Flip or Flop? Tobin Taxes in the Real Estate Market *

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Abstract

This paper estimates the optimal tax on property flips using a sufficient statistics approach applied to a 2011 reform in Taiwan which levied a sales surcharge of up to 15% on investment properties held for two years or less. Linking the universe of personal income tax returns to transaction records, we show via an hedonic bunching design that the tax generated a 75% drop in one-year flips and a 40% drop in overall second home sales volume. We use shocks to housing net worth from inheritances received after decedents' untimely deaths to show that investors with more portfolio exposure pass through the tax to buyers. While low-wealth out-of-town investors account for most of the drop in sales volume, locals and non-residents earn similar holding period returns in the pre-reform period. We use spatial and time variation in the severity of typhoon seasons to estimate a 20% share of noise trading prior to the reform. We combine our estimates of the noise trading share and change in short-term sales volume to parametrize a model of optimal financial transaction taxes. The optimal transfer tax on short-term sales is 4%, at most, which is close to the flat transfer tax rates imposed in many global real estate markets. Our results point to segmentation and inventory effects as key constraints on the ability of Tobin taxes to promote housing affordability.

Keywords: Tobin tax, second homes, housing affordability, noise trading, out-of-town investors, bunching, lock-in effects, inheritance, weather shocks

JEL classifications: G11, G12, H22, R31, R38

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1 Introduction

Recent booms in real estate investment have fueled concerns about housing affordability and macroeconomic stability, leading policymakers in many large cities to call for property taxes which target speculators. Much of the debate surrounding such policies has focused on the role of out-of-town (OOT) investors and the scope for additional taxes on some combination of non-owner occupied or vacant properties and sales to foreign buyers. However, evidence on the ability of transfer taxes to prevent property bubbles and improve welfare remains scarce. Transfer taxes render real estate less attractive as an investment good, thus lowering demand and putting downward pressure on prices. But such taxes may also crowd out noisy trades and reduce housing inventory, leading to an overall ambiguous effect on prices.

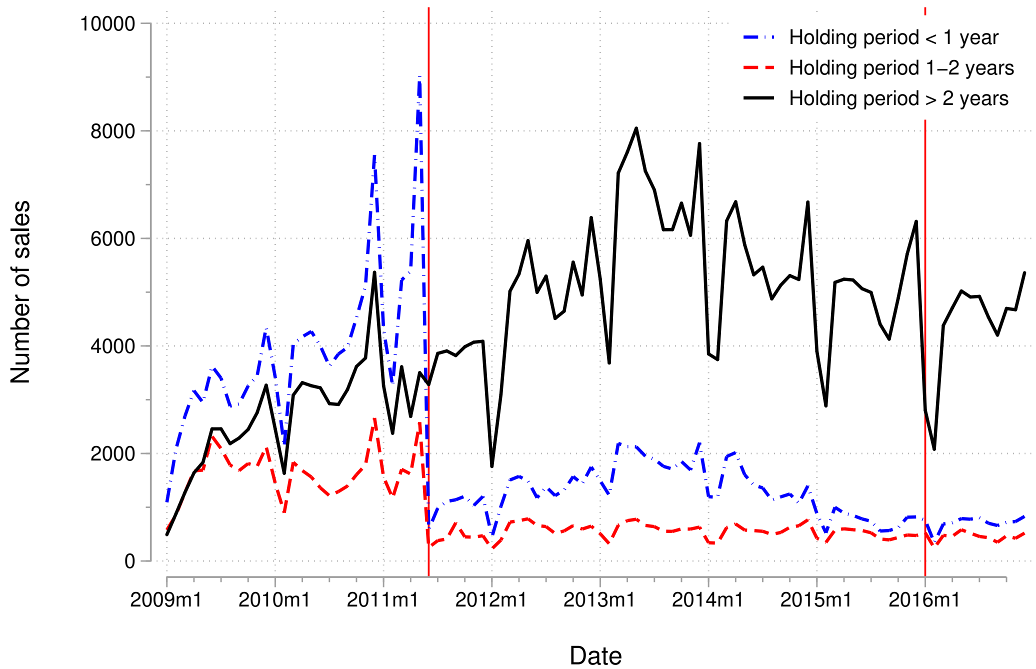
This paper quantifies these competing demand and supply effects using a major transfer tax reform in Taiwan which introduced surcharges as high as 15% of the sale price on short-term sales of non-owner occupied properties. Linking the universe of personal income tax returns to property registrations and transfer tax records, we highlight three main findings: (i) the tax was very effective at reducing the number of property flips. The tax generated a 75% drop in one-year flips, and a 40% drop in overall sales volume. (ii) The tax did not generate a significant decline in house prices. Negative price movements were concentrated among cheaper apartment units for which realized capital gains would have been small relative to the tax bill incurred by selling. Such sales disproportionately involve low-wealth, non-local investors. (iii) We estimate an upper bound of a 20% share of noise trading in the second home market prior to the transfer tax reform. We use our noise trading share and crowd out measures to calibrate a model of optimal financial transaction taxes and compute an upper bound optimal tax rate on flips of 4%, indicating the government taxed too much. Our results suggest the policy generated substantial lock-in effects while doing little to improve housing affordability.

A unique feature of our setting is that we examine behavior around discontinuities, or "notches," in the transfer tax schedule delineated by the *holding period* of the property. This is in contrast to several recent papers on transaction taxes which have all analyzed bunching around home sale price notches (Dachis et al. 2012; Besley et al. 2014; Kopczuk & Munroe 2015; Slemrod et al. 2017; Best & Kleven 2018). Sellers in Taiwan pay a 15% surcharge on the sale price if they resell the property within one year, 10% if they resell after one year but within two years, and no surcharge if the holding period exceeds two years. This focus on short-term trading is also present in capital gains taxation, which typically offers preferential treatment for long-term investments, and which like transfer taxes, induces lock-in effects (Auerbach 1988; Burman & Randolph 1994; Cunningham & Engelhardt 2008; Dai et al. 2008; Gao et al. 2020).[1]

The fact that the discontinuities in the transfer tax are defined in units of time presents a challenge

[1] Agarwal et al. 2020 study a reform in China which increased the capital gains tax rate for properties sold within five years but find minimal bunching due to rampant tax evasion. As prices underlying the transfer tax reform are not self-reported by taxpayers in Taiwan, the scope for tax evasion is more limited in our setting.

FIGURE 1. Taiwan Monthly Housing Sales by Holding Period



Notes: Total sales of existing homes subject to transfer taxation by holding period length. Holding periods calculated as number of days passed since the seller's original purchase date. Vertical solid red lines indicate the introduction of the transfer tax surcharge on non-owner occupied property sales on June 1, 2011, and its subsequent repeal and replacement by a capital gains tax on January 1, 2016.

when it comes to identifying an appropriate counterfactual. The standard approach in the bunching literature is to use local polynomial regressions to fit a counterfactual distribution using data from segments of the housing market which are located away from discontinuities in the tax schedule (Kleven & Waseem 2013; Kleven 2016; Glogowsky 2021). But a property owner's decision to sell today has a mechanical and direct effect on the mass of sales at longer holding period lengths, meaning there is no "unaffected region" of the post-reform holding period distribution. We posit an hedonic-logit model of house flips which we train using data from the pre-reform period and then apply to the post-reform period to estimate a counterfactual which adjusts for compositional changes over time which may have been due to the tax reform or macroeconomic factors. Our identifying assumption is that the market would have priced property amenities in the same fashion as in the pre-reform period in the absence of the tax. We test this by confirming the absence of pre-trends on the loadings for factors included in our hedonic-logit model.

The Taiwan transfer tax policy also features time discontinuities, as pictured in Figure 1. We examine the short-run activity of sale prices and unit prices around the implementation date. For the entire second home market, prices are smooth across the time cutoff, but this masks significant segmentation. For properties in the bottom quintile of the pre-reform sale price distribution –

namely smaller apartment units – there is a clear negative trend break whereby home values decline by 28% over the three years after the reform. Conversely, in the prime property segment, prices rose by 10% around the date cutoff, implying full pass-through of the tax by one-year flippers, as wealthy buyers paid a premium to expedite purchases and offset the seller's tax bill. We also look at price movements using the notch that naturally forms around sellers' original purchase dates two years prior to the reform (grandfathering), comparing sales never subject to the tax to those which could be subject to the tax. We again find that prices for high-end properties slightly increase by 2% around the June 2009 cutoff for initial purchase dates, indicating that sellers shift at least part of the incidence of the tax to buyers.

We provide causal evidence of the inward shift in the supply curve in the prime property market using sellers' differential exposure to the tax, captured by recent and unexpected inheritances as a shock to *ex ante* housing net worth. Given existing evidence that heirs anticipate inheritances (Bernheim et al. 1985) and that individuals exercise some control over the timing of their death (Kopczuk & Slemrod 2003), we use the cause of death provided in inheritance tax records to identify inheritances derived from untimely deaths. We define untimely deaths as those attributed to either a sudden or accidental cause of death, or cases in which the deceased died two standard deviations or more below the average age at death.

Consistent with the short-run results around the time notch, a one standard deviation positive shock to sellers' housing net worth induced sellers to charge 9.5% more than in the pre-reform period for a comparable property. The strength of this inventory reduction channel explains why we observe such muted changes in housing prices, and we argue it is the main threat to the housing affordability objectives flip taxes are designed to achieve. The negligible aggregate pricing effects we find accord with the housing search theory of Piazzesi et al. (2020), where investors with preferences for low-inventory properties dampen the spread of shocks to other market segments.

Our study most closely relates to the recent proliferation of papers documenting the contributions of property investors to the magnitude of real estate cycles. Sales involving OOT buyers account for one-third of transactions, but 60% of missing sales derived from our bunching analysis, indicating that the transfer tax effectively targeted this group. Chinco & Mayer (2016) show that demand from OOT second-home buyers predicts house price appreciation in the 2000s U.S., but argue that non-local investors earn lower capital gains than their local counterparts. The positive pricing effects of the "OOT shock" to local housing markets have been echoed in the U.K. (Sá 2016; Badarinza & Ramadorai 2018), Paris (Cvijanović & Spaenjers 2020), Vancouver (Pavlov & Somerville 2020), and in large U.S. markets like California (Li et al. 2018) and New York (Suher 2016). Gorback & Keys (2020) argue that a more recent wave of transfer taxes targeting non-residents in Singapore, Hong Kong, and Australia drove up prices in the U.S. by generating an influx of Chinese capital into major U.S. real estate markets.

Contrary to the aforementioned papers, our results undermine the narrative of the novice investor who buys several bottom-tier properties and earns low returns (Haughwout et al. 2011; Chinco &

Mayer 2016; García 2019; Garriga et al. 2020). Exploiting the richness of our transactions records linked to personal income tax returns and wealth statements allows us to move beyond capital gains and compute total *tax-adjusted* holding period returns, which include mortgage interest payments and rental income. We compute the term structure of holding period returns and find that it is downward sloping, as shown for pre-tax returns for commercial real estate in Sagi (2020) and for housing in Giacoletti (2021), and that the transfer tax shifted returns from shorter to longer horizons. A downward-sloping term structure for second homes is consistent with the intuition of the model in Lovo & Spaenjers (2018), where a negative correlation between returns and holding periods arises in private-value asset markets because wealthier investors select higher reserve prices.

While OOT and low-wealth investors account for the majority of property flips that were crowded out by the transfer tax, short-term speculators *do not* appear to be misinformed. Prior to the flip tax, locals and OOT sellers earned statistically similar returns, and leveraged property investors earned capital gains similar to those of full equity holders. Hence, as noted in Bayer et al. (2020), tags like non-residency status and leverage which are synonymous with housing speculation in the literature may not necessarily translate to noise trading.

Besides achieving housing affordability, policymakers often invoke macroprudential considerations to support real estate transaction taxes. A common theme in the macro-housing literature is that investors' access to mortgage credit helped amplify the housing boom-bust cycle in the 2000s U.S. (García 2019; Graham 2019; Gao et al. 2020), leading to higher default and foreclosure rates (Haughwout et al. 2011; Albanesi et al. 2017). The Taiwan transfer tax reform also occurs during a period of rising levels of mortgage debt and price-rent ratios. Favilukis & Van Nieuwerburgh (2021) use a mono-city model to study the effects of OOT investors in general equilibrium and find that targeted transfer tax hikes are welfare-improving. DeFusco et al. (2017) build a model with short-term and long-term investors with extrapolative beliefs, and conclude that short-term capital gains taxes on real estate sales promote financial stability. Our work provides a real-world laboratory to test whether property flip taxes can mitigate bubbles by deterring noise trading.

The real estate transfer tax we analyze shares several features with financial transaction taxes (FTTs). Tobin (1978) famously introduced the idea of using FTTs to curb excessive volatility arising from non-fundamental trading. Early empirical evidence on whether Tobin taxes accomplish this objective is mixed. Umlauf (1993), Campbell & Froot (1994), and Jones & Seguin (1997) all note that increased transaction costs are associated with lower trading volume but increased price volatility in Swedish and U.K. equity markets. We find, within one year of the reform, a paltry 2% decline in volatility of per square-meter prices entirely driven by a 20% drop in unit price volatility in the prime property segment. Our finding that the transfer tax generated lock-in effects mirrors more recent evidence from equity markets which highlights reductions in asset liquidity as an important determinant of the overall pricing effects of FTTs (Foucault et al. 2011; Colliard & Hoffmann 2017; Deng et al. 2018).

