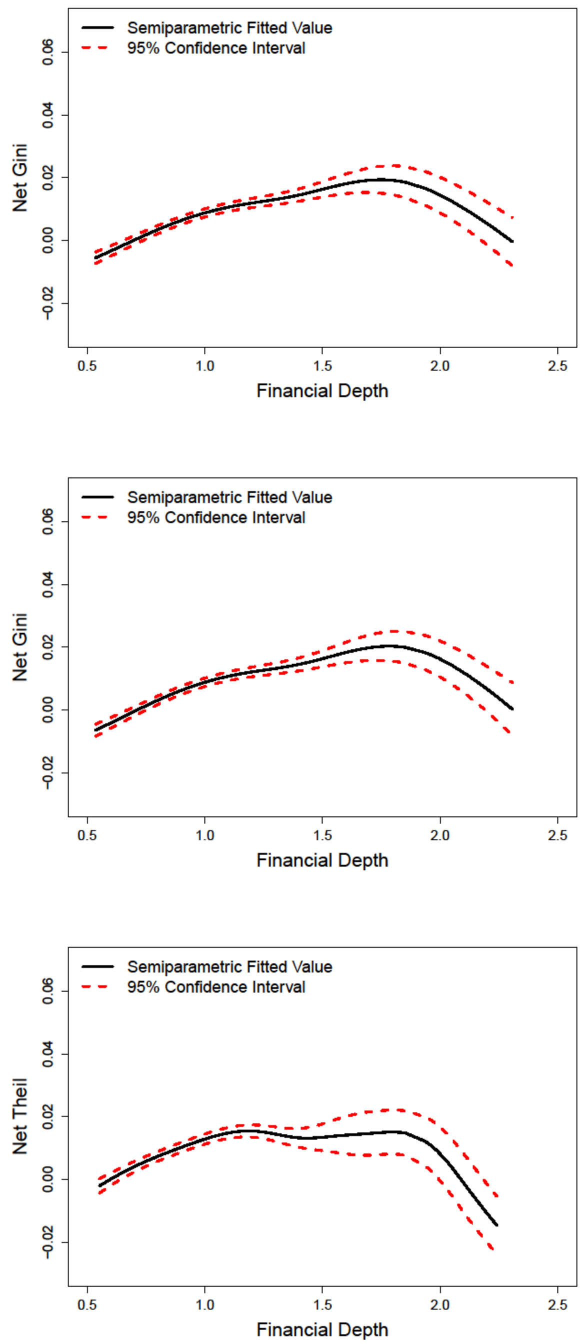
Note: This figure plots the estimated negative relationship between the IV and financial depth after controlling for all other variables in equation (2). The horizontal axis is the IV and vertical axis is the fraction of financial depth explained by the IV, *i.e.*, $\hat{f}$ in equation (2). Panel 1 shows the relation when none of the additional control variables is considered in the vector ω except for the two-way fixed effects; panel 2 shows the relation when all control variables discussed in section 2.4 are also considered in ω.

Figure 2: Net Gini and Financial Depth



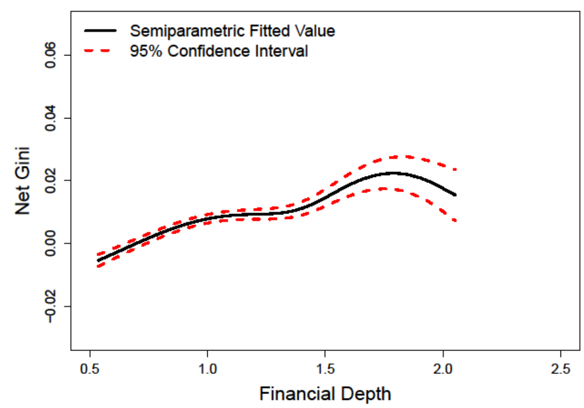
Notes: This figure reports the estimated relation between financial depth on the horizontal axis and net Gini on the vertical axis after executing the three-step procedure. Estimations in panel 1 does not include any control variable in step 2; Estimations in panel 2 include control variables. The net Gini is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

Figure 3: Robustness Checks with Alternative Measures of Income Inequality



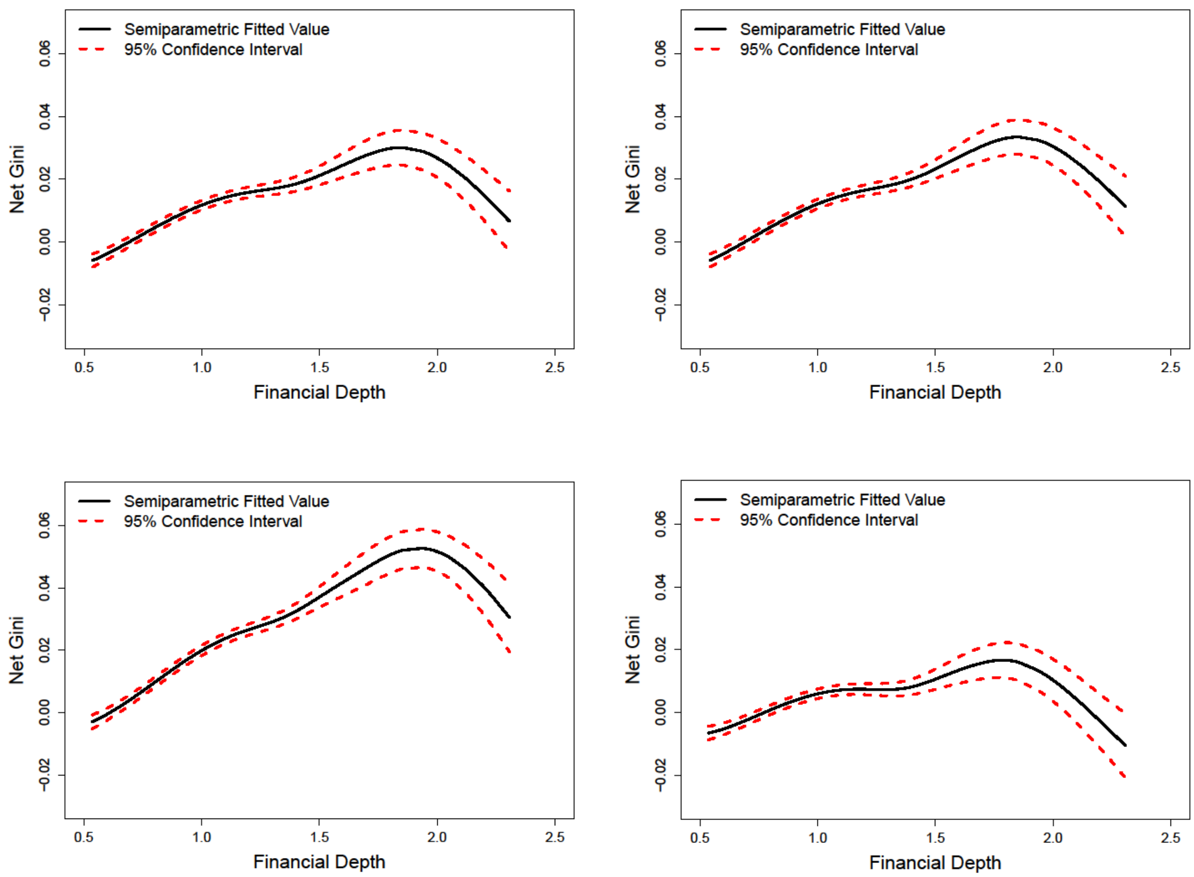
Notes: This figure reports the robustness checks for the estimated relation between financial depth and net Gini (net Theil) after executing the three-step procedure with alternative measures of income inequality. Panels 1 to 3 adopt the inequality measure of Gini1, Gini2, and Theil index, respectively. The net Gini (or net Theil) is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

Figure 4: Robustness Checks with Alternative Measures of Financial Depth



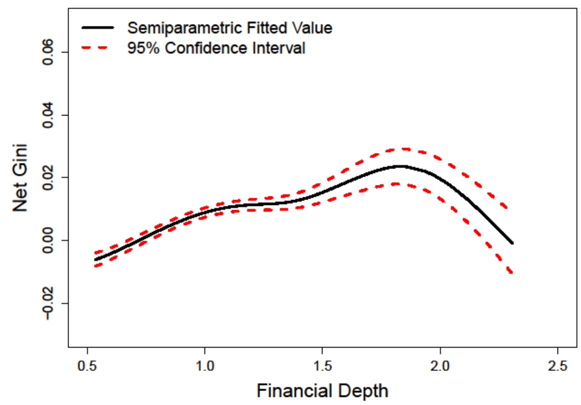
Notes: This figure reports the robustness checks for the estimated relation between financial depth and net Gini after executing the three-step procedure with alternative measures of financial depth. Here the financial depth measure, FD2, is adopted. The net Gini is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

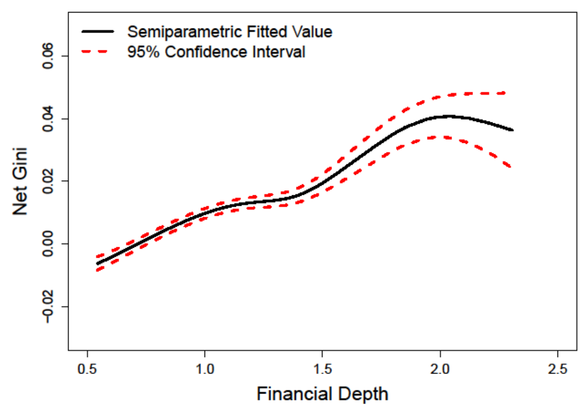
Figure 5: Robustness Checks with Alternative Measures of IV



Notes: This figure reports the robustness checks for the estimated relation between financial depth and net Gini after executing the three-step procedure with alternative measures of instrumental variables. The top two panels adopted the baseline IV but lagged by one and two periods, respectively. The bottom left panel adopted an IV constructed solely by the entry behavior of foreign banks augmented with an exogenous time trend. The bottom right panel adopted the IV based solely on the competitive behavior among provinces. The net Gini is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

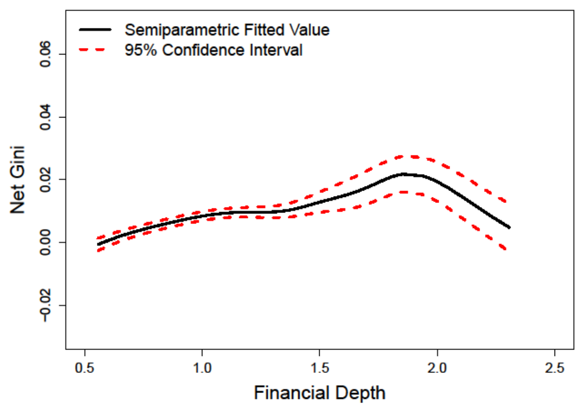
Figure 6: Robustness Checks with a Linear Trend





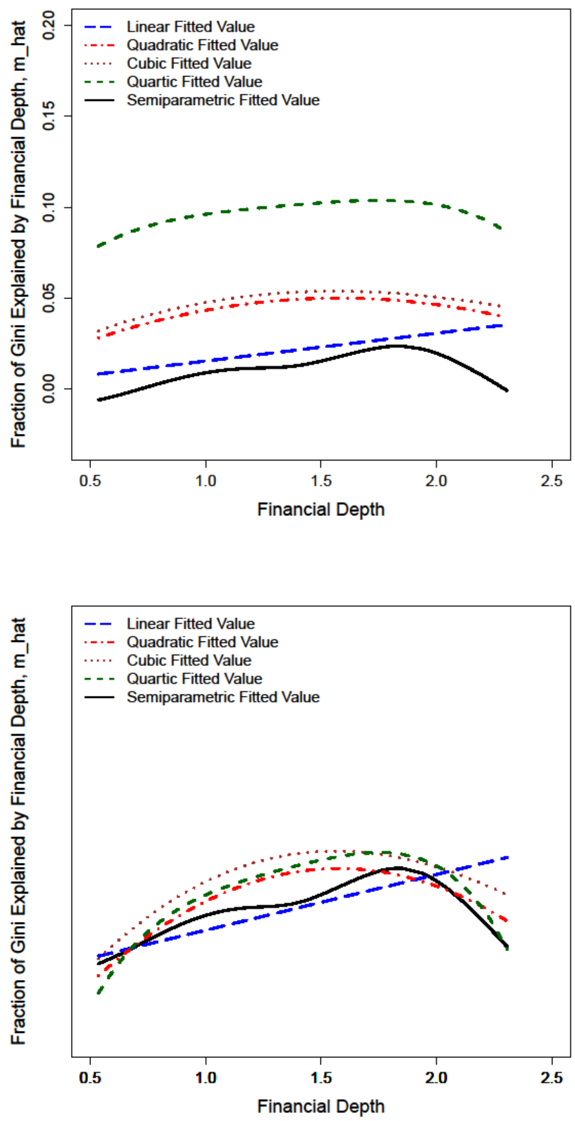
Notes: This figure reports the robustness checks for the estimated relation between financial depth and net Gini after executing the three-step procedure with a linear trend included in the model. Panel 1 reports the results when a linear trend is directly added into the model. Panel 2 corresponds to the case that growing variables are detrended before a linear trend is added to the model. The net Gini is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

Figure 7: Robustness Checks with a Dynamic Model Specification



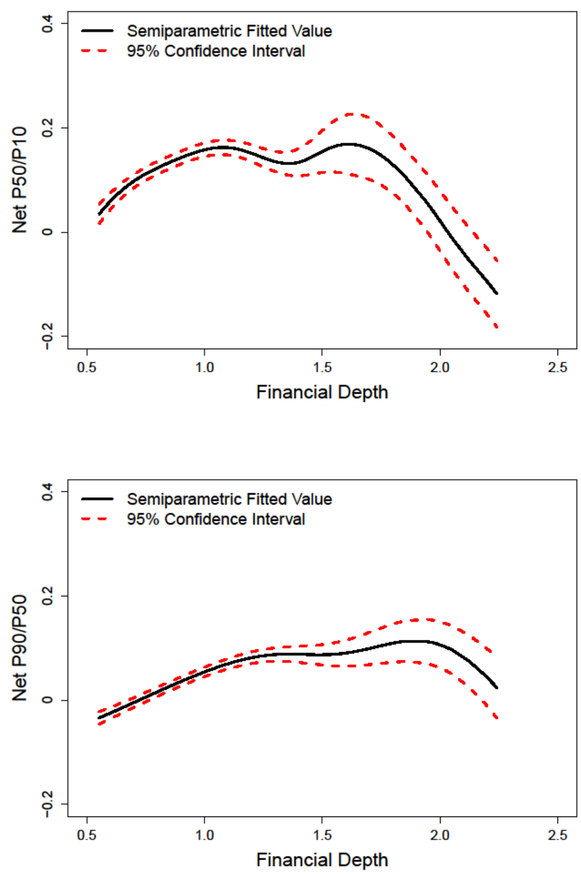
Notes: This figure reports the robustness checks for the estimated relation between financial depth and net Gini after executing the three-step procedure with a dynamic model specification. The net Gini is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

Figure 8: Comparison with Parametric Estimations



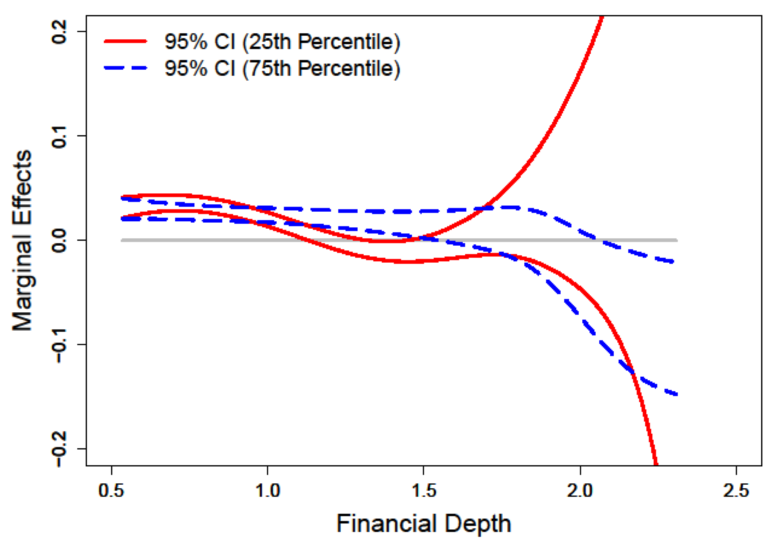
Notes: This figure compares the estimated finance-inequality relationship between different parametric formulations and the baseline semi-parametric formulation. Panel 1 reports the results with the original scale and panel 2 stacks all five curves together.