Building on FTT experiments considered in heterogeneous investor frameworks like Kupiec (1996) and Scheinkman & Xiong (2003), Dávila (2020) characterizes the optimal FTT and shows that the net effects on prices and volatility are *ex ante* indeterminate. Whether prices go up or down depends on investors' prior beliefs and the relative impacts of the tax on supply and demand for the asset. Even if asset supply is perfectly inelastic, round-trip transaction taxes have competing effects on demand; if the tax is successful at crowding out traders with incorrect beliefs, then price efficiency improves, which may bid up asset demand. The optimal tax sets aggregate trading volume equal to fundamental volume, implying a rate which scales the *ex ante* share of non-fundamental trading by the semi-elasticity of volume with respect to the transfer tax rate.

In the final part of the paper, we calibrate the optimal flip tax rate by combining our estimates of the reduction in trading volume from our bunching design with new estimates of the noise trading share in the second home market. We exploit spatial and time variation in severe weather during typhoon seasons in the pre-reform period as a shock to the fixed cost of selling second homes. Our use of weather shocks is inspired by Cho (2020), who documents heat waves in the 19th century reduced noise trading on the NYSE. In recognizing that weather conditions may increase fixed costs of selling properties, we build upon an emerging finance literature which has so far focused on the relationship between weather-induced sentiments and economic activity (Hirshleifer & Shumway 2003; Goetzmann et al. 2014; Cortés et al. 2016; Dehaan et al. 2017).

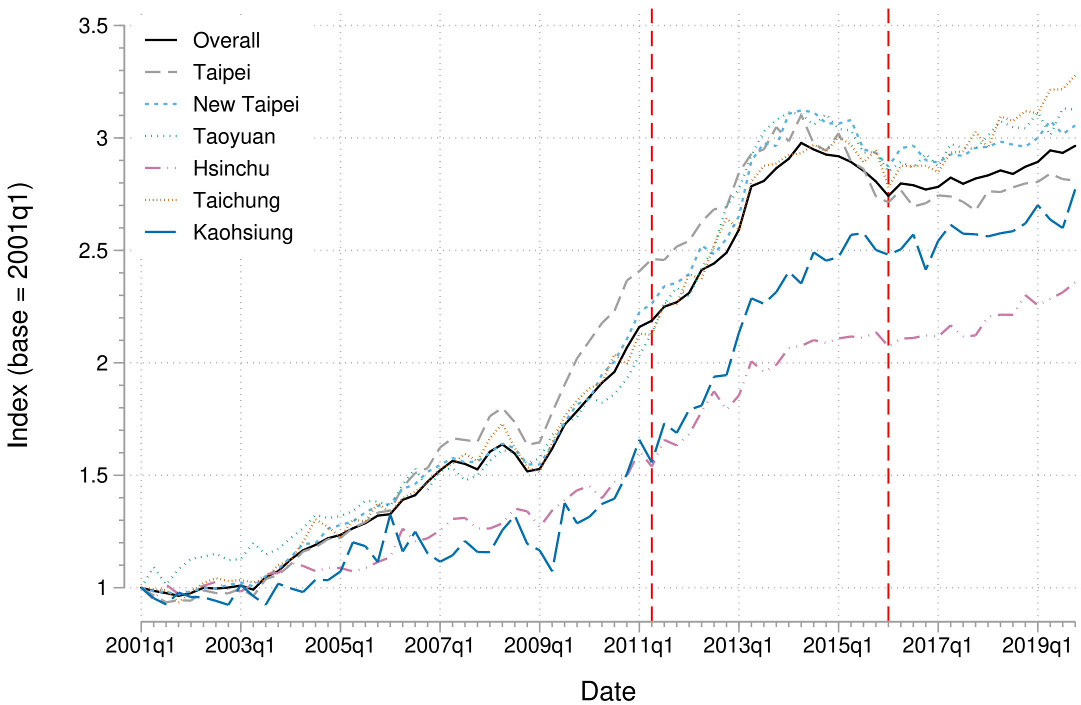
We find that torrential rainfall events generate a robust 20% drop in aggregate sales volume that does not rebound once the typhoon season ends, which yields an upper bound estimate for the noise trading share of 20%, and an upper bound estimate for the optimal real estate Tobin tax of 4%. Reassuringly, we estimate similar drops in local sales volume and a lack of pent-up demand when we match properties to documented typhoon pathways to exploit more granular variation in severe weather conditions. Ultimately, besides failing to promote housing affordability, the tax was excessively punitive towards second home sellers, crowding out more than just the noisy trades that predated the transfer tax.

The paper proceeds as follows. Section 2 provides a short description of the implementation of the transfer tax with a comparison to other transaction taxes. Section 3 describes our data. Section 4 presents our main results on the incidence of the transfer tax and real estate investment responses. Section 5 characterizes short-term property investors and documents heterogeneous returns by property and investor types. Section 6 offers a weather-based strategy for identifying noise trading volume and links our analysis to optimal financial transaction tax theory. Section 7 concludes.

2 Policy Background

This section offers an overview of the property tax regime in Taiwan and the 2011-2015 transfer tax reform we use as our policy experiment. We then compare Taiwan's system to transaction taxes in other major real estate markets.

FIGURE 2. Quarterly Housing Price Levels in Taiwan



Notes: The figure plots the Sinyi Residential Property Price Index, constructed by Sinyi Realty, for all of Taiwan and six major cities. All indices normalized to unity in the base period of 2001Q1.

2.1 Taiwan's Real Estate Transfer Tax

Housing prices in Taiwan dramatically increased after the onset of the Global Financial Crisis in 2008. Figure 2 plots the time series of housing price levels for the entire state and separately for Taiwan's six major cities using the Sinyi Residential Property Price Index. Overall prices rose by 116% (94% in real terms) from 2001Q1 to 2011Q1, with 41 p.p. of this increase occurring in the two years between 2009Q1 and 2011Q1, prompting concerns from policymakers about a future housing affordability crisis.[2]

Attributing this house price appreciation to an increase in property flips, the Taiwanese government announced in January 2011 the passage of a transfer tax surcharge (TTS) on short-term sales of non-owner occupied properties, effective on June 1, 2011.[3] Under the new law, sellers were

[2]We describe our indexing methods and compare price movements under alternative indices in Section 3.2 and Appendix B. Publicly available aggregate indices do not show any dip in price levels after the transfer tax reform. But officials in the Taiwan Ministry of Finance thought this policy was initially successful at reducing prices, reporting that average transaction values in Taipei fell by around 12% in the quarter after implementation. Existing price indices exclude sales occurring within a six month holding period. In Appendix B, we incorporate such short-term flips into a hybrid repeat sales-hedonic index and find a 7% decline in aggregate housing price levels.

[3]The transfer tax surcharge is included in a policy officially known as the Specifically Selected Goods and Services Tax. According to our translation of the Ministry of Finance website introducing the surcharge:

required to pay a fraction of the sale price according to the following rate schedule:

$$\tau = \begin{cases} 15\% & \text{if} \quad T < 1 \\ 10\% & \text{if} \quad 1 \leq T < 2 \\ 0\% & \text{if} \quad T \geq 2 \end{cases} \tag{2.1}$$

where T is the length of the holding period in years, measured from the seller's purchase date. With these rules, owners of investment properties are clearly incentivized to wait until at least two years have passed before reselling.

This surcharge only applies to arms-length transactions; gifts between family members, transfers involving employers and their employees, or transfers of government properties are exempted. We exclude from our analysis transactions that satisfy any of these exemption criteria. For transfers involving newly built properties, only the value of land transferred is subject to the surcharge. We drop transactions involving only new constructions or properties which recently underwent major renovations because the holding period is undefined in such cases.[4]

The transfer tax surcharge is large relative to payments required under other provisions of the property tax system. Important for our purposes, the June 2011 reform only added the surcharge to short-term sales, leaving untouched all other features of property tax policy. Other provisions in the property tax code include the following six taxes:

- *Building property tax* (paid by owners): 1.2% to 5% of the appraised building value, depending on whether the house is self-occupied, the number of houses the taxpayer holds, and whether the property is residential or commercial use. Building appraisals occur once every three years.

- *Land value tax* (paid by owners): progressive tax ranging from 1% to 5.5% of the "announced land value," which is an appraised value based on land transactions occurring in the area within the past three years.[5]

> *The ministry of finance realized that housing prices in certain areas were unreasonably high and the existing transfer tax on properties with short holding periods was too low (or even subject to zero transfer tax), and both brought a negative impact on citizens' living standard as the living cost increased. The ministry of finance, therefore, decided to levy the "Specifically Selected Goods and Services Tax Act", starting in June 2011, to achieve a well-functioning housing market with fair taxes that satisfies social expectation. The tax revenue will be used to finance expenses related to social welfare.*

The surcharge also applies to self-reported transfers of special categories of goods, such as passenger vehicles valued at more than 3 million NTD.

[4]The transfer tax therefore incentivizes landowners to engage in property development prior to selling when the cost of development is less than the implied tax savings from reducing τ to zero. In spite of this potential tax avoidance opportunity, we do not observe any spike in the number of transactions involving "unregistered partitions" (i.e. renovations) or newly built properties during the reform period.

[5]The law allows taxpayers to pay the land value tax on a "declared land value" which must be within 80%-120% of the most recently announced land value. If the taxpayer does not declare a land value, the government automatically applies the tax rate to 80% of the announced value. This is essentially a scheme whereby property owners have the ability to donate money to the tax authority.

- *Deed tax* (paid by buyers at the time of transaction): 6% of the appraised value of the property. Property appraisals are conducted by the government once every three years.

- *Stamp duty tax* (paid by buyers at the time of transaction): 0.1% of the sum of the appraised building value and "current land value" (CLV). The CLV is reassessed annually and based on recent transactions in the area.[6]

- *Land value increment tax* (paid by sellers at the time of transaction): 10% tax on CLV for sales of owner-occupied homes. Otherwise, this is a flat tax on a fraction (between 0 and 1, but close to 0.3 on average) of the CLV, with tax rates weakly decreasing in the holding period and ranging between 20% to 40%.

- *House transfer income tax* (paid by sellers at the time of transaction): liability is determined by the seller's personal income tax bracket and a local scale factor applied to transfer income, ranging from 0.08 for rural districts to 0.37 for the capital city of Taipei.

Sellers may thus incur three fees: a land value increment tax, a house transfer income tax, and the transfer tax surcharge. Since the surcharge rate directly applies to gross transfer income, for short-term sales it accounts for the largest portion of the total transfer tax payment due.[7]

The transfer tax surcharge remained in place from June 1, 2011 until December 31, 2015. On January 1, 2016, the Taiwanese government replaced the surcharge with a new capital gains tax where the rates are decreasing in the holding period length.[8] The capital gains tax rates differ depending on whether the taxpayer's registered address is overseas, according to the schedule:

$$\tau^R = \begin{cases} 45\% & \text{if} \quad T < 1 \\ 35\% & \text{if} \quad 1 \leq T < 2 \\ 20\% & \text{if} \quad 2 \leq T < 10 \\ 15\% & \text{if} \quad T \geq 10 \end{cases} \qquad \tau^{NR} = \begin{cases} 40\% & \text{if} \quad T < 1 \\ 35\% & \text{if} \quad T \geq 1 \end{cases} \tag{2.2}$$

where τ^R is the tax rate for residents, τ^{NR} is the tax rate for non-resident sellers, and T is the holding period length in years. Under the capital gains tax, the seller's payment depends on the appreciation of the property, not the transaction value at the time of sale:

$$\mathcal{T}^i = \tau^i \cdot \Big(P_T - P_0\Big), \text{ for } i = R, NR \tag{2.3}$$

[6] According to official descriptions of the deed tax, the CLV is computed to be smaller than the appraised land value determined every three years, although no computation methods are disclosed.

[7] We provide further details and examples of how property tax liabilities are computed in Appendix A.

[8] The January 1, 2016 reform also repealed the progressive value added tax on land transactions which was in place during the transfer tax surcharge period. All other components of the property tax system were left intact.

We also examine sales volume and pricing behavior around the introduction of the 2016 capital gains tax for properties, but we find no immediate effect around the new time notch along either dimension. We argue that the original transfer tax surcharge was sufficiently punitive towards short-term OOT investors that the new capital gains tax legislation did not alter the investment horizons of this group.[9]

2.2 Comparison to Other Property Transaction Taxes

We now briefly summarize transaction taxes enacted in other global housing markets. We emphasize that the two distinguishing features of Taiwan's TTS reform are the high tax burden it imposes on sellers, and its focus on very short-term sales. To illustrate this, in Table 1 we catalogue real estate transfer tax policies for the four "Asian Tigers" (Taiwan, Hong Kong, Singapore, and South Korea) and top 25 cities by value of investable real estate stock.[10] With the exception of Dallas, Houston, and Phoenix, all of these major markets have either a transfer tax or a capital gains or value-added tax which applies to real estate sales. Outside of Taiwan only four markets impose a tax where the rates depend on the holding period of the seller, and for the two cities in Japan this preference for long-term investing comes through the capital gains tax system rather than through a transfer tax.[11]

The other takeaway from Table 1 is that among economies which impose a flat-rate transfer tax, the rates tend to be fairly low, ranging from 0.055% in San Diego to 11% for luxury properties in Madrid. In Taiwan, the transfer tax surcharge we study here is levied on top of two other taxes, the land value increment tax and house transfer income tax, which can easily amount to a rate of 10% paid by the seller for high-value properties. If behavioral responses to transfer taxes are non-linear in the tax rate, this could help explain why we find such large effects on trading volume relative to other studies, such as Kopczuk & Munroe (2015) on the 1% "mansion tax" in New York and New Jersey and Slemrod et al. (2017) on a 0.8 p.p. rate increase in Washington, D.C.[12]

Gorback & Keys (2020) argue that a series of stamp duty tax hikes levied on non-residents in

[9]Since the capital gains tax rate drops sharply by 15 p.p. after the two-year holding period threshold, the 2016 property tax reform may have encouraged some sellers of recently purchased properties to delay sales until 2017 or 2018. Unfortunately this is beyond the December 31, 2016 end date of our sample of confidential transaction records.