Figure 9: Impacts of Financial Depth on the Rich and Poor People



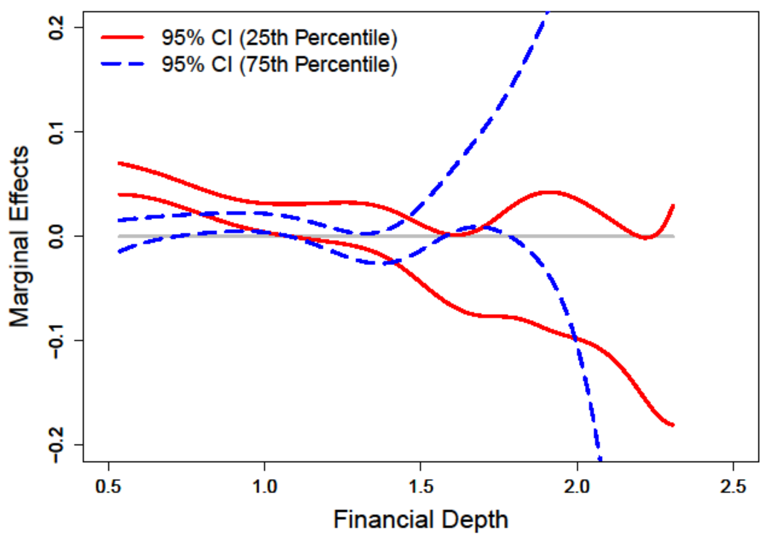
Notes: This figure reports the impacts of financial depth on the rich and poor people, respectively, after executing the three-step procedure. Panel 1 focuses on the middle income group relative to the lowest income group. Panel 2 focuses on the highest income group relative to the middle income group. The net P50/P10 (or net P90/P50) is obtained from equation (4) in step 2 and, by construction, it is not affected by other explanatory variables except for financial depth.

Figure 10: Working Channel: Credit Constraint



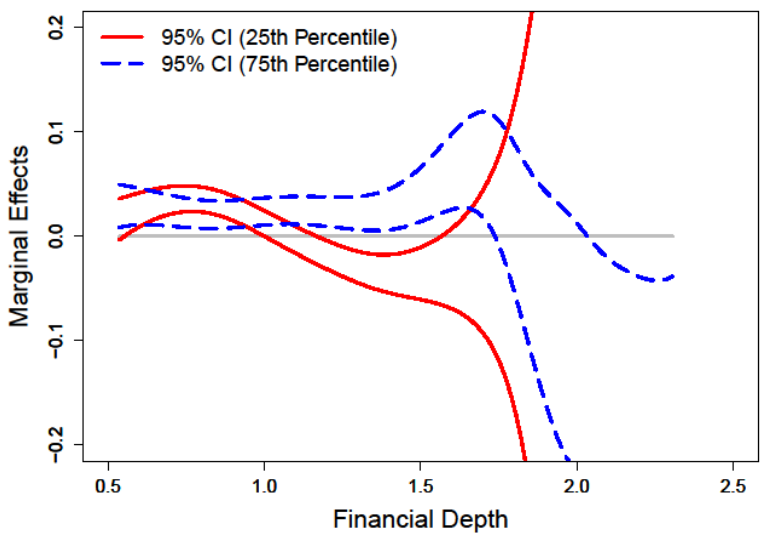
Notes: This figure examines whether financial depth comes to affect income distribution through the channel of credit constraint. The red and solid (blue and dotted) lines show the 95% confidence interval of the estimated marginal effects of financial depth on the net Gini, conditional on a low (high) level of housing price at the 25th (75th) percentile.

Figure 11: Working Channel: State Ownership



Notes: This figure examines whether financial depth comes to affect income distribution through the channel of economic ownership. The red and solid (blue and dotted) lines show the 95% confidence interval of the estimated marginal effects of financial depth on the net Gini, conditional on a low (high) fraction of state owned enterprises at the 25th (75th) percentile.

Figure 12: Working Channel: Economic Development



Notes: This figure examines whether financial depth comes to affect income distribution through the channel of economic development. The red and solid (blue and dotted) lines show the 95% confidence interval of the estimated marginal effects of financial depth on the net Gini, conditional on a low (high) level of real GDP per capita at the 25th (75th) percentile.

Table 1: Summary of Variables

Variable Type	Variable Name	Variable Definition
Dependent variable	Income inequality	Gini coefficients, Theil index
Key explanatory variable	Financial depth	(Year-end loans)/GDP
Economic development	Real GDP per capita	Log[(Real GDP) / (Year-end population)]
	Industrialization	(Value-added in the secondary and tertiary industries)/GDP
	Urbanization	(Year-end population living in urban area)/(Total population)
Public factors	Government size	(Provincial government expenditure)/GDP
	Ownership	(Workers employed by SOEs)/(Total workers)
Institution & demography	Population size	Log(year-end population)
	Minority	(Minority population)/(Total population)
	Unemployment	Urban unemployment rate
	Years of education	Log(average years of education)
Price fluctuations	Inflation	Log difference of CPI
	Housing price	Log(average selling price of commercialized building)
Technical progress	Technology	(Transaction value of technical contracts)/GDP
Open-economy factors	Trade openness	Trade volume/GDP
	Foreign direct investment	FDI/GDP

Table 2: Descriptive Statistics of Variables

Variables	Mean	Median	Maximum	Minimum	Std. Dev.
Gini1	0.2484	0.2562	0.3932	0.1056	0.0555
Gini2	0.2568	0.2646	0.4042	0.1241	0.0565
Gini3	0.2587	0.2670	0.4056	0.0855	0.0571
Theil index	0.1084	0.1091	0.2572	0.0036	0.0466
FD1	0.9623	0.8932	2.6453	0.1991	0.3724
FD2	0.9427	0.8872	2.6453	0.1991	0.3384
Real GDP per capita#	3.9401	1.9814	43.204	0.1961	5.1714
Industrialization	0.7939	0.8166	0.9961	0.3942	0.1228
Urbanization	0.3832	0.3603	0.8960	0.0760	0.1861
Government size	0.1805	0.1426	1.3792	0.0492	0.1416
Ownership	0.6796	0.7214	0.9637	0.1091	0.1663
Population#	0.4053	0.3642	1.1430	0.0185	0.2769
Minority	0.1259	0.0168	1.0000	0.0000	0.2167
Unemployment rate	0.0320	0.0330	0.1260	0.0020	0.0122
Years of education	7.7432	7.8400	12.341	3.2932	1.4151
Inflation	0.0518	0.0306	0.2577	−0.0325	0.0586
Housing price#	2.4772	1.4970	27.497	0.1855	2.8615
Technology	0.0079	0.0037	0.1535	0.0001	0.0166
Trade openness	0.2682	0.1081	3.8122	0.0021	0.4313
Foreign direct investment	0.0243	0.0142	0.2426	0.0000	0.0316

Note: Real GDP per capita is converted into constant-price thousands of yuan using 1978 as the base year. Population size is in the unit of 100 millions. Housing price is converted into thousands of yuan per squared meter. Government size is larger than one in Tibet during 2009-2016 due to the heavy input from the central government.

Table 3: Baseline Estimation Results from Step 2

Variables	(1)	(2)	(3)
Real GDP per capita		−0.0309	−0.0805**
		(0.0557)	(0.0343)
Squared real GDP per capita		0.0047*	0.0066***
		(0.0028)	(0.0021)
Industrialization		−0.0893	
		(0.0787)	
Urbanization		−0.0291	
		(0.0538)	
Government size		−0.0000	0.0005**
		(0.0007)	(0.0002)
Ownership		−0.0122	
		(0.0263)	
Population		−0.0475	−0.0603
		(0.0537)	(0.0467)
Minority		0.0042**	0.0023
		(0.0019)	(0.0018)
Unemployment rate		0.0031	
		(0.0035)	
Years of education		0.0665	
		(0.0416)	
Inflation		0.0990	
		(0.0972)	
Housing price		−0.0160	−0.0172*
		(0.0124)	(0.0099)
Technology		−0.0000	
		(0.0000)	
Trade openness		0.0158	0.0101*
		(0.0097)	(0.0056)
Foreign direct investment		0.0212	
		(0.1216)	
Significance test of IV	6.3796***	5.1114***	10.3401***
	[0.0000]	[0.0000]	[0.0000]
HPP (2013) test of IV	1.0778	1.4515	1.0345
	[0.3767]	[0.1548]	[0.4122]
Endogeneity test of finance	6.0393***	3.5070***	3.4172***
	[0.0000]	[0.0002]	[0.0002]
Significance test of finance	4.1339***	4.0947***	2.3271**
	[0.0000]	[0.0000]	[0.0106]
Akaike information criterion	-4012.481	-2877.847	-4078.321
No. of observations	815	567	812

Note: This table reports part of the estimation results of step 2. Column 1 did not consider additional control variables in ω. Column 2 incorporates all control variables discussed in the text. Column 3 only incorporates those that survive after the variable selection process. Robust standard errors are in parentheses. P-values are in square brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1%, respectively.

Table 4: Estimation Results for Parametric Regressions

Variables	(1) Linear Model	(2) Quadratic Model	(3) Cubic Model	(4) Quartic Model
Financial depth	0.0153	0.0633***	0.0750	0.2526
	(0.0108)	(0.0208)	(0.0858)	(0.2569)
Financial depth to the second power		−0.0201**	−0.0299	−0.2587
		(0.0082)	(0.0730)	(0.3181)
Financial depth to the third power			0.0026	0.1256
			(0.0189)	(0.1646)
Financial depth to the fourth power				−0.0233
				(0.0303)
Endogeneity test of finance	0.0924	0.1038	0.0682	0.6256
	[0.7613]	[0.9015]	[0.9768]	[0.6444]
Significance test of finance	2.0126	4.8970***	3.3867**	3.2357**
	[0.1564]	[0.0077]	[0.0178]	[0.0120]

Note: This table reports the estimation results for parametric models. Robust standard errors are in parentheses. P-values are in square brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1%, respectively.

Online Appendices (Not For Publication)

A Income Inequality

A.1 Gini Coefficients

The Gini coefficient is defined as a ratio, *i.e.*, the area between the Lorenz curve and the 45-degree line divided by the area below the 45-degree line. In Figure A1 this is equivalent to $Gini = \frac{A}{A+B} = 1 - 2B$, where the horizontal (vertical) axis represents the cumulative share of population (income).

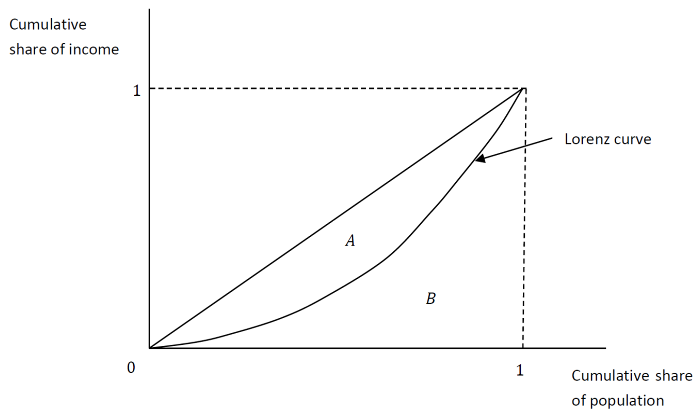


Figure A1: A Lorenz Curve

Since no official Gini coefficients were reported periodically on the provincial level, we have to calculate them separately for each year during the sample period for all 30 provinces. Moreover, only grouped income data are available in the yearbook, we use three different approaches to calculate the Gini coefficients to minimize the possible bias induced by the calculations. Each approach takes a different assumption on the Lorenz curve.

According to its disposable income, a household with income y in province i and year t falls into the k^{th} income group $[a_{k-1}, a_k)$, $k = 1, ..., K$, and $a_0 = 0 < a_1 < a_2 < ... < a_{k-1} < a_K = \infty$. The income distribution of all households in this province at period t can be represented by the following income horizon in Figure A2

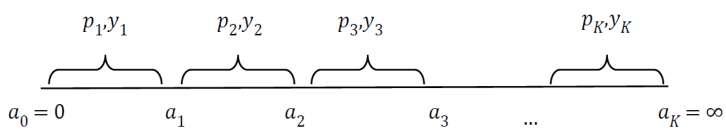


Figure A2: Grouped Income Data

where p_k denotes the population share of income group k. The same set of information can then be transformed into a Lorenz curve by calculating the cumulative share of population, $c_k = \sum_{j=1}^{k} p_j$, and the cumulative share of income, $b_k = \frac{\sum_{j=1}^{k} p_j y_j}{\sum_{j=1}^{K} p_j y_j}$. We collected grouped income and calculated the required series $\{c_k, b_k\}_{k=1}^{K}$ according to the above definitions. Whenever inconsistent statistics occurred in the yearbook of different years, we stick with the recently updated one.

A.1.1 Area Approach

The first approach assumes homogeneous income of all households within the same income bracket $[a_{k-1}, a_k)$, $k = 1, ..., K$. Compared to Figure A1, this assumption gives rise to a piecewise linear Lorenz curve as shown in Figure A3

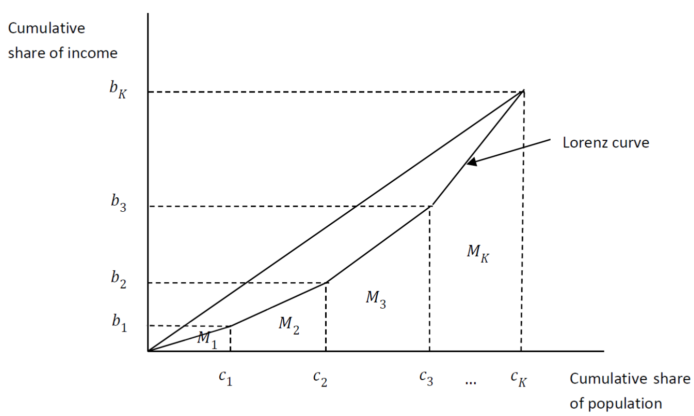


Figure A3: A Piecewise Linear Lorenz Curve

The Gini coefficient can be calculated as

$$Gini = 1 - 2\sum_{k=1}^{K} M_k \tag{A1}$$

where M_k is the area of the triangle or trapezoid shown in Figure A3

$$\begin{aligned} M_k &= \frac{1}{2}(b_{k-1} + b_k)p_k \\ &= \frac{1}{2}(b_{k-1} + b_k)(c_k - c_{k-1}) \end{aligned}$$

A.1.2 Polynomial Approach

The second approach relaxes the assumption of homogeneity of income within an income group. Instead, we fitted a $(K-1)$ order of polynomial for the Lorenz curve directly using the cumulative income share and population share $\{c_k, b_k\}_{k=1}^{K}$

$$b = L(c) = \alpha_1 c^{K-1} + \alpha_2 c^{K-2} + ... + \alpha_{K-1} c + \alpha_K$$

where $\alpha_1, \alpha_2, ..., \alpha_K$ are K parameters that need to be estimated with K observations. The Gini coefficients can then be calculated by the numerical integration

$$Gini = 1 - 2\int_0^1 L(c)dc \tag{A2}$$

A.1.3 World Bank Approach

The third approach uses the POVCAL software distributed by the World Bank. Essentially the program takes a similar technique as in the polynomial approach. The difference lies in that this program is based on two alternative functional forms of the Lorenz curve: the Generalized Quadratic (Villasenor and Arnold, 1989) and Beta (Kakwani, 1980) parameterization. The program first estimates both Lorenz curves using the cumulative income share and population share $\{c_k, b_k\}_{k=1}^{K}$. It then chooses one that fits the data better and calculates the Gini coefficients according to equation (A2).

A.2 Theil Index

The Theil index characterizes the discrepancies between the distribution of income and the distribution of population between different income groups. Essentially, it calculates the sum of the weighted logarithm of the ratio between each group's income share and population share

$$Theil = \sum_{k=1}^{K} w_k \log \frac{w_k}{p_k} \tag{A3}$$

where $w_k \equiv p_k y_k / \sum_{k=1}^{K} p_k y_k$ is the income share of group k out of total income and p_k is the population share of group k, $k = 1, ..., K$. Theil index is always positive and a higher index indicates a higher level of inequality. Conceição and Ferreira (2000) show that Theil index is sensitive to transfers of income from poor to rich, constituting an additional benefit of using it for transitional economy with worsening inequality. In this paper, we use the same set of data sources stated above to calculate the required series: the grouped income and population data $\{w_k, p_k\}_{k=1}^{K}$.

B Financial Depth

Two measures of financial depth are calculated. Both are defined as the year-end loans divided by provincial GDP. It can be interpreted as a measure of financial deepening because it measures the unit of financial resources corresponding to one unit of output. With the rapid expansion of international trade and the large increase of international capital flow, there arises a significant amount of loans denominated in foreign currency, in particular in the coastal provinces. We make a distinction between loans denominated in Renminbi (RMB) only and loans denominated in both RMB and foreign currencies. Specifically, $FD1$ is the ratio of total (RMB and foreign currency denominated) loans to provincial GDP and $FD2$ is the ratio of RMB loans to provincial GDP. It is expected the above two measures should be identical in the early stage of the sample period when no or few non-RMB loans exist. Table B1 reports the detailed year of each province in and after which $FD1$ becomes different than $FD2$. A '-' indicates that either no foreign currency denominated loans exist in this province by the end of the sample period or the amount is not significant and there is no statistics recorded in the provincial yearbooks.