[10]We use the ranking of cities provided by commercial real estate investment firm CBRE in their 2017 report available here. CBRE apply a rule of thumb in the real estate investment industry to value investable real estate stock, which assumes the real estate capital stock is roughly equal to 45% of output once the economy achieves some threshold level of per capita GDP of roughly 27,000 USD.

[11]Using the CBRE method applied in Table 1 we obtain an estimate of $253,973 million USD for investable real estate stock in Taiwan. This means Taiwan's real estate stock is about the same as the 10th largest market (Houston). Second, we total the transaction value of all purchases made in 2017 and obtain a value of $111,425 million USD. The latter estimate only takes into account observed transactions (flow) rather than the stock. Together these two numbers imply annual property turnover equivalent to 44% of Taiwan's entire real estate stock.

[12]The relatively small lock-in effects found in Kopczuk & Munroe (2015) and Slemrod et al. (2017) stand in contrast to Dachis et al. (2012) who find a 15% drop in single-family home sales in response to the introduction of a 1.1% land transfer tax in Toronto.

TABLE 1. Key Features of Transfer Taxes in Major Real Estate Markets

	RE stock value	Transfer tax	Capital gains tax (CGT)	Rate(s)	Holding period notch(es)	Exemptions	Legal Incidence
Taiwan	253,973	Yes	Yes	10-15% (flat)	Yes (both)	Inheritance/public entity	Seller
Hong Kong	196,706	Yes	No	1.5-20% (progressive)	✓(buyer surcharge)	N/A	Seller & buyer surcharge
Singapore	217,042	Yes	No	0.33-16% (progressive)	✓(seller stamp tax)	Certain uses (e.g. childcare center)	Buyer & seller (separate rates)
South Korea	758,376	Yes	No	4.6% (flat)	No	N/A	Buyer
Tokyo	711,255	Yes	Yes	3% (flat)	Yes (CGT)	Inheritance	Buyer
New York	656,903	Yes	No	1-2.625% (flat)	No	Sales by public agency	Seller (buyer if seller exempt)
Los Angeles	482,065	Yes	No	0.45% (flat)	No	Court order/collateral/gifts	Seller
Paris	342,389	Yes	No	0.71-6.41% (flat)	No	N/A	Seller
London	333,683	Yes	Yes	2-12% (progressive)	No	New homeowner/value < 125k GBP	Buyer
San Francisco	307,076	Yes	No	0.5-2.5% (flat)	No	Gifts/inheritance/refinancing/trusts	Buyer
Chicago	299,593	Yes	No	1.05% (flat)	No	Collateral/public/divorce	70-30 buyer-seller split
Seoul	290,695	Yes	No	0.02-5% (flat)	No	N/A	Buyer
Osaka	287,726	Yes	Yes	3% (flat)	Yes (CGT)	Inheritance	Buyer
Houston	254,515	No	No	N/A	N/A	N/A	N/A
Washington, D.C.	239,336	Yes	No	1.1-1.45% (flat)	No	Public/gifts/collateral/inheritance/non-profits	Seller
Boston	165,320	Yes	No	0.456% (flat)	No	Gifts/public/value < 2 mil. USD	Seller
Dallas	164,475	No	No	N/A	N/A	N/A	N/A
Atlanta	142,551	Yes	No	0.1% (flat)	No	Court order/divorce/inheritance/firm-to-firm	Seller
Miami	140,244	Yes	No	0.7% (flat)	No	Divorce/inheritance/trusts	Seller
Toronto	130,279	Yes	No	0.5-2.5% (progressive)	No	Public/nursing homes/hospitals/schools	Buyer
Philadelphia	128,534	Yes	No	4.28% (flat)	No	Gifts between family	50-50 buyer-seller split
Seattle	125,147	Yes	No	1.28% (flat)	No	Gifts/refinancing	Seller
Minneapolis	114,309	Yes	No	0.34% (flat)	No	Public/inheritance/refinancing/divorce	Seller
Sydney	113,395	Yes	No	1.25-5.5% (progressive)	No	Inheritance/spouse	Buyer
Detroit	107,711	Yes	No	0.11-0.75% (flat)	No	Gifts/inheritance/energy storage	Seller
Madrid	107,007	Yes	Yes (VAT)	6-11% (flat)	No	Transfer of ownership shares	Buyer
Phoenix	102,956	No	No	N/A	N/A	N/A	N/A
San Diego	99,343	Yes	No	0.055% (flat)	No	Collateral/public/share transfer	Seller
Milan	97,492	No	Yes (VAT)	N/A (10% VAT)	No	Residential/share transfers (VAT)	Buyer

Notes: The table summarizes the provisions of real estate transfer tax and real estate capital gains tax policies in place among the top 25 cities by investable real estate stock (in millions of USD), plus the four "Asian Tigers:" Taiwan, Hong Kong, Singapore, and South Korea. We use the methods outlined by CBRE (2017) to compute real estate stock in a way that allows direct comparison across markets. We note whether the transfer tax charges a flat rate based on the value and other features of the property, or whether the tax rate rises progressively with sale value. While Taiwan has several taxes incurred by a real estate transaction, for simplicity here we only list provisions of the transfer tax surcharge. We also list common cases in which a transfer would be tax exempt, such as transfers related to posting collateral, divorce, or inheritance. Information on tax policy sourced from various official government websites and research reports from real estate investment firms.

Singapore (SG) in 2011 and Hong Kong (HK) in 2012 incentivized Chinese capital to flow into U.S. housing markets.[13] Stamp tax duty schedules in HK and SG are quite complicated and vary by holding period, sale prices, and non-residency status. These schedules have been continuously reformed over the last decade, and now feature rates as high as 16-20% in the top brackets for non-residents. However, since neither HK nor SG impose capital gains tax on income from property sales, the effective rates paid by the seller are comparable to those for a flipper in Taiwan once all other transfer tax bases are included (see Section 2.1 and Appendix A).[14]

3 Personal Income Tax and Property Data

This section describes how we combine the universe of property transaction records with information from personal income tax returns to identify short-term property investors and assess the incidence of the transfer tax.

3.1 Linking Tax and Property Data

We combine four main datasets made available to us for years 2006 to 2016 by the Financial Information Agency of the Ministry of Finance. The first two datasets consist of records underlying the building property tax and deed tax bases described in Section 2.1. The deed tax records consist of daily data with transaction dates, buyer and seller identifiers, and taxes paid by the buyer on the appraised property value, which we use to link property owners to their personal income tax returns and other files estimating taxpayer wealth. The deed tax data distinguish unique properties, so together with the transaction date, we can compute holding periods between sales for the 43% of observations where the previous sale date falls within our sample period.[15]

The deed tax files also classify sellers and buyers based on their institutional and residency status. In particular, the tax authority identifies for-profit organizations, Taiwanese living abroad, and non-domestic counterparties. We also observe whether buyer-seller pairs share an employer, school,

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[13]While Gorback & Keys (2020) do not discuss the Taiwan transfer tax surcharge, price-rent ratios grew by a similar magnitude in the Taipei/New Taipei metro area as in HK and SG in the run up to these tax reforms. In results not shown here, we collect lease records for Taipei/New Taipei and find median price-rent ratios rose from 10 to 22 in Taipei, and from 18 to 30 in New Taipei between 2009Q2 and 2011Q2.

[14]SG and HK both have foreign homebuyer stamp duty tax surcharges, and HK's surcharge penalizes short-term sales. SG has a progressive stamp duty tax schedule for buyers (1-4% for domestic buyers) and a progressive set of schedules for sellers which depends on the holding period (higher tax on short-term) and the original purchase date. Deng et al. (2019) study rate changes at holding period discontinuities in the SG context and, as we do, uncover clear lock-in effects and find sellers who persist in spite of the tax charge a premium.

[15]We can also estimate (up to the nearest year) the holding period for properties which were initially built and then subsequently sold for the first time within our sample period. To do so, we use cumulative building depreciation recorded in the deed tax records to back out the construction year. However, since we cannot precisely distinguish whether a sale of a new property has crossed the one or two-year holding period tax notches at the transaction date, in our main analysis we do not include sales of newly constructed buildings. This has little influence on our results, as newly constructed buildings are exempt from the TTS.

or other institutional affiliation. We use these markers to remove from our sample non-arms-length transactions, sales involving a public entity, and probate transfers, as such sales may not reflect market conditions and are not subject to the transfer tax surcharge.

We use the unique property identifiers in the deed tax data to link transactions to information on property characteristics – such as address, building material, zoning, use category (e.g. residential, commercial, industrial), number of floors, layout, area, and floor space, among other features – contained in the building property tax records. These records are collected annually, while building characteristics are updated every three years when an appraisal occurs. Because the building property tax rate depends on the number of houses owned by the taxpayer and owner-occupied status of the structure, we combine the previous holding period with these records to identify sales subject to the transfer tax surcharge. We find 28% of taxpayers own more than one home, and roughly a third of owners of second homes have a portfolio of three or more properties.

Our third dataset consists of the universe of personal income tax returns which we link to property owners via the same taxpayer ID listed in the property tax records. Taxpayers provide two addresses when they file income taxes: a contact address (i.e. the tax bill address) and an address used to determine residency and any local components of income tax liability. Following Chinco & Mayer (2016), who use a similar dataset of merged property tax bills and transaction-level deeds, we define out-of-town (OOT) buyers or sellers as taxpayers with a residency address outside one of the 22 administrative regions where the transacted property is located.[16] Given this definition, 73% of sales involve at least one OOT counterparty; and sales where both the seller and buyer are OOT account for 27% of all arms-length transactions over our sample time period.

Income tax returns in Taiwan contain information on wages and salaries, as well as special sources of income such as lottery income and inheritances. Taxpayers also record interest payments towards mortgages, rental income and certain types of deductions for losses, donations, and insurance premia. While we do not observe outstanding mortgage balances, we use the information on interest payments to adjust for net-of-tax mortgage payments in our definition of holding period returns.

Our final dataset consists of personal wealth records created by the government from a combination of property registrations and information reported by taxpayers on income tax returns, as described in Chu et al. (2017). We observe estimated values of properties, vehicles, equities, and savings and other liquid wealth. Since triennial building and land appraisals significantly underestimate market values, we focus on heterogeneous responses to the TTS reform by wealth quantiles rather than by levels of wealth. For vehicles, the tax authority uses information from DMV registrations to assign an average retail price for the make and model (including foreign and luxury vehicles), and subtracts linear depreciation. We compute savings deposits and other liquid wealth such as corporate bonds from interest income items in personal tax returns. Finally, we follow the

[16] Administrative regions in Taiwan are roughly equivalent to the size of a combined statistical area (CSA) in the U.S. The 22 regions include the six special municipalities (Taipei, New Taipei, Taichung, Taoyuan, Tainan, Kaohsiung), three cities (Chiaiyi, Hsinchu, Keelung), and 13 counties.

procedures in Chu et al. (2017) to value stock shares; we price non-publicly traded stocks at face value and price publicly-traded stocks at the closing price of the annual ex-right date.[17]

3.2 Merging Tax and Transaction Records

Property sale values were not collected by the tax authority in a systematic fashion prior to the TTS reform in 2011, as the existing transfer taxes only applied to appraisal values (see Section 2.1). Prior to 2012 transaction records were scattered across 109 local land offices covering all 368 districts. We collect these records and append them to the public transaction records which cover all regional markets beginning in 2012Q3. We merge the public transaction records to the confidential property and deeds tax data using the address string, geo-coordinates, and transaction dates.[18]

For our analysis of holding period returns in Section 5, we need to take a stance on the correct concept of property "market value" during filing years when the property does not sell. We inflate the last observed sale price to current market value using a price index which applies to the property type (i.e. apartment vs. single-family home) and metro area combination. To this end, we consider four candidate price indices:

1. First, we use our local land office data to create an index from hybrid repeat sales-hedonic regressions covering the period 2000Q1 to 2019Q4 and based on the matching estimator approach of McMillen (2012). We describe the estimation procedures in Appendix B.

2. Second, we estimate a translog production model of properties which takes floor space, area, age, and distance to the nearest commuting hub as inputs. We discuss the assumptions underlying this method in Appendix F.

3. Third, we consider the Sinyi Residential Property Index, as plotted in Figure 2. The Sinyi Index is based on a hedonic model estimated by one of Taiwan's largest realty companies, Sinyi Realty, using proprietary housing sale records. This index has the advantage of being publicly available and goes back to 2001Q1, but only covers six major cities (approximately 70% of all sales volume).

4. Fourth, another proprietary quarterly hedonic price index, the Taiwan Cathay Real Estate Index (CREI) offered by Cathay Real Estate Development Co., dates from 2004Q1 and divides the residential market into five large geographic regions.[19]

As a check on the validity of our index methods and the two proprietary indices, we compare our results to the official housing price index available from 2012Q3, which is constructed from a subset

[17]For companies that do not distribute dividends, there is no ex-right date. In such cases we use the closing price on July 31 of each year.

[18]We describe our methods for matching properties across datasets based on observables in Appendix B.