All series come from various issues of provincial statistical yearbooks (1982-2017) for 31 Chinese provinces, supplemented by the China Compendium of Statistics 1949-2008. Since Chongqing was part of Sichuan province before 1997, we combined Sichuan with Chongqing to keep data consistency. In practice, whenever inconsistent statistics occurred in the yearbook of different years, we stick with the recently updated one.

Table B1: Foreign Currency Denominated Loans

Province	Year	Province	Year	Province	Year
Beijing	1994	Zhejiang	2002	Hainan	2002
Tianjin	2002	Anhui	2003	Sichuan	1996
Hebei	-	Fujian	-	Guizhou	-
Shanxi	2006	Jiangxi	2009	Yunan	-
Inner Mongolia	-	Shandong	2010	Tibet	-
Liaoning	2011	Henan	-	Shaanxi	-
Jilin	-	Hubei	-	Gansu	2005
Heilongjiang	-	Hunan	2010	Qinghai	-
Shanghai	1990	Guangdong	2000	Ningxia	-
Jiangsu	2005	Guangxi	2005	Xinjiang	-

Notes: This table summarizes the detailed year for each province in and after which the foreign currency denominated loans were recorded in the yearbooks.

C Other Variables

Two control variables, urbanization and education, and their construction procedure are worth further discussions.

C.1 Population and Urbanization

As introduced in section 2.4, urbanization in this paper is defined as the ratio of year-end population living in urban area to total population. In the process of data collection, we find that the statistics of urban and rural population from the provincial statistical yearbooks are problematic: instead of observing smoothing transition of population series, we observe abnormal jumps and unreasonable trend reversal for both urban and rural population series in 15 provinces. Figure C1, with a longer time span (1949-2016), plots the series of urban and rural series for these provinces that exhibit the unreasonable jumps. Let us take Jiangsu province (row 3 and column 1 in Figure C1) as an example. In the year 1989, we observe a sudden and significant drop of urban population following a substantial rise of this series in the early 1980s. A careful inspection of the whole series suggests that what appears between early 1980s and 1989 obviously deviates from the long term trend.

We checked the history and found out the reason behind the abnormal structural breaks in these provinces. Since the People's Republic of China was established in 1949, the population in the urban and rural areas have been counted according to people's Hukou status: a household is identified either as an agricultural Hukou holder or a non-agricultural Hukou holder. People with an agricultural Hukou are classified as rural residents and people with a non-agricultural Hukou are counted as urban residents. Before 1980 the calculation of urban and rural populations is roughly accurate because there were very few migrants across regions or between rural and urban areas. Therefore a non-agricultural (agricultural) Hukou holder is indeed an urban (rural) resident.

This situation changed in the 1980s with the process of economic reform. Due to the relaxed regulation on Hukou system and emerging migrant workers from rural to urban areas, the recorded rural (urban) population according to Hukou status can no longer matches the actual rural (urban) residents. Statistical bureau realized this problem and, instead of sticking with the Hukou status, they began counting rural and urban population according to the residency status. However, this process did not happen simultaneously in all provinces. In the case of Jiangsu, it began in the year of 1990. Table C1 summarized the time period of each province, during which either Hukou or residency status is used to identify rural and urban residents.

By combining Figure C1 with Table C1, we find that the abnormal structural breaks in Figure C1 are essentially caused by the policy change or alternative definition of rural and urban populations. For Jiangsu, the deviation from the long term trend coincides with the period before 1990. Ideally, resident population is a better measure of population to calculate urbanization. Before the year 1980, the Hukou population is very close to resident population because migration from rural to urban area was very difficult. After the year 1990, Jiangsu began to record population according to residency status. In this case, we can fit the resident population data before 1980 and after 1990 to a polynomial of time and estimate the trend of resident population over time. Then we could use the fitted value of resident population to replace the problematic records of the *original* series of population during the period 1981-1989. We then perform similar estimations and adjustment separately for each of the other 14 provinces; the adjustment period is summarized in the last column of Table C1. Figure C2 shows the adjusted resident populations in urban and rural areas of these 15 provinces, in which the abnormal breaks disappear.

C.2 Education

Education is measured by the average years of schooling for all people of 6 years old and above. In each province, we classify a person's degree of education (years of schooling) according to his/her highest degree obtained. This includes five cases:

(a) An illiterate or semi-illiterate person: a person with no or very limited experience of schooling is assumed to receive 2 years of schooling on average.

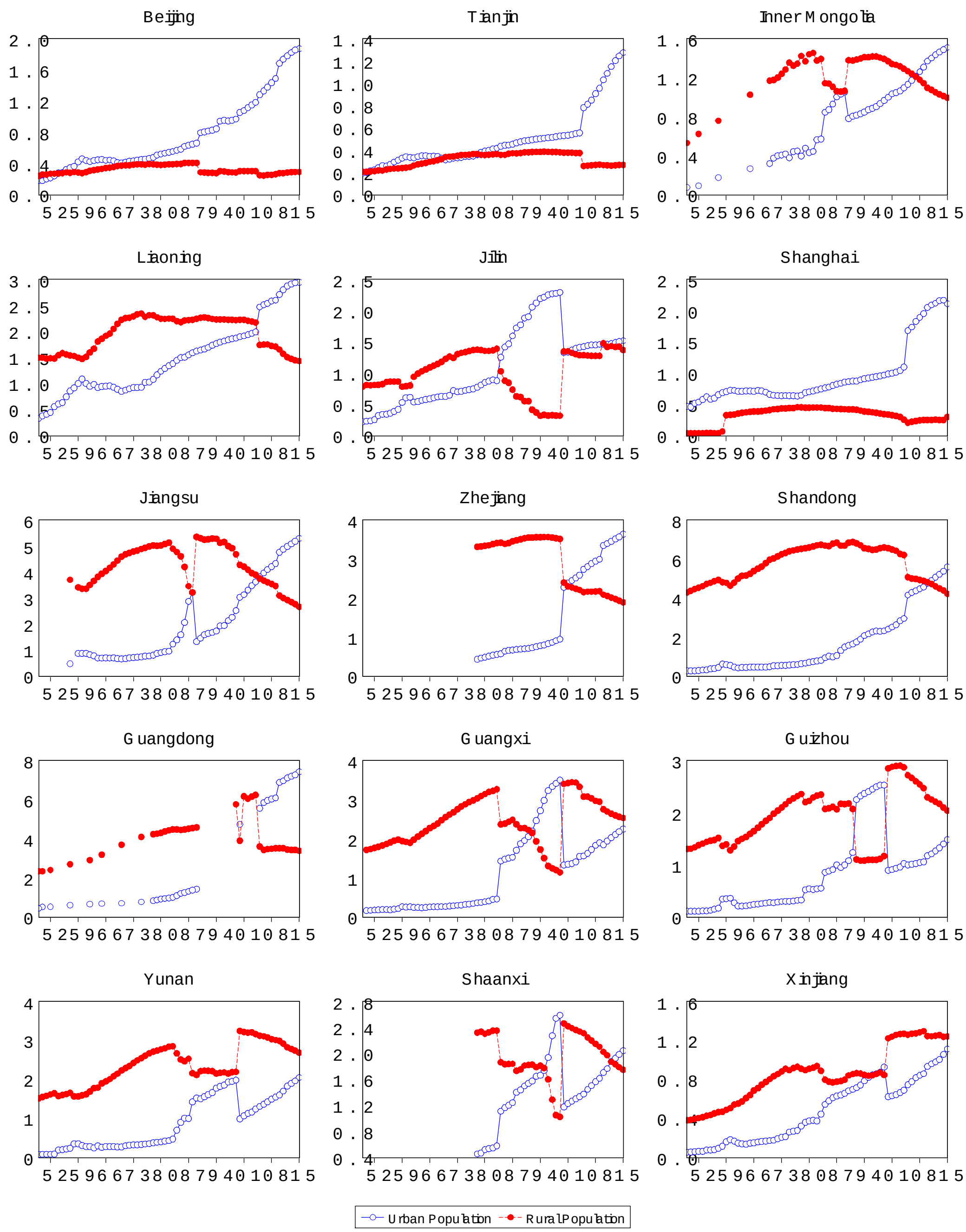
(b) Primary school students: a person graduated from a primary school is assumed to receive 6 years of schooling.

Table C1: From Hukou Population to Resident Population

Province	Hukou Population	Resident Population	Adjustment Period
Beijing	1949-1989	1990-2016	1981-1989
Tianjin	1949-2004	2005-2016	1981-2004
Hebei	-	-	no adjustment
Shanxi	1949-1980	1981-2016	no adjustment
Inner Mongolia	1949-1984	1985-2016	1981-1989
Liaoning	1949-2004	2005-2016	1981-2004
Jilin	1949-1999	2000-2016	1981-1999
Heilongjiang	1949-1980	1981-2016	no adjustment
Shanghai	1949-2004	2005-2016	1981-2004
Jiangsu	1957-1989	1990-2016	1981-1989
Zhejiang	1978-1999	2000-2016	1981-1999
Anhui	1953-2004	2005-2016	no adjustment
Fujian	-	2000-2016	no adjustment
Jiangxi	-	1978-2016	no adjustment
Shandong	1949-2004	2005-2016	1981-2004
Henan	1949-2016	not apply	no adjustment
Hubei	not apply	1949-2016	no adjustment
Hunan	1949-2016	not apply	no adjustment
Guangdong	1949-1999	2000-2016	1999-2004
Guangxi	1950-1999	2000-2016	1981-1999
Hainan	1952-1987	1988-2016	no adjustment
Sichuan	-	2005-2016	no adjustment
Guizhou	1949-2004	2005-2016	1981-1999
Yunan	1949-1980	1981-2004	1981-1999
Tibet	1970-1989	1990-2016	no adjustment
Shaanxi	1978-1989	1990-2016	1981-1999
Gansu	1949-1999	2000-2016	no adjustment
Qinghai	1952-1989	1990-2016	no adjustment
Ningxia	1949-1999	2000-2016	no adjustment
Xinjiang	1949-1989	1990-2016	1981-1999

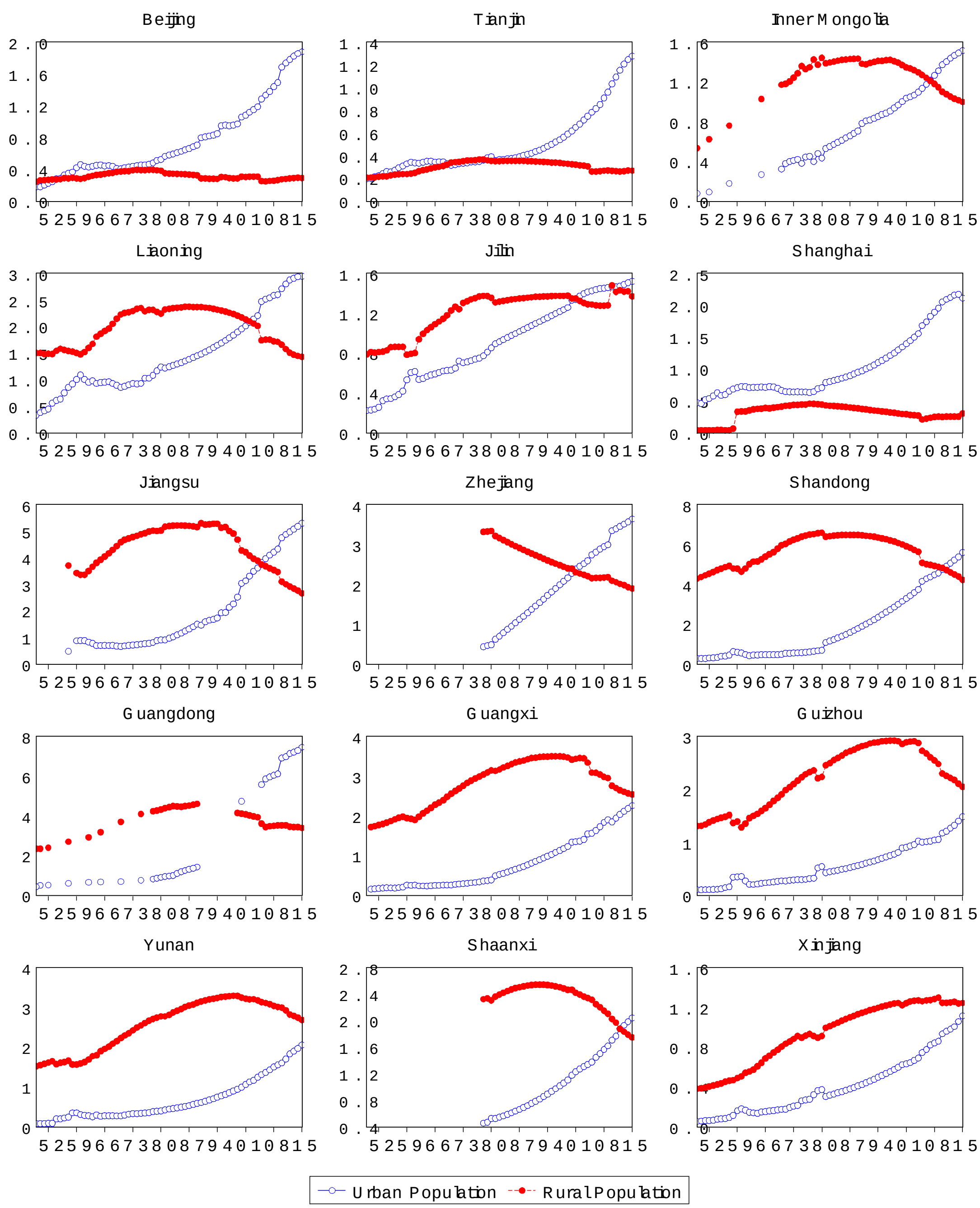
Notes: This table summarizes the time period of each province, during which either Hukou or residency status is used to identify rural and urban residents. The last column indicates the period of data adjustment for provinces experiencing abnormal jumps in the population series.

Figure C1: Series of Rural and Urban Populations Before Adjustment



Notes: This figure plots the non-adjusted series of urban and rural populations for provinces that exhibit unreasonable jumps due to policy changes, from a Hukou-based to a residency-based definition of rural and urban populations.

Figure C2: Series of Rural and Urban Populations After Adjustment



Notes: This figure plots the adjusted series of urban and rural populations for provinces that exhibit unreasonable jumps due to policy changes, from a Hukou-based to a residency-based definition of rural and urban populations.

(c) Junior secondary school students: a person graduated from a junior secondary school is assumed to receive 9 years of schooling.

(d) Senior secondary school students: a person graduated from a senior secondary school is assumed to receive 12 years of schooling.

(e) College students: a person graduated from a college is assumed to receive 16 years of schooling.

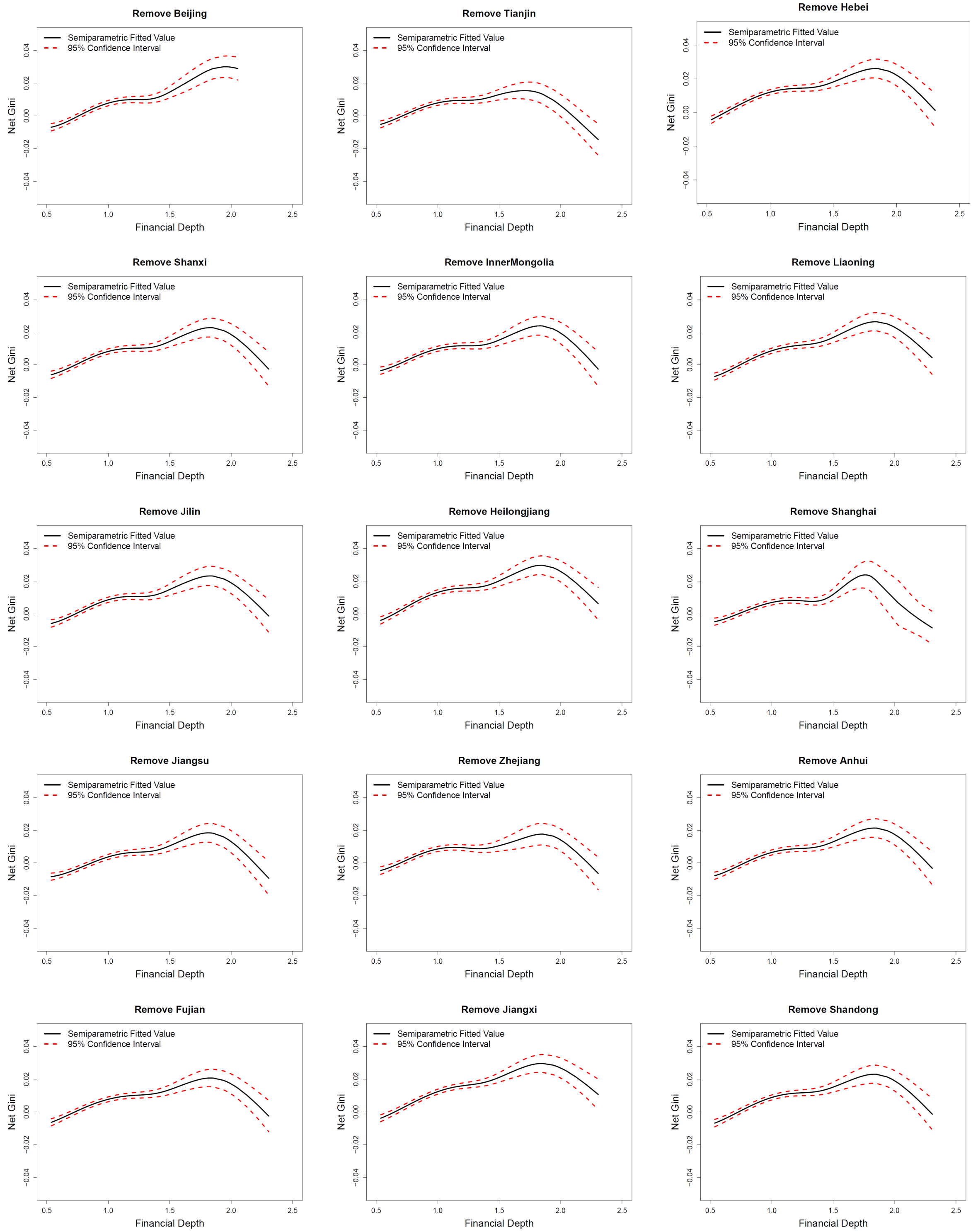
From the China Statistical Yearbook and China Population Statistics Yearbook, we collected the number of people in each of the above five categories and then calculated the average years of schooling for each province in each year during the sample period.