[19]We hand-collected quarterly entries from the PDF reports available here from Cathay Real Estate.

of the same public transaction records we use to build our own index. In the end, the above four indices based on transaction records closely track each other. Over the period 2012Q3 to 2019Q4 when the aggregate indices overlap, the correlation between our matching estimator index and the official index is 98%, with a correlation between our index and the Sinyi index of 73%. We therefore adopt our matching estimator index to compute returns, since it reflects the near universe of sales (including short-term sales) and covers the longest time period in the pre-reform period.

4 Incidence and Investment Outcomes

In this section we present our main results for the effects of the transfer tax surcharge reform on sales volume and prices, exploiting the time notch and bunching around the holding period thresholds, as well as inheritance net worth shocks.

4.1 Summary Statistics: Before vs. After the Reform

We start by comparing some key summary statistics before and after the June 2011 reform for sales of second homes which were targeted by the new surcharge. Table 2 demonstrates how sales volume, holding period length, unit prices, and unit price volatility changed after the reform. In the top panel of the table, we present summary statistics for sales conducted within one year on either side of the reform, as well as for different windows of within less than one year of the reform. Overall sales volume declines by 44% within a year of the TTS, and holding period lengths nearly double. The tax appears to have been immediately salient to investors, who shift their horizon beyond two years to avoid paying the surcharge.

The bottom panel of Table 2 shows how the composition of second home properties changes across different parts of the *ex ante* sale value distribution within one year on either side of the TTS reform. Second home sales volume contracts by 45% at the top of the price distribution, and holding period length almost doubles regardless of property value. Interestingly, unit prices grow for properties in the top 60% of the pre-reform price distribution, but exhibit a mild 1% decline at the bottom of the distribution. This price growth could be due to two potential channels: one is a selection effect whereby only relatively high quality properties with a holding period above two years get offloaded in the aftermath of the reform, leading to a mechanical increase in average prices paid. Another channel is increased bargaining power of sellers, who may now seek a higher price as compensation for the increased tax burden. Since sales volume collapses following the reform, investment-grade real estate may very well have become a "seller's market." We provide evidence in favor of the latter channel in Section 4.4.

We find that overall volatility in the second home market declined by 2% within a year of the reform, with volatility initially dropping by around 30% within the first few months of the reform before recovering to pre-reform trend within a year, as investors who waited to reach the two-year

TABLE 2. Summary Statistics for Second Home Sales around the TTS Reform

	Sales volume			Holding period length			Unit prices			Unit price volatility		
	Before	After	Growth	Before	After	Growth	Before	After	Growth	Before	After	Growth
< 1 year	120,265	67,197	−44%	579	1,071	85%	81,138	81,906	1%	61,281	60,269	−2%
< 6 months	65,761	30,748	−53%	566	1,059	87%	81,533	81,347	−0%	68,028	57,463	−16%
< 3 months	34,215	14,350	−58%	534	1,083	103%	82,040	78,479	−4%	78,127	54,516	−30%
< 2 months	24,488	9,252	−62%	505	1,102	118%	85,328	78,549	−8%	86,275	56,324	−35%
< 1 month	14,944	4,120	−72%	486	1,137	134%	83,511	73,764	−12%	81,342	51,363	−37%
First quintile	2,707	1,740	−36%	624	1,148	84%	42,675	42,036	−1%	25,132	25,870	3%
Second quintile	3,124	1,966	−37%	591	1,110	88%	63,419	63,261	−0%	36,426	38,336	5%
Third quintile	2,684	1,785	−33%	566	1,033	83%	79,985	82,988	4%	42,399	50,384	19%
Fourth quintile	2,061	1,371	−33%	558	1,073	92%	103,242	105,670	2%	44,657	54,404	22%
Fifth quintile	1,721	946	−45%	530	978	85%	149,127	157,506	6%	100,694	80,277	−20%

Notes: The table shows summary statistics around the transfer tax surcharge implementation date of June 1, 2011. The top panel shows how overall sales volume, average holding period length, average unit prices (in NTD per square meter of floor space), and unit price volatility evolve by window length around the reform. For instance, < 1 month subsets to second home sales occurring either one month before or after the reform, whereas < 1 year looks at a symmetric 365 day window around the reform. Unit price refers to the price per square meter of land, or in the case of an apartment unit, price per square meter of floor space. The bottom panel instead shows how the same variables change within a one-year window before vs. after the reform, split by quintiles of the last observed pre-reform sale price for the property.

threshold began to sell. The 20% drop in unit price volatility for prime properties while volatility increased for more affordable properties suggests significant market segmentation. More generally, the summary statistics echo the analyses in Umlauf (1993) and Jones & Seguin (1997), who provide evidence that increasing transaction costs in securities markets increases price volatility, which goes against the logic of Tobin's (1978) proposal for a round-trip sales tax. Whether volatility increases or decreases for specific market segments is theoretically *ex ante* ambiguous and depends on buyer and seller outside options.[20] We return to this point in our discussion of noise trading in Section 6.

4.2 Bunching Estimates of Market Unraveling

4.2.1 Before vs. After Comparisons

We now investigate in more detail the quantity effects implied by the summary statistics. Figure 3 compares the distribution of sale frequency for second homes by holding period for three years before (panel A) versus three years after (panel B) the transfer tax was implemented on June 1, 2011. The figure illustrates three behavioral responses: first, there is clear evidence of bunching above the one-year and two-year holding period notches. The bunching response is much larger around the two-year notch where the transfer tax rate drops from 10% to 0%, implying that many investors simply delay sales by up to two years to avoid paying the tax.

Second, the TTS reform was very effective at reducing the number of sales with a holding period of less than one year. Prior to 2011, about two-thirds of all flips occurring within two years have a holding period of less than one year. Even though the surcharge rate drops from 15% to 10% across the one-year holding period notch, compared to the pre-reform distribution the implied excess mass for a six-month window around this notch is negative. Interestingly, since newly constructed buildings are not subject to the transfer tax surcharge, the high volume of short-term flips in the *ex ante* period reflects the relative absence of other search frictions in the second home market.[21]

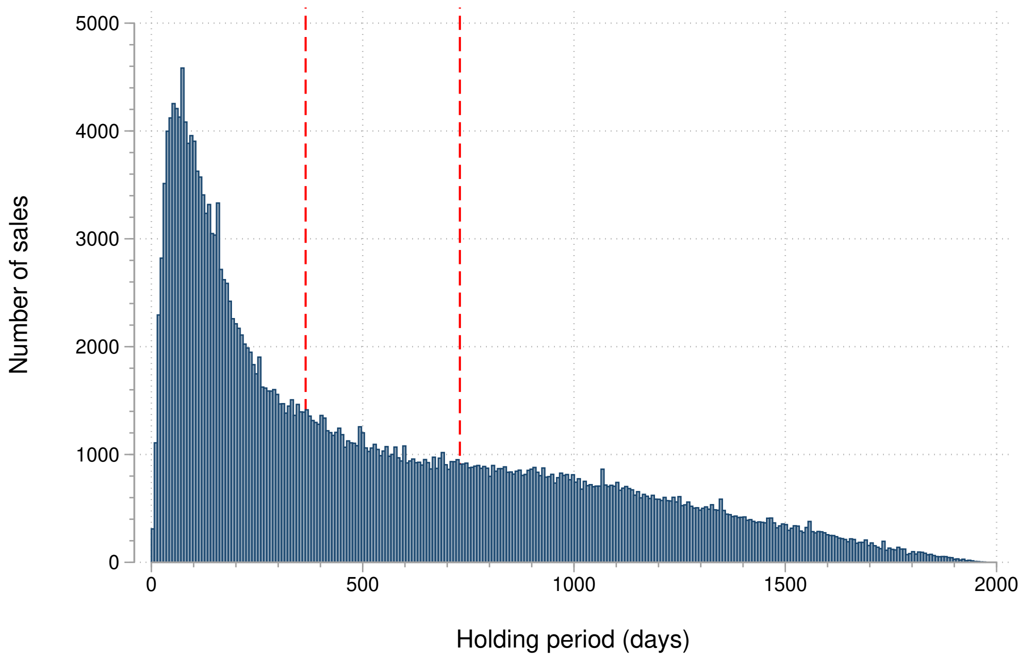
Third, the comparison between the pre-reform and post-reform distributions shows short-term unraveling in the market for investment properties. In the post-reform period, sales to the right of the two-year holding period notch only account for the drop in sales to the left of the notch once we include all properties with holding periods up to 2,000 days. Hence, in many cases, investors may already hold a property long enough to incur no surcharge but are unable to quickly find a

[20] Similarly, Umlauf (1993) finds return volatility in the Swedish equity market declines *relative* to volatility in the NYSE and LSE, as investors can avoid a 2% transaction tax by shifting investments to other markets. Cai et al. (2020) show a tripling of the Chinese stamp tax on stock market trading led to a trading frenzy in the untaxed warrant market, illustrating the "whack-a-mole" game inherent in Tobin taxes.

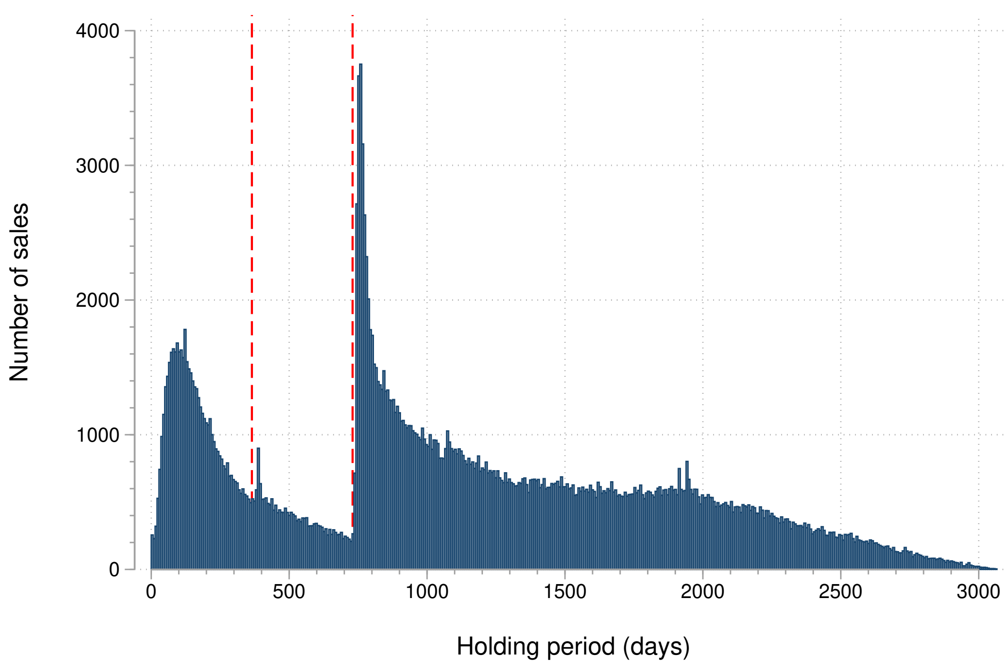
[21] In Appendix A, we estimate the minimum amount of time required to close a residential property sale after identifying a buyer to be 38 days, with an average duration of 113 days for transactions in the capital city of Taipei. Thus, the high number of sales occurring within a six-month holding period pre-2011 is completely plausible, conditional on sellers being able to quickly identify interested buyers.

FIGURE 3. Distribution of Sales Volume by Holding Period

A. Pre-reform Period

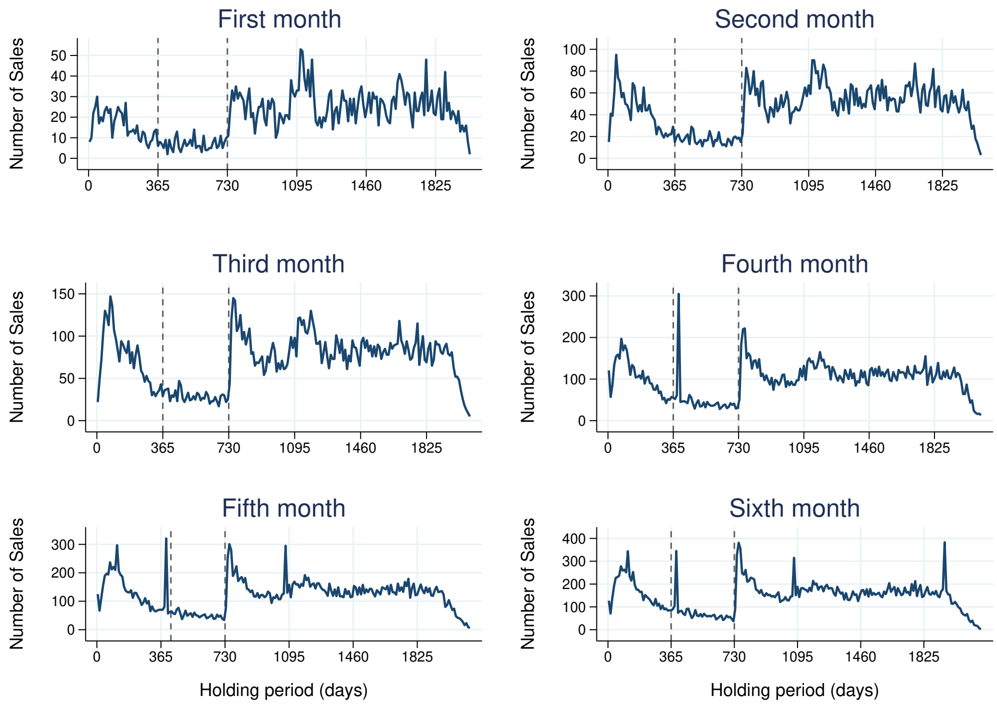


B. Post-reform Period



Notes: Each panel shows the distribution of total property sales, restricting to properties with a clearly defined holding period. Panel A is the distribution for the three years prior to June 1, 2011, while Panel B is the distribution for the three years following the TTS reform. The vertical red dashed lines indicate the one-year and two-year holding period notches.

FIGURE 4. Bunching Dynamics within Six Months of the Reform



Notes: Each panel shows the distribution of property sales by holding period in one of the six months following the June 1, 2011. For instance, the first panel refers to sales occurring between June 1, 2011 and June 30, 2011. The vertical dashed lines indicate the one-year and two-year holding period notches.

buyer, implying that the transfer tax surcharge renders second homes more illiquid.[22] In other words, while the surcharge reduces demand from buyers looking for second homes, it also induces a short-term negative supply response.

Short-term sales volumes converged to a new steady state within six months, as demonstrated by the bunching dynamics in Figure 4. Sales volume drops substantially, both relative to the previous month and on a year-on-year basis, in the first month following the reform, but gradually begins to recover as more second homeowners surpass the two-year holding period threshold. However, some bunching at the two-year notch is present even in the first month, with bunching around the one-year notch stabilizing by the fourth month following the reform. This almost immediate convergence suggests a minor role for the optimization frictions documented in other bunching contexts (Chetty et al. 2011; Kleven & Waseem 2013; Gelber et al. 2020), and is consistent with Best & Kleven (2018) who find similarly fast reactions to changes in the U.K. Stamp Duty Tax

[22] In Appendix H we provide further evidence of this liquidity crunch problem using listings data from a large, anonymous brokerage firm. We find that mean time on market (TOM) increases by roughly 7 days after the TTS reform (p-value = 0.000) among listings closed within a year on either side of the June 1, 2011 reform date. This increase in TOM is driven entirely by non-owner occupied homes which are subject to the flip tax.

schedule. Our finding that sellers responded almost immediately to the policy is likely due to the large implied tax savings from delaying sales. For example, flipping a home after two years instead of after one year at the median post-reform value of 5.3 million NTD (177,000 USD) would lower the surcharge payment due by 17,700 USD.

4.2.2 An Hedonic-Logit Counterfactual Model

A simple excess mass calculation based on comparing the pre-reform and post-reform distributions in Figure 3 may not be informative about the true extent of missing sales due to the tax. For instance, there may be macroeconomic trends unrelated to the tax which lead to changes in the composition of properties sold. A common approach to constructing counterfactuals in the literature is to fit local polynomial regressions to transactions data around the policy cutoff of interest (e.g. Chetty et al. 2011; Kleven & Waseem 2013; Best & Kleven 2018). In our setting such an approach can be summarized by the following regression:

$$q_j = \sum_{k=0}^{p} \beta_k \cdot (h_j)^k + \sum_{j=h_-}^{h_+} \gamma_k \cdot \mathbb{1}\{h_j = k\} + \nu_j \tag{4.1}$$

where q_j refers to the mass in holding period bin j and h refers to the length of the holding period within the bin. $[h_-, h_+]$ is an excluded range of holding period lengths around either the one-year or two-year threshold. The counterfactual bin counts are then obtained as the fitted values from the polynomial of order p via: $\widehat{q_j} = \sum_{k=0}^{p} \widehat{\beta_k} \cdot (h_j)^k$.

We obtain nonsensical results when we use this excluded range method to construct a counterfactual distribution of sales by holding period. Excluding properties around the one-year and two-year thresholds generates a counterfactual where sales volume for holding periods of six months or less is actually higher in the post-reform data than the predicted volume. If we took these results seriously, we would erroneously conclude that the transfer tax surcharge increased net trading volume!

The problem is, unlike most transfer taxes which introduce price notches, the discontinuities in our setting are in terms of units of time. Since a homeowner's decision to sell a property today has a persistent influence on sales in future dates, there can be no well-defined concept of an excluded region when the tax regime introduces holding period notches. Doubly problematic is the fact that the transfer tax we study features two time discontinuities which are relatively close together, so any behavioral responses around the one-year threshold will likely have large effects on sales volume around the two-year threshold.

Our strategy to address these concerns is to estimate an hedonic-logit model on the pre-reform transaction data.[23] We then apply the fitted sale probabilities from that model to construct what the distribution of sales would have looked like in the absence of the tax, conditional on property amenities in the available housing stock. The procedure can be described by the following equations:

$$f_{i,t} = \Pr\Big(y_{i,t} = 1 | \mathbf{X_{i,t}}, \delta_t, \beta\Big) = \frac{1}{1 + \exp(-\delta_t - \beta' \cdot \mathbf{X_{i,t}})} \tag{4.2}$$

$$y_{i,t} = \mathbb{1}\{\delta_t + \beta' \cdot \mathbf{X_{i,t}} + \epsilon_{i,t} > 0\} \tag{4.3}$$

$$\widehat{q}_j = \sum_{i=1}^{N_j} \widehat{f}\Big(\mathbf{X_{i,t}};\ \widehat{\delta}_{\mathbf{t}}, \widehat{\beta}\Big) \tag{4.4}$$

The first two equations specify a logit model of sale probability where we include month-year, day-of-week, and week-of-month fixed effects, as well as a holiday dummy in the vector of time fixed effects δ_t. A set of potentially time-varying property characteristics $\mathbf{X_{i,t}}$ adjusts for compositional changes in the market, and includes a polynomial of holding period length. The last line computes the counterfactual sales volume in holding period bin j by integrating up from the fitted probabilities $\widehat{f_{i,t}}$ for each property i in the *post-reform* period.

The identifying assumption for $\widehat{q}_j$ to be an appropriate counterfactual for sales volume is that, in the absence of the TTS, the market would have priced property amenities in $\mathbf{X_{i,t}}$ in the same way as in the pre-reform period. We assess the validity of this assumption in two ways. First, we check how well the model can fit the empirical distribution in the pre-reform period. Figure 5 shows that our model fits the empirical distribution quite well. We obtain a p-value of 0.86 for the Kolmogorov-Smirnov test of the null of no difference between the empirical and model-implied sales distributions.[24] Second, in Appendix I we run versions of the model in (4.2)–(4.3) where we interact property characteristics such as age with quarter-year fixed effects and check for pre-trends in the estimated factor loadings.[25]

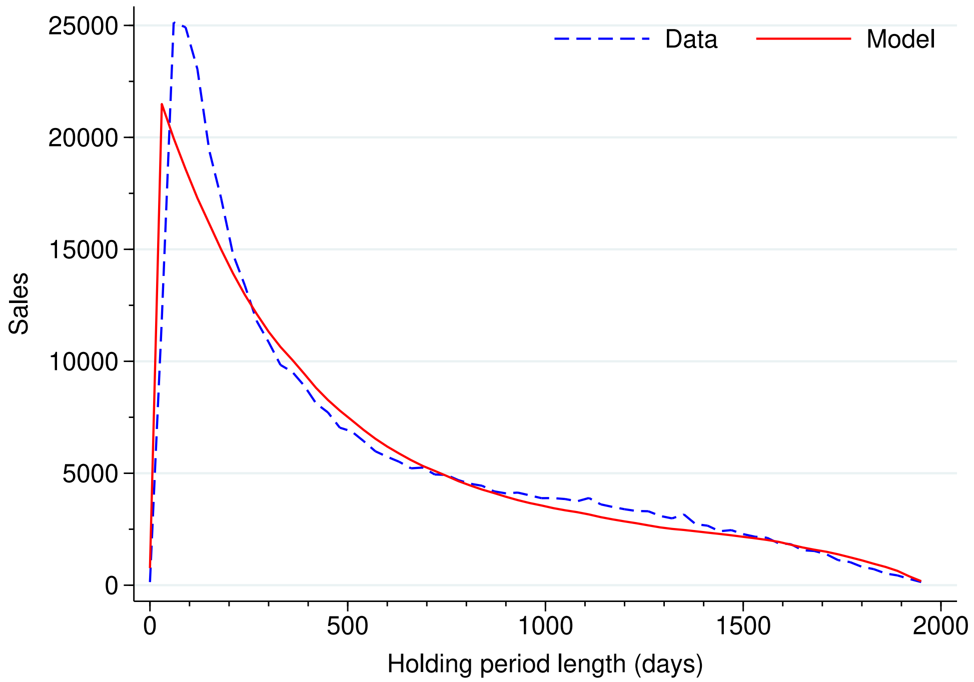
Figure 6 illustrates that the TTS reform crowded out about 33,000 sales, or 40% of a year's worth of pre-reform sales volume, and generated a 75% drop in one-year flips. Interestingly, the estimated counterfactual curve suggests the tax not only discouraged sales to the left of the two-year threshold,

[23] Our counts of sales crowded out by the Tobin tax are similar when we instead estimate a linear probability model (LPM) or probit version of our model. Under each type of model, conditional on the same RHS set of covariates, we find the tax generated missing sales volume equal to approximately half of average annual sales in the pre-reform period. The LPM frequently generates fitted probabilities in excess of one, leading to overestimates of the counterfactual amount of short-term trades, and therefore overestimates of missing sales.

[24] In Appendix G, we show our missing mass estimates are quantitatively similar when we restrict to older properties which are more likely to have recently been renovated. This suggests any model misspecification in Figure 5 is not due to unobserved home improvements (Goetzmann & Spiegel 1995). We discuss how our failure to fully predict *ex ante* short-term sales volume influences our optimal tax results in Section 6.

[25] An alternative exercise would be to run specifications of the form: $f_{i,t} = \delta_t + \beta_t' \cdot \mathbf{X_{i,t}} + \epsilon_{i,t}$, and conduct Sup-Wald tests for the null of a structural break in the components of β_t. We do not adopt this as our main identification check given the relatively small number of quarter-years in our pre-reform period and the fact that such tests are known to be under-powered in small time samples.

FIGURE 5. Hedonic-Logit Model Fit to Pre-Reform Data



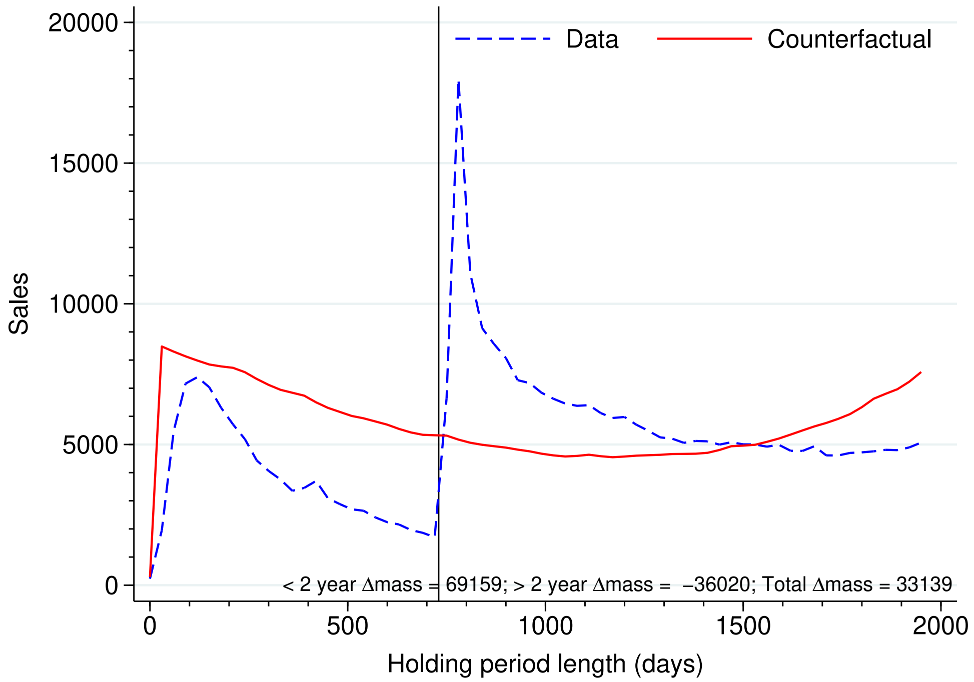
Notes: The figure plots the distribution of sales volume by holding period length estimated via the system of equations in (4.2)–(4.4) in red. The empirical pre-reform distribution appears in the blue dashed line. The full logit model includes month-year, week-of-month, day-of-week fixed effects, a holiday dummy, a quadratic in property age (measured from the construction date), dummies for structure material, dummies for use category (e.g. apartment vs. single family home), floor space, land area, holding period length, number of floors and building floor dummies.

but also at holding periods beyond four years in length.[26] By increasing the cost of engaging in flips, the transfer tax rendered housing even less liquid for potential investors. Hence, a seller may have trouble finding a buyer in the market for vacation properties even if that seller does not face the tax liability themselves.

Which types of investors are most discouraged by the flip tax? Table 3 tabulates missing sales by sellers' estimated quintile of net worth as of 2010. We obtain these numbers by applying the model in (4.2)–(4.4) to obtain fitted values for properties sold to taxpayers within each net worth quintile. About half of the overall missing mass originates from sellers in the bottom fifth of the wealth distribution. The proportion is also roughly the same when we examine the fraction of sales within a two-year holding period crowded out. In light of this evidence that low-wealth individuals are an important source of speculative activity, we analyze in Section 5 whether the speculators that were crowded out in the low-end of the wealth distribution were misinformed, but find that

[26] Our finding of distortions beyond the two-year cutoff echoes the results in Kopczuk & Munroe (2015), who come to a similar conclusion regarding the 1% mansion tax in the New York metro area.