D City Provinces and Extreme Observations

In our baseline model, we considered a panel data model with both time- and province-specific effects, as well as a set of control variables. If those city provinces indeed differ from other places, these differences will be accounted for by either the control variables or the fixed effects in the first two steps of our three-step procedure. In other words, the estimated finance-inequality linkage from step 3 is immune to specific characteristics of either a city province or a particular year. The following exercises confirm our conjecture.

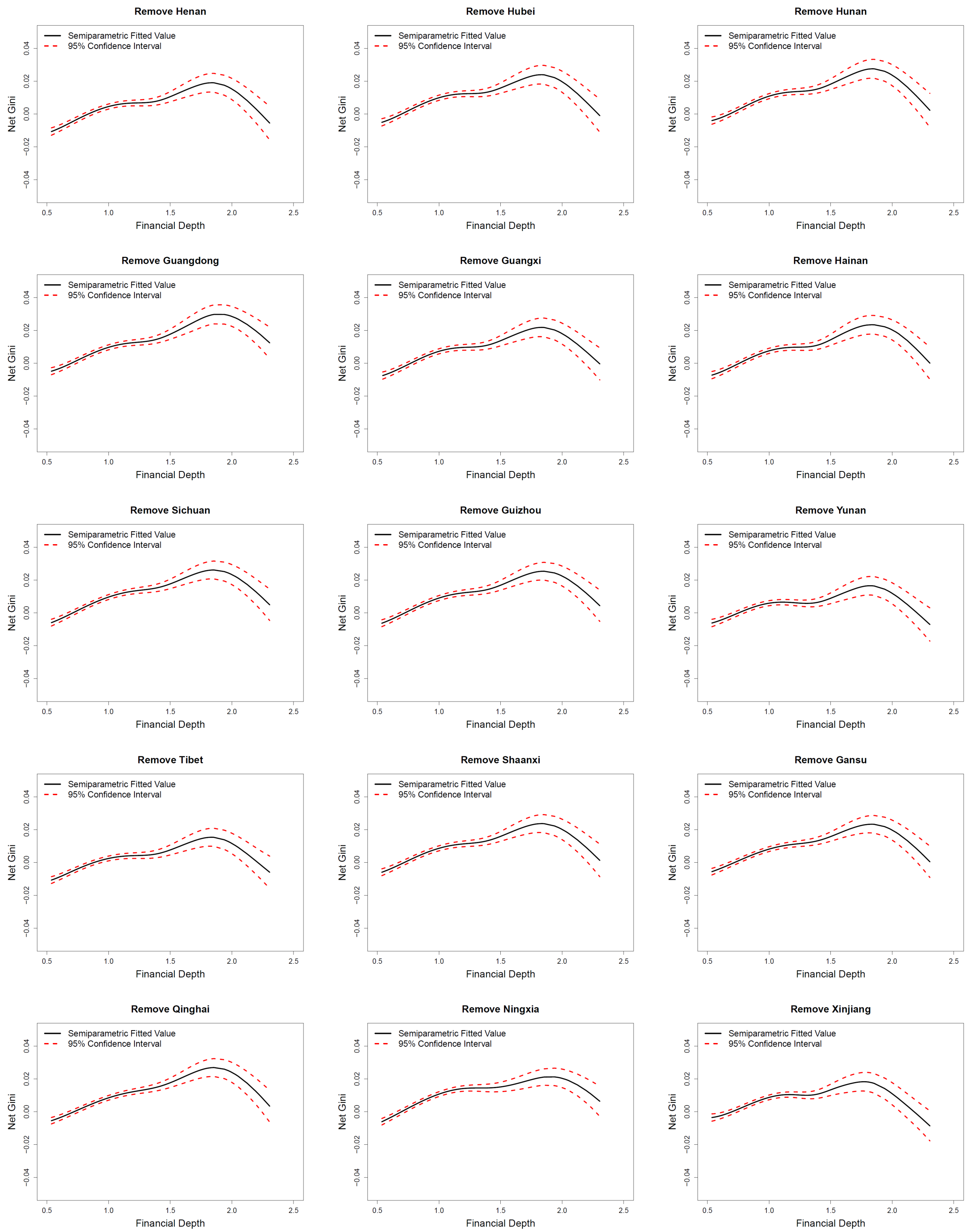
What we show here is that, by removing each time the observations of either one specific province or one specific year from the benchmark sample, the estimated pattern of $\widetilde{m}$ remains similar. Figures D1 and D2 report the estimation results after removing one province at a time from the whole sample. As it turns out, a similar pattern occurs in all cases, including those without Beijing, Tianjin, or Shanghai. The pattern without Beijing looks slightly different, because removing Beijing from the sample gives rise to a smaller range of financial depth on the right tail. Even in this case, the turning point still occurs after which financial depth reduces income inequality. These results suggest that the pattern is robust to either the inclusion or the exclusion of those city provinces. Figures D3 to D5 depict the estimation results after removing one year at a time from the whole sample. Essentially, none of these cases delivers qualitatively different results compared to the benchmark estimations. Therefore, robustness to potential outliers is confirmed.

Figure D1: Robustness Checks without Observations from a Specific Province (I)