FIGURE 6. Empirical and Counterfactual Sales by Holding Period Length



Notes: The figure plots the distribution of second home sales volume by holding period length estimated via the system of equations in (4.2)–(4.4) in red. The empirical post-reform distribution appears in the blue dashed line. The full logit model includes month-year, week-of-month, day-of-week fixed effects, a holiday dummy, a quadratic in property age (measured using the construction date), dummies for the structure material, dummies for the use category (e.g. apartment vs. single family home), floor space, land area, holding period length, number of floors and building floor dummies.

they earned *higher* tax-adjusted holding period returns than their wealthier counterparts.[27]

4.3 High-Frequency Evidence of Short-run Effects on Prices

The government implemented the transfer tax surcharge to increase housing affordability by targeting short-term investors. Was the reform successful in lowering housing prices? Our evidence suggests it was not. Overall, while the reform helped reduce price volatility, we find that the negative pricing effects were limited to low-end apartments for which realized capital gains would have been small relative to the hike in tax liability.

We explore the pricing effects of the TTS by looking at how sale prices for all arms-length transactions evolved around the time notch on June 1, 2011. Figure 7 plots daily average log sale prices and fits a quadratic polynomial estimated using a uniform kernel on either side of the reform

[27]When we apply the same counterfactual model to local and out-of-town (OOT) sellers, we find OOT sellers account for 60% of the net missing sales.

TABLE 3. Missing Sales Volume by Seller's Net Worth Quintile

	HP $\leq$ 2 yrs.	HP $>$ 2 yrs.	Net missing	% of total
First quintile	32,669	$-17,999$	14,670	44%
Second quintile	520	137	657	2%
Third quintile	4,958	-65	4,893	15%
Fourth quintile	11,999	$-6,693$	5,306	16%
Fifth quintile	19,013	$-11,400$	7,613	23%
Total	69,159	$-36,020$	33,139	100%

Notes: The table shows the number of missing sales volume above (column 2) and below (column 1) the two-year holding period threshold, and the net missing sales (sum of the first two columns). Each row represents missing sales within each 2010 taxpayer net worth quintile implied by the hedonic-logit model in equations (4.2)–(4.4). Negative missing sales indicates there are more sales than the counterfactual model would predict for that section of the holding period distribution.

date.[28] The transfer tax reform applied only to short-term second home sales and special categories goods such as passenger vehicles, while leaving all other components of the regulatory environment intact. In the absence of any other shocks that would influence prices in the second home market around June 1, 2011, a jump in prices around that date represents a shift due to changes in relative buyer-seller bargaining power induced by the surcharge.

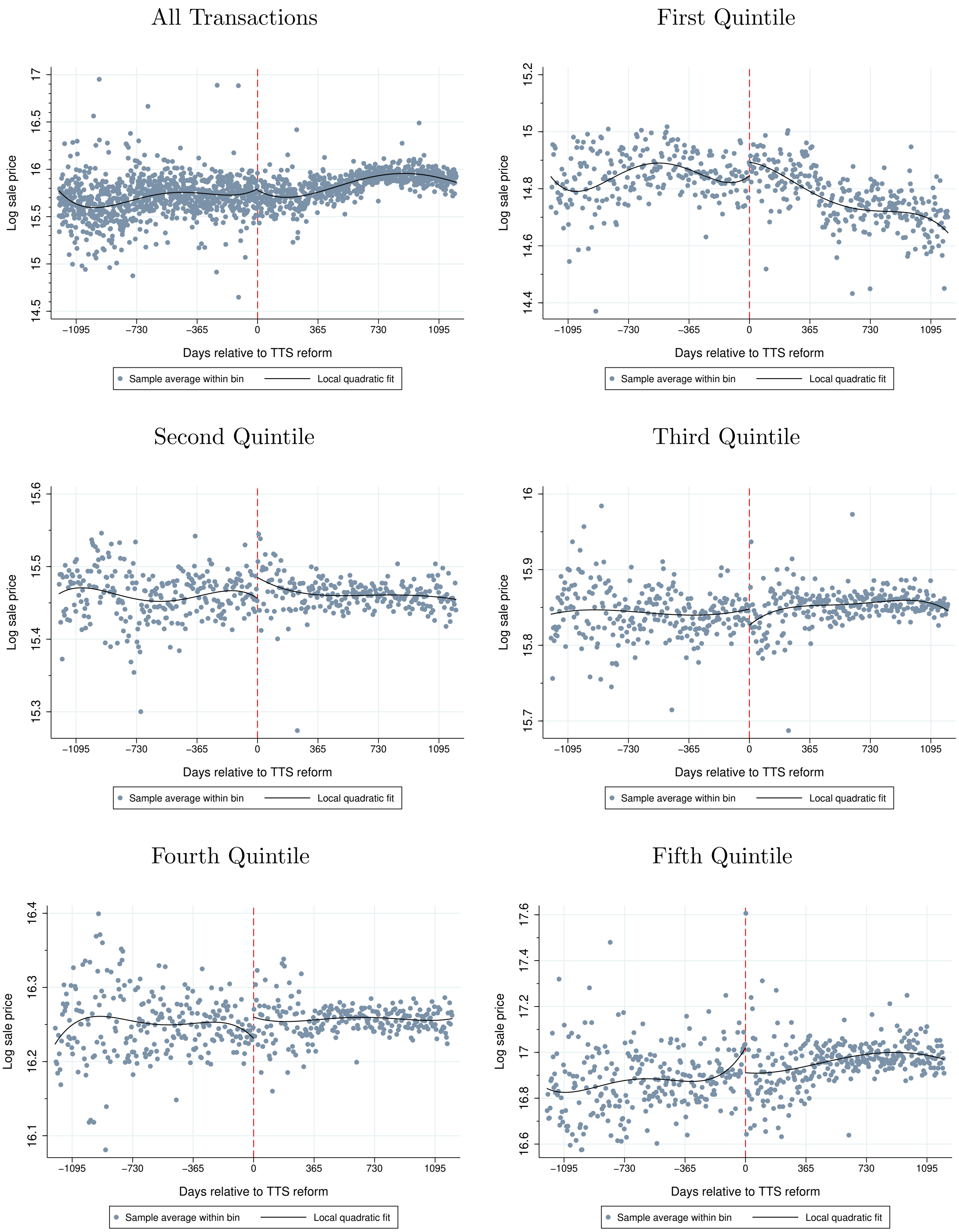
Prices jump by 2% around the implementation date for the bottom two quintiles, but by 10% among properties in the top quintile of transaction values. For two-year flips in the top quintile, this would imply sellers completely pass through the increased tax burden to buyers. We show in Section 4.4 that taxpayers with exogenously more housing wealth on the eve of the reform fall into this category and successfully extracted a premium from buyers in the post-reform period.

The surcharge applied retroactively to any properties purchased before the reform date. We perform a similar exercise using as the cutoff the seller's original purchase date relative to June 1, 2009, after which any property sold within two years would be subject to the transfer surcharge (results not shown here). Given that the TTS was announced at the beginning of 2011, buyers of second homes in 2009 would not have any incentive to alter the sale date to avoid transfer tax liability; there were no reforms to other transfer taxes around that time. Hence, in contrast to Figure 7, there is no scope for manipulation on the left-hand side of the grandfathered date cutoff.

We interpret any jump in prices around the June 1, 2009 cutoff as a premium charged by sellers to offset the tax bill associated with a flip, when the alternative would be to wait a matter of days

[28] We fit local quadratic polynomials to the data on either side of the time notch to avoid the issues with higher-order polynomials in regression discontinuity designs outlined in Gelman & Imbens (2019).

FIGURE 7. Sale Prices around Reform Implementation



Notes: Each panel presents the evolution of log transaction prices relative to the reform implementation date of June 1, 2011. Each point in a graph represents the average sale price observed within a daily bin. The first panel pools all transactions, while the remaining five panels divide the universe of transactions into sale price quintiles computed over the entire sample period.

to finalize the sale. The results qualitatively mirror those in Figure 7, in that sale prices are smooth across the time notch for all but the top quintile of property values, where prices jump discretely by about 2%. In sum, our high-frequency evidence points to a negative trend break in prices for cheaper apartments, with prices declining by 28% in the three years after the TTS reform (−8.6% annualized growth), but a sharp jump in sale prices for high-end properties before a return to trend.[29] While the tax may have improved housing affordability at the very low-end of the market in the medium-run, the net effect on prices across the entire housing market was virtually nil.[30]

4.4 Segmented Pass-through: Evidence from Inheritance Shocks

We now turn to identifying causal impacts of the transfer tax surcharge reform on transaction prices. Whether prices and volatility go up or down in response to a financial transaction tax is theoretically ambiguous, since such taxes influence both asset demand and supply (Dávila 2020).[31] Tobin's (1978) argument of FTTs as price stabilizers focused on the partial equilibrium effect of taxes on demand, assuming asset supply remained fixed. The transfer tax surcharge renders owning short-term investment properties substantially less attractive, thus lowering demand, but also discourages current owners from engaging in flips, which lowers market inventory. Contrary to the objectives of the transfer tax, prices may therefore increase if the latter effect dominates.

We leverage our detailed information on taxpayer portfolios to determine the extent to which sellers in the post-reform period are able to extract a premium from buyers to offset the increased transfer tax bill. Our idea is to compare households with more vs. less inherited housing wealth as of the filing year directly prior to the reform.[32] Taxpayers with more inherited housing wealth are more exposed to the reform in that they hold more assets which could be subject to the transfer tax surcharge. Because it is well-established that heirs anticipate close relatives' deaths (Bernheim et al. 1985) and the timing of death is endogenous to estate tax avoidance opportunities (Kopczuk & Slemrod 2003), we also consider inheritances arising from cases where the decedent unexpectedly

[29] We document similar heterogeneity by price tier in Appendix H where we examine differences in liquidity among single family home listings around the TTS reform. We find mean time on market increases by 7.5 days in the bottom quintile (p-value = 0.001) and by 9.5 days in the top quintile (p-value = 0.002), but only by 4-5 days in the middle of the price distribution.

[30] We replicate the high-frequency analysis using prices per square meter instead of transaction values. The main difference is that unit prices are smooth across the June 1, 2011 time notch for the top quintile of properties, indicating larger properties comprised a greater share of volume in the post-reform period. Our hedonic-logit bunching methods in Section 4.2 account for these compositional changes in measuring the extent of market unraveling.

[31] Even if asset supply is fixed, the effect of the tax on prices is *ex ante* ambiguous. The intuition is that in a disagreement model of asset markets in which traders differ in their beliefs, the cost of buying and selling the asset goes up after a transaction tax, but fundamental traders may want to increase their holdings if the tax crowds out noise traders and price efficiency improves.

[32] The flat estate tax rate is 10%, before applying any deductions for debts, conservation easements, and lineal dependents. Although there is an exemption threshold for the entire estate of of 12 million NTD (roughly 400,000 USD), the executor is still required to file an estate tax return when the value does not exceed this amount. This structure is consistent with the administration of inheritance and estate tax schemes in other economies. See Appendix D for more details.

died. In Appendix G we use the reported cause of death to distinguish between deaths arising from chronic conditions (e.g. cancers) and "sudden deaths" arising from accidents or untimely deaths due to non-chronic conditions (e.g. heart attack or stroke).[33]

In particular, we estimate the following model relating sale prices to taxpayer net worth (NW):

$$Y_{i,j,t} = \alpha_2 + \beta_2 \cdot \Big(NW_{i,\tau} \times Post_t\Big) + \gamma' \cdot \mathbf{X_{i,j,t}} + \delta_t + \epsilon_{i,j,t} \tag{4.5}$$

$$NW_{i,\tau} = \alpha_1 + \beta_1 \cdot \underbrace{\sum_{t=0}^{k} IW_{i,\tau-t}}_{\equiv NWShock_{i,\tau}} + \eta_i \tag{4.6}$$

$$\mathrm{cov}\Big(NWShock_{i,\tau}, \epsilon_{i,t}\Big) = 0 \tag{4.7}$$

where $Y_{i,j,t}$ is an outcome at the level of property j (i.e. log sale price, probability of property sale) attached to taxpayer i on date t. $IW_{i,\tau}$ is value of inheritances received in tax filing year τ, net of the estate tax bill and any deductions.[34] NW_τ is estimated net worth in a tax filing year τ prior to the announcement of the TTS reform in early 2011. δ_t are time fixed effects, including month-year, day-of-week, and week-of-month fixed effects to strip out different frequencies of seasonality in property sales. The vector of potentially time-varying property controls $\mathbf{X_{i,j,t}}$ accounts for the fact that inheritance shocks may alter heirs' preferences over house characteristics.

Equations (4.5)–(4.7) characterize a difference-in-differences model where we instrument the potentially endogenous pre-treatment exposure measure NW with $NWShock$. The first stage in equation (4.6) produces a fitted value $\widehat{NW}_{i,\tau}$ which reflects the component of an agent's housing wealth observed directly prior to the reform which can be explained by the cumulative amount of any inheritances received up to k years prior to τ.[35] In our baseline specification, we set $k = 4$. Setting a longer k increases the number of taxpayers in the treated group of inheritors, but at a cost; the longer the pre-reform horizon we use to define $NWShock$ the more potential there is for portfolio exposure to the reform to be based on heirs' pre-reform investment decisions in response

[33]The inheritance tax records indicate more than 360,000 unique causes of death. Rather than take a stance on the probability that the reported cause of death is associated with a known terminal illness, we simply use clear-cut cases where the heirs are unlikely to have sufficient lead time to rebalance their portfolios in anticipation of a windfall. We obtain qualitatively similar results when we instead restrict to inheritances received from a decedent who died ten years or more before their life expectancy (i.e. two standard deviations younger than the average age at death).