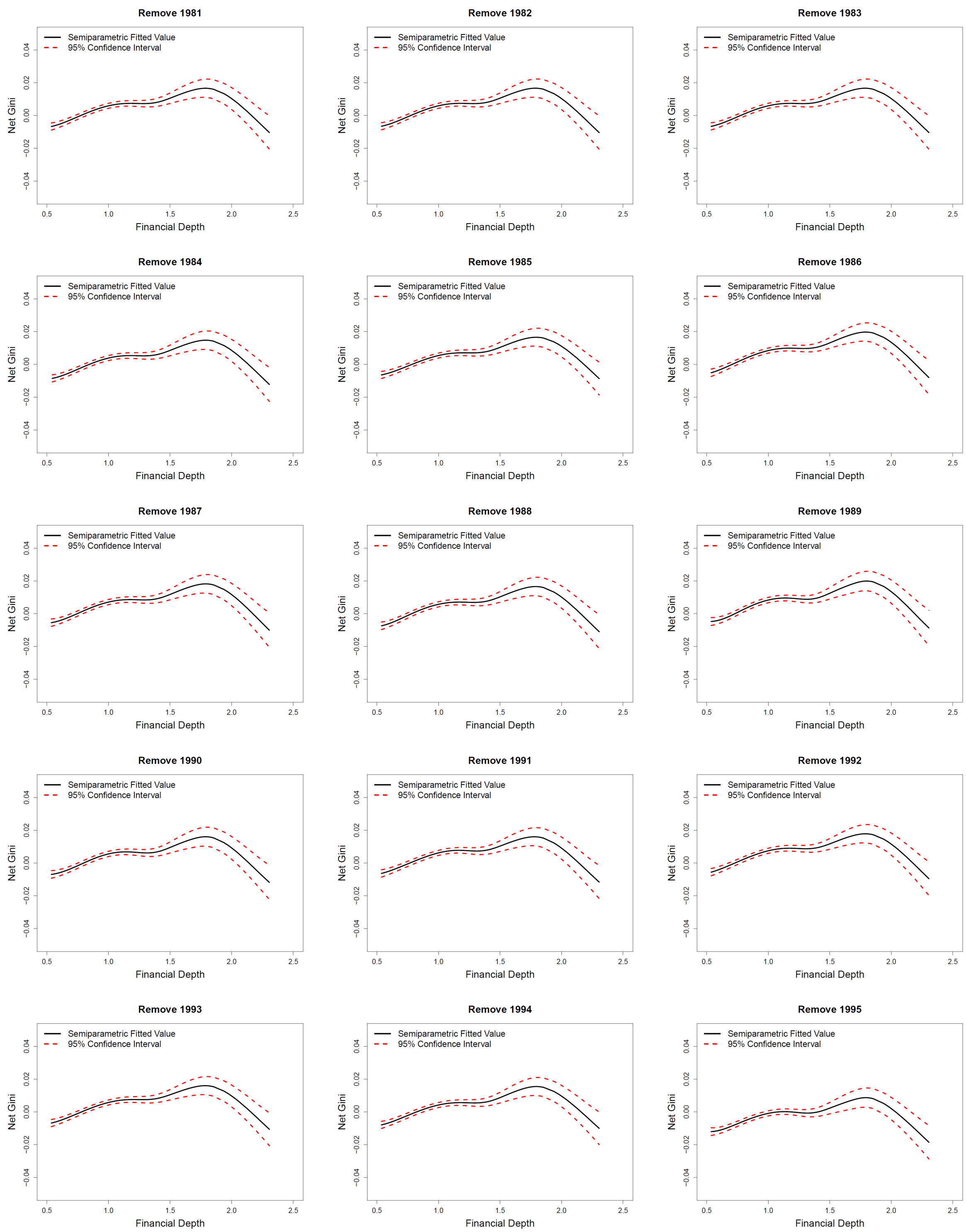
Notes: This figure shows the robustness checks by removing each time the observations of a specific province from the benchmark sample.

Figure D2: Robustness Checks without Observations from a Specific Province (II)



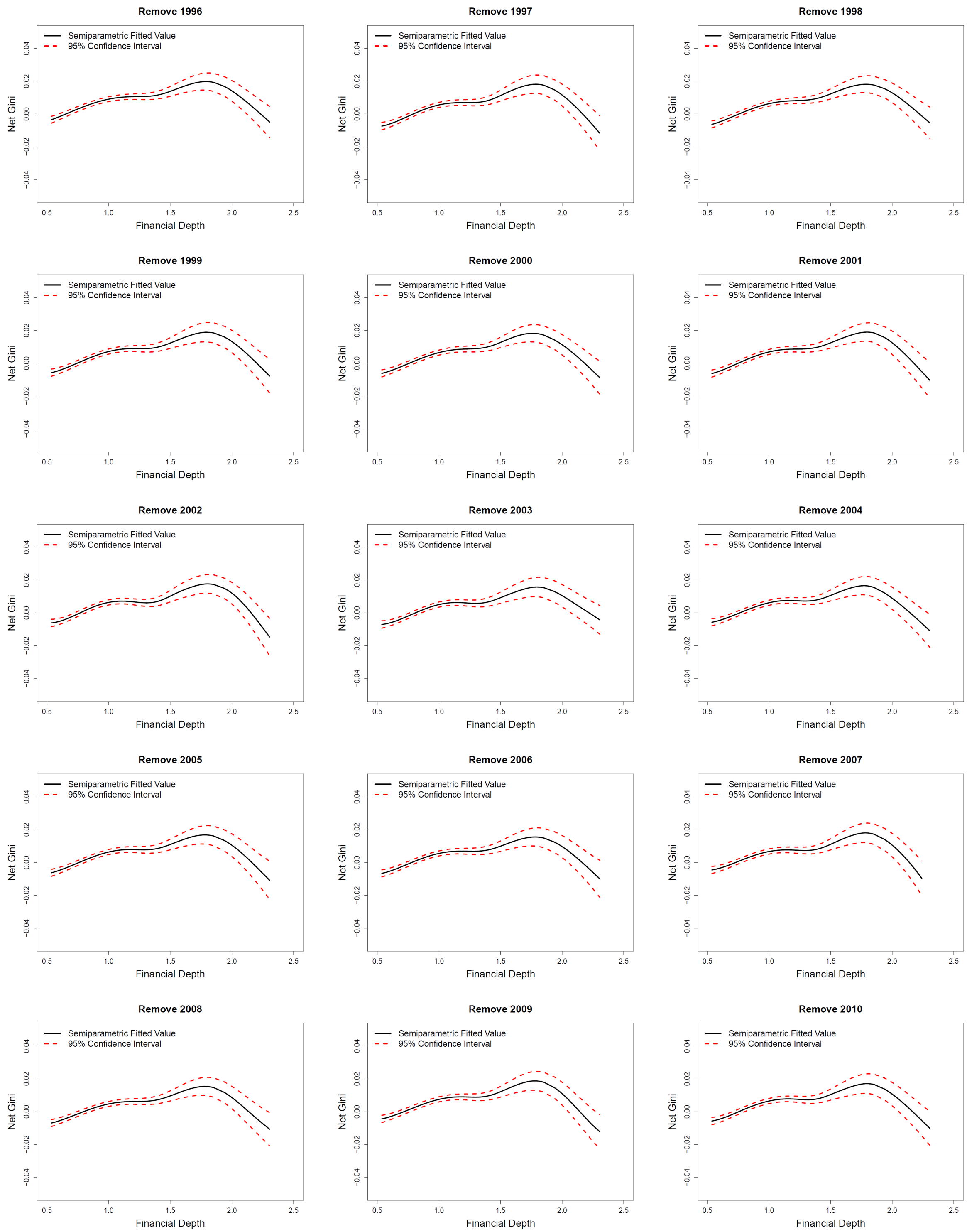
Notes: This figure shows the robustness checks by removing each time the observations of a specific province from the benchmark sample.

Figure D3: Robustness Checks without Observations from a Specific Year (I)



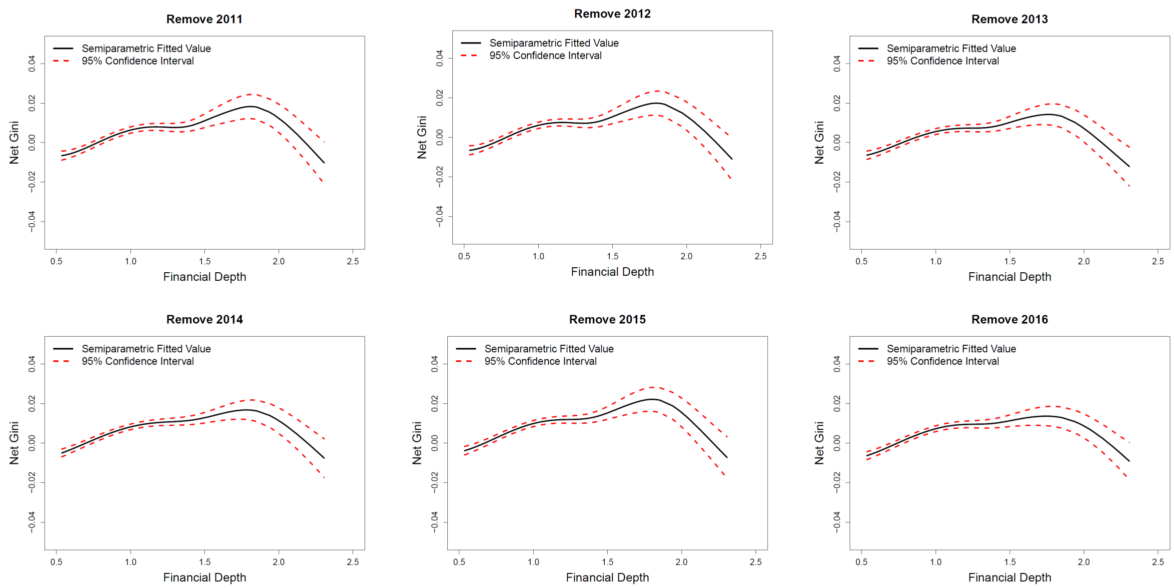
Notes: This figure shows the robustness checks by removing each time the observations of a specific year from the benchmark sample.

Figure D4: Robustness Checks without Observations from a Specific Year (II)



Notes: This figure shows the robustness checks by removing each time the observations of a specific year from the benchmark sample.

Figure D5: Robustness Checks without Observations from a Specific Year (III)



Notes: This figure shows the robustness checks by removing each time the observations of a specific year from the benchmark sample.

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