[34]Tax years in Taiwan run from January 1st to December 31st, meaning the last full tax year prior to the TTS reform is 2010. Taxpayers normally must file personal income tax returns by May 31st of the following year. Hence, any information recorded on 2010 tax returns only reflects taxpayer earnings and wealth prior to reform implementation on June 1, 2011. Since the reform was first announced in January 2011, any information on 2010 returns captures a taxpayer's financial status prior to the announcement, and thus should not reflect anticipatory responses.

[35]We inflate up to estimated values as of filing year τ using portfolio weights and price indices constructed for each asset type: real estate (weighted by the distribution of taxpayer properties), vehicles, and equities.

to inherited wealth rather than the inheritance windfall itself.[36]

To be more explicit, our DD-IV design has two identifying assumptions:

1. Exclusion restriction: equation (4.7) says that cumulative pre-reform inheritances must only influence outcomes related to property sales through their effect on pre-reform taxpayer net worth (measured from filing year $\tau = 2010$).

2. Parallel trends: taxpayer outcomes were similar in the pre-reform period with respect to the component of net worth explained by inheritances received between 2007-2010. In other words, characteristics of sales involving people with large vs. small inherited housing wealth were demonstrably similar prior to June 2011.

Both assumptions could be violated if, for instance, individuals with large inheritances are able to charge a premium for their properties due to social capital or market power (e.g. access to better realtors), regardless of their initial wealth balances. To the extent that property characteristics may not be absorbed by taxpayer fixed effects, we include on the RHS a vector $\mathbf{X}_{i,t}^{j}$ of features of property j bought or sold by taxpayer i.[37]

We find clear evidence that inheritance shocks pass through to net worth on the eve of the transfer tax reform. Table 4 reports first and second stage results from estimating 2SLS models in the form of equations (4.5) and (4.6) for different versions of the net worth shock. We consider shocks to both the seller's and buyer's wealth, and to both overall wealth and to only housing wealth. In our preferred estimate (column 2), 0.57 cents of every one dollar increase in inherited wealth passing through to the seller's pre-reform net worth. Pass-through is weaker, in a first stage F-stat sense, when we restrict to housing inheritances (columns 1 and 3), and when consider shocks to the buyer's portfolio (columns 3 and 4). Our first stage estimates for buyers are relatively weak because buyers are more likely to be at an earlier point in the life cycle and still accumulating assets. Since investment responses prior to the reform may influence market prices in the post-reform period, independent of the direct effect of inheritances on buyers' wealth, we focus on how sellers respond to the shock. In all specifications where we use inheritance shocks to sellers, the Montiel-Olea-Pflueger F-test exceeds the thresholds for 5% worst case bias relative to OLS at the 5% level, indicating that our research design does not suffer from a weak instrument problem.

[36] The pass-through of inheritances to housing wealth can differ across taxpayers because inherited wealth IW may be assessed differently from asset values used to compute NW. Identification in this model comes from cross-sectional variation in the estimated value of taxpayer portfolios. Hence, we only require that either assessment rules for NW and IW are applied uniformly across taxpayers, or, that any taxpayer-specific components to assessments do not systematically vary across the tax implementation.

[37] Inheritances account for a large fraction of the stock of tangible assets in Taiwan. We report basic summary statistics on wealth and inheritances among property buyers and sellers in our sample in Appendix D. On average, inherited properties account for 15% of 2010 taxpayer housing wealth, with a slightly higher share of 17% among buyers. The differences in the importance of inheritances for buyers vs. sellers reflects the fact that buyers tend to be younger and hence more likely to be a point in the life cycle where asset accumulation is accelerating.

TABLE 4. First and Second Stage Results by Inheritance Shock Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NWShock$ (β_1)	1.938***	0.574***	0.827***	−0.008	0.218***	0.226***	0.230***	0.228***
	(0.221)	(0.170)	(0.186)	(0.262)	(0.003)	(0.003)	(0.108)	(0.008)
First stage $Y \times Post$ (β_2)	0.017***	0.013***	0.031***	0.030***	0.024***	0.024***	0.063***	0.053***
	(0.002)	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.015)	(0.014)
First stage Y	HNW^S	NW^S	HNW^B	NW^B	$ln(HNW^S)$	$ln(NW^S)$	$ln(HNW^B)$	$ln(NW^B)$
IV	IHW^S	IW^S	IHW^B	IW^B	$ln(IHW^S)$	$ln(IW^S)$	$ln(IHW^B)$	$ln(IW^B)$
Montiel Olea & Pflueger F-test	12.27	100.31	3.59	0.60	694.38	851.10	452.78	739.59
First stage F-test (Kleibergen-Paap)	12.23	99.99	3.58	0.60	696.62	852.61	454.90	741.27
First stage F-test (Cragg-Donald)	856.15	1304.31	130.56	522.00	1243.02	1272.54	1221.65	1294.02
Property controls	✓	✓	✓	✓	✓	✓	✓	✓
Time & district FEs	✓	✓	✓	✓	✓	✓	✓	✓
Adj R^2	0.697	0.699	0.700	0.711	0.713	0.717	0.716	0.716
N	182,646	182,646	182,646	182,646	22,658	27,074	20,076	23,721

Notes: The table provides first stage and 2SLS estimates from the model specified in equations (4.5) and (4.6). $NWShock$ refers to the estimated pass-through of inheritance shocks over 2007-2010 to overall taxpayer net worth as of the 2010 filing year. First stage $Y \times Post$ refers to the 2SLS estimate of the premium charged by a seller or buyer). We check how inheritance shocks differentially influence the behavior of sellers and buyers, and how the pass-through to net worth changes depending on whether we restrict to housing inheritances (IHW) or all inheritances (IW). All inheritance measures are net of estate tax liability and applicable deductions. The last two columns provide estimates in logs, and therefore only include taxpayers with strictly positive inheritance receipts (intensive margin). There are $N = 368$ districts in total, and in some specifications we include district fixed effects as well as month-year, week-of-month, day-of-week fixed effects, and a holiday dummy. Property controls include a polynomial in age, area, floor space, use category, structure type, unit floor number (for apartments), and number of floors (for single family homes). Robust standard errors in the second stage regression clustered at the district of the property. $***p < 0.01, **p < 0.05, *p < 0.1$

TABLE 5. Seller Pass-through of Transfer Tax to Buyers

A. Overall Responses: Sale Price Response to Changes in Seller's Wealth

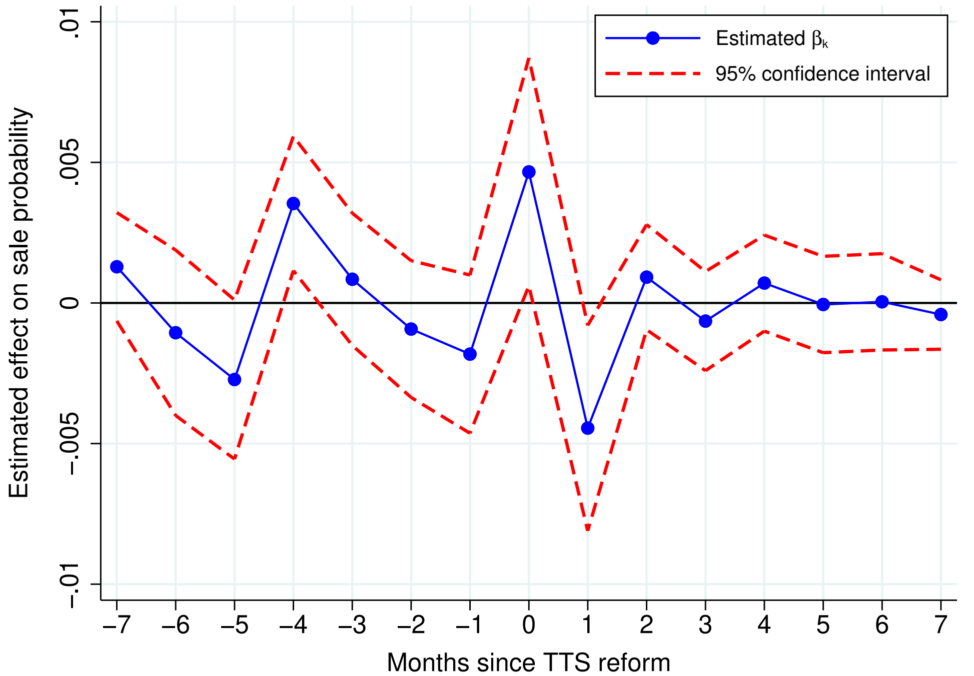
	(1)	(2)	(3)	(4)	(5)	(6)
$NW^S \times Post$	0.0003**	0.0088**	0.0095**	0.0127**	0.0126**	0.0126**
	(0.0001)	(0.0031)	(0.0032)	(0.0043)	(0.0043)	(0.0046)
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
Montiel Olea & Pflueger F-test	–	100.72	99.03	100.31	132.44	89.60
First stage F-test (Kleibergen-Paap)	–	100.31	98.62	99.99	132.08	89.35
First stage F-test (Cragg-Donald)	–	1337.85	1,312.08	1,304.31	1,286.73	1,288.99
Property controls	✓		✓	✓	✓	✓
Time & district FEs	✓			✓	✓	✓
Clustering	$district^P$	$district^P$	$district^P$	$district^P$	$district^S$	$district^B$
Adj. R^2	0.672	0.009	0.085	0.689	0.689	0.690
N	182,646	183,007	182,660	182,646	180,256	179,634

B. Intensive Margin Responses: Change in Price-wealth Elasticity across Reform

	(1)	(2)	(3)	(4)	(5)	(6)
$\log NW^S \times Post$	0.023***	0.015***	0.016***	0.023***	0.023***	0.023***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
Montiel Olea & Pflueger F-test	–	714.58	674.20	851.10	743.00	915.18
First stage F-test (Kleibergen-Paap)	–	711.12	670.88	852.61	741.71	913.67
First stage F-test (Cragg-Donald)	–	1466.66	1,402.87	1,272.54	1253.18	1,245.60
Property controls	✓		✓	✓	✓	✓
Time & district FEs	✓			✓	✓	✓
Clustering	$district^P$	$district^P$	$district^P$	$district^P$	$district^S$	$district^B$
Adj. R^2	0.707	0.016	0.106	0.707	0.710	0.707
N	161,049	27,183	27,121	27,091	26,722	26,640

Notes: The dependent variable in each regression is the log transaction value. In panel A, for 2SLS specifications we instrument overall seller net worth with $NWShock$ as in equation (4.6). In Panel B, we estimate the change in the elasticity of prices with respect to exogenous wealth by regressing log seller net worth with log inherited wealth in the first stage. Regressions in Panel B only include transactions involving sellers who received a strictly positive amount of inheritances in the pre-reform period. There are $N = 368$ districts in total, and in some specifications we include district fixed effects as well as month-year, week-of-month, day-of-week fixed effects, and a holiday dummy. Property controls include a polynomial in age, area, floor space, use category, structure type, unit floor number (for apartments), and number of floors (for single family homes). Robust standard errors in the second stage regression clustered at either the district of the property, of the buyer, or of the seller. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

FIGURE 8. Changes in Sale Probability in Response to Inheritance Shocks



Notes: The figure plots the estimated event study coefficients $\widehat{\beta}_k$ from event study reduced form equation (4.8). The dependent variable is a dummy for whether property j sells in month t. 95% confidence intervals for the point estimates with standard errors clustered by district of the property plotted in red dashed lines.

Table 5 checks robustness of our preferred 2SLS specification to the inclusion of property controls, time and district fixed effects, and the level of clustering. Sale prices increase by 1.3% for every 1 million NTD ($\approx$ 35,000 USD) increase in the seller's wealth (panel A). Or, a 1 s.d. increase in inherited (housing) wealth induces sellers to charge 9.3% (9.5%) more relative to the pre-reform period for a comparable property. A seller who receives the average inheritance amount of around 72,000 USD thus completely passes through the increase in their transfer tax bill on short-term sales to the buyer. On the intensive margin (panel B), a 1% increase in the seller's wealth leads to a 2.3 p.p. increase in the sale price elasticity of wealth relative to the pre-reform period.

On the extensive margin, how do taxpayers with more exogenous housing wealth respond to the tax? Figure 8 plots the coefficients from the following event study version of the reduced form in our 2SLS model:

$$Y_{i,j,t} = \alpha_j + \delta_t + \sum_{k=-7}^{+7} \beta_k \cdot \left(\log(\widehat{NW})_{i,\tau} \times Post_{t-k}\right) + \varepsilon_{i,j,t} \qquad (4.8)$$

where $\widehat{NW_{i,\tau}}$ is the fitted value for taxpayer i obtained from a log-log version of the first stage regression in equation (4.5), α_j are property fixed effects, and δ_t are time fixed effects. A 1%

increase net worth means inheritors are 0.3 p.p. more likely to sell around the announcement of the transfer tax ($k = -4$), and 0.5 p.p. more likely to sell just prior to implementation ($k = 0$). Thus, savvy taxpayers who have more portfolio exposure to the second home tax pass through the incidence to buyers and expedite sales to avoid paying the tax.

5 Heterogeneity: Who are the Misinformed Speculators?

A commonly recounted narrative of the 2000s U.S. boom is that many cities which experienced a pricing boom in the absence of clear restrictions on new real estate supply saw an influx of capital from non-local, or "out-of-town" (OOT) investors. Second home investors in that episode were more likely to be low-income or low-wealth individuals buying bottom tier properties, were heavily mortgaged, and earned lower capital gains (Haughwout et al. 2011; Chinco & Mayer 2016; García 2019; Garriga 2020). Many of these findings on heterogeneity in capital gains earned by locals vs. non-locals have been affirmed in other settings, such as London (Badarinza & Ramadorai 2018, Paris (Cvijanović & Spaenjers 2020), and Vancouver (Pavlov & Somerville 2020).

The richness of our transactions records linked to personal income tax returns and wealth statements allows us to go one step further – we can analyze the role of taxes, mortgage interest payments, and rental income in generating heterogeneous returns. OOT investors may not have local knowledge which allows them to time the market as proficiently as locals, yet they may have more flexibility with regards to location, and therefore may garner higher returns due to property and income tax arbitrage. We test for this possibility using the following definition of (net) total holding period returns at the taxpayer level:

$$r^j_{t-1,t} = \frac{\sum_{i=1}^{n}(1-\tau_{i,t}) \cdot \widetilde{V}^j_{i,t} + (1-c^j_{i,t}) \cdot Y^j_{i,t} - T^j_{t-1,t}}{\sum_{i=1}^{n} \widetilde{V}_{i,t-1}} - 1 \tag{5.1}$$

where r^j_t is the holding period return for the set of properties held by taxpayer j between periods $t-1$ and t. $\tau_{i,t}$ is the fraction of the market value $\widetilde{V}$ the seller pays in transfer taxes, $c^j_{i,t}$ is the income tax paid by j on rental income $Y^j_{i,t}$ accumulated between $t-1$ and t, and $T^j_{t-1,t}$ refers to the total property tax bill on land and buildings incurred by j during the holding period. We discuss the schedules underlying all the tax terms in Appendix A and Section 2.1. If a property i does not transact in period t, we inflate up from the previous transaction price in $t-1$ using our estimated price index $\widehat{P}$ described in Appendix B, and assuming a linear rate of depreciation that we estimate to be 2% in Appendix F:

$$\widetilde{V}_{i,t} = (1-\delta) \cdot V_{i,t-1} \times \frac{\widehat{P_{i,t}}}{\widehat{P_{i,t-1}}} \tag{5.2}$$

We annualize returns by computing $(1 + r^j_{t-1,t})^{365/n}$, with N days in the holding period.[38]

Using this return definition, we offer five facts about heterogeneity in returns earned by holding investment properties:

1. Over our entire sample period (2006-2015) locals earn a premium from selling to out-of-town (OOT) buyers, even when compared to the premium OOT sellers earn from selling to OOT buyers. Table 6 illustrates this premium in a difference-in-differences table (panel A) which compares different local/non-resident buyer-seller combinations. However, as shown in Panel B, this wedge between local and OOT seller returns only appears in the post-reform period; instead, OOT sellers earn a statistically insignificant premium of 1.75 p.p. in the pre-reform period. The sign of this premium reverses in the post-reform period, as the tax creates an average wedge of 5.48 p.p. in holding period returns between local and OOT sellers. This reversal arises, in part, because OOT sellers are more likely to be flippers in the pre-reform period, and the tax flattened out the term structure (see fact #5 below).[39]

2. Holding period returns decline with taxpayer wealth. Sellers in the first quintile of taxpayer net worth earn average annualized returns of 28.0%, compared to 18.3% among sellers in the top quintile (p-value on difference in means < 0.001).

3. On average, mortgaged investors earn similar capital gains to those earned by investors with full equity. Table 7 breaks down the components of returns by year and by mortgaged and full equity investors. In all years except 2007 there is no statistically significant difference in average capital gains ($\mu_{capital}$) earned by the two types of sellers. Although full owners earn about a 1 p.p. higher annualized return in our sample, this is almost entirely due to interest payments ($\mu_{interest}$) less income tax deductions.

4. Stockholders earn lower returns (12.7% annualized) compared to non-stock holders (24.8% annualized). Returns are also decreasing in the share of wealth from equities.[40]

5. As pictured in Figure 9, the term structure of holding period returns is downward sloping, consistent with short-horizon results for equities (van Binsbergen et al. 2012), as well as nominal Treasury bonds and corporate bonds (van Binsbergen & Koijen 2017). The pattern in Figure 9 agrees with the results in Giglio et al. (2021) who use price-rent ratios and national accounts data to argue that at long horizons the term structure of real estate discount rates is

[38]Our results in this section are robust to using either our matching estimator indexing method of Appendix B or the translog hedonic method of Appendix F to inflation-adjust holding period returns. An advantage of the translog hedonic method is that it allows us to leverage the full set of transactions to create regional indices.

[39]In additional results in Appendix C, we breakdown holding period returns into capital gains vs. other components by year and by local vs. OOT investors. We find that prior to the reform there is no statistically significant local premium even in terms of capital gains. We find limited evidence that owners of properties subject to the tax responded by substituting towards rental income.

[40]Stock market participation in Taiwan is high by international standards. 40% of taxpayers and 82% of second homeowners hold stocks.

TABLE 6. Differences in Mean Holding Period Returns across Counterparty Pairs

A. Difference-in-differences: Local vs. OOT Buyers/Sellers

	Local buyer	*OOT buyer*	**Difference**
OOT seller	11.43%	12.89%	**1.46*****
Local seller	14.99%	16.98%	**1.99*****
Difference	**3.56*****	**4.09*****	**0.53*****

B. Difference-in-differences: Local vs. OOT Sellers Pre vs. Post-reform

	Pre-reform	*Post-reform*	**Difference**
OOT seller	25.18%	8.71%	**−16.47*****
Local seller	23.43%	14.19%	**−9.24*****
Difference	**-1.75**	**5.48*****	**7.23*****

C. Triple Differences: Local vs. OOT Sellers Pre vs. Post-reform

Pre-reform

	Local buyer	*OOT buyer*	**Difference**
OOT seller	25.06%	25.17%	**0.11**
Local seller	23.16%	24.09%	**0.93**
Difference	**−1.90**	**−1.08**	**0.82**

Post-reform

	Local buyer	*OOT buyer*	**Difference**
OOT seller	7.96%	9.37%	**1.41*****
Local seller	13.42%	15.69%	**2.27*****
Difference	**5.46*****	**6.32*****	**0.86*****

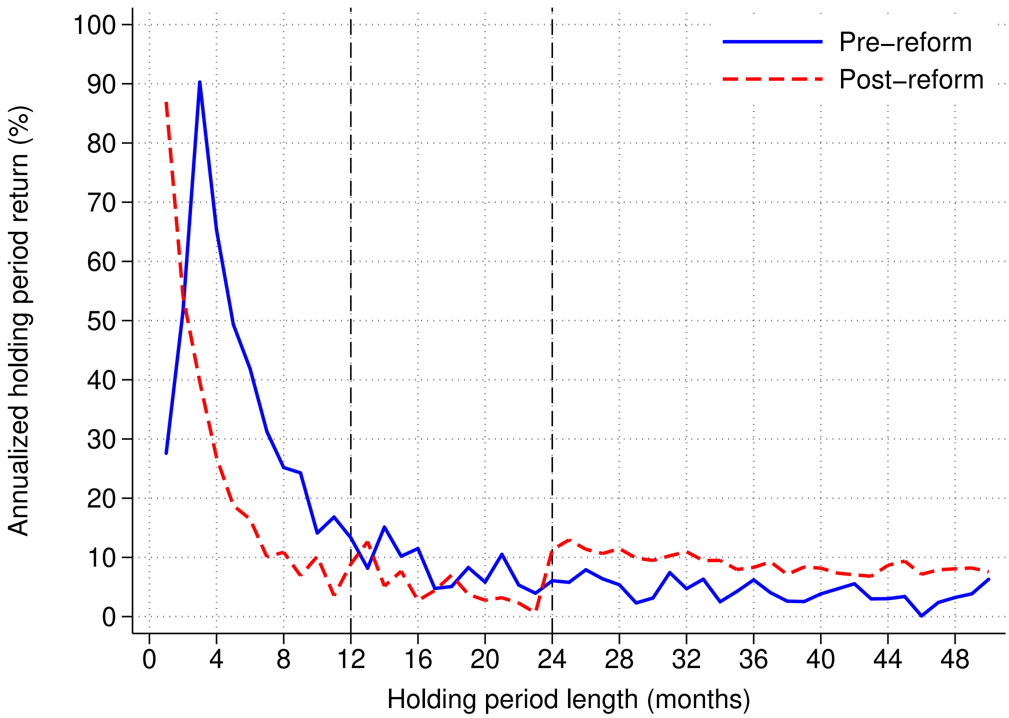
Notes: Each cell in the above tables shows the mean total holding period return for either a buyer-seller pair (Panels A and C), or for sellers in the pre or post-reform period (Panel B). Returns calculated using the procedures described in the text and equations (5.1) and (5.2). In each table, the "difference" column displays the difference between the first two columns. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$ on the t-test for differences in means across the first two columns.

TABLE 7. Breakdown of Returns Earned by Mortgaged and Full Equity Investors

Year	Investor type	N	μ_{HPR}	$\mu_{capital}$	μ_{rental}	$\mu_{interest}$
2007	Mortgaged	3,859	1.15	2.30	0.20	1.19
	Full equity	11,514	7.47	6.80	0.95	0.00
2008	Mortgaged	6,494	2.06	2.61	0.23	0.65
	Full equity	22,359	3.41	3.07	0.71	0.00
2009	Mortgaged	9,384	−0.24	−0.31	0.78	0.60
	Full equity	32,864	−0.22	−0.48	0.61	0.00
2010	Mortgaged	13,652	9.14	8.92	1.28	0.87
	Full equity	44,709	6.47	6.22	0.64	0.00
2011	Mortgaged	21,175	6.94	9.46	0.61	2.97
	Full equity	57,948	8.56	8.00	1.04	0.00
2012	Mortgaged	32,445	6.52	6.88	0.78	0.98
	Full equity	77,335	6.35	5.87	0.91	0.00
2013	Mortgaged	47,376	10.59	10.70	1.30	1.18
	Full equity	99,708	11.39	10.92	0.89	0.00
2014	Mortgaged	53,626	8.30	8.18	1.15	0.87
	Full equity	141,035	8.59	8.17	0.69	0.00

Notes: The table breaks down the components of annualized holding returns for mortgaged sellers and sellers with full equity in their house. HPR indicates the overall rate of return, which equals the net of transfer tax capital gain plus the market-value-weighted (across properties in the taxpayer's real estate portfolio) rental income minus the market-value-weighted mortgage interest payment and minus the annual holding tax, divided by the last market value. *capital* indicates the capital gain. *rental* indicates the rental income divided by the last market value. *interest* indicates the ratio of mortgage interest payments to the last market value of the property. The market value is defined as the real transaction price, or, if a sale price is not available, we use the appraisal value times the city-year specific price-appraisal value ratio to proxy for market value. For years during which a property was not transacted, the market value is defined as the last transaction price inflated by the city-year price index, less linear depreciation of 2% per year. We winsorize capital gains at the top and bottom 1%.

FIGURE 9. Term Structure of Total Holding Period Returns



Notes: The figure plots the term structure of annualized total holding period returns, computed using the steps outlined in the text and equations (5.1) and (5.2). Vertical dashed lines indicate the holding period notches introduced by the transfer tax surcharge in the post-reform period (red dashed line).

downward sloping. We document a downward-sloping term structure for *realized returns* from the universe of investment property sales for a particular market.[41] The transfer tax reform flattens out the term structure at the short end ($\leq$ 24 months), and produces a positive shift in returns at longer horizons (> 24 months) due to the drop in tax rates from 10% to 0% after the two-year holding period.

To summarize, our bunching analysis in Section 4 generally agrees with the patterns witnessed in other real estate markets – namely, that OOT and low wealth investors account for the majority of property flips that were crowded out by the transfer tax. However, our tax and income-adjusted returns show that short-term speculators *do not* appear to be misinformed. This echoes the argument in Bayer et al. (2020) that short-term flippers may function as intermediaries in housing markets and actually improve price efficiency. Prior to the flip tax, locals and OOT sellers earned

[41] Chambers et al. (2021) compute property-level annualized net total returns for a set of Oxford-Cambridge colleges over a 70-year period. They do not discuss the term structure in their analysis, but like Giglio et al. (2021), conclude that long-term gross income yields for residential properties trend towards zero. Sagi (2020) documents a downward sloping term structure for realized gross returns to commercial real estate and Giacoletti (2021) does the same for housing.

similar returns, and leveraged property investors earn similar capital gains to full equity holders. Our results on heterogeneity demonstrate that simple tags like non-residency status, leverage, or stock market participation may not necessarily translate to noise trading. We propose an alternative method for capturing the fraction of non-fundamental property sales volume in the next section.

6 Noise Trading and Optimal Transaction Taxes

What do the behavioral responses we have documented imply for the optimality of property transfer taxes as a policy instrument to improve pricing efficiency? In this section we address this question by providing a measure of the pre-existing fraction of sales volume due to noise trading.

6.1 Optimal Transfer Tax Framework

Dávila (2020) studies the optimal financial transaction tax (FTT) on an arbitrary risky asset in a disagreement model where investors are heterogeneous in the proximity of their beliefs to the fundamental value of the asset. The planner cares about maximizing price efficiency of the market, and so the optimal linear FTT functions as a Pigouvian tax; the planner sets the tax rate to eliminate the spread between the average expected returns of buyers and sellers of the asset.

Importantly, even in a simplified framework where risky asset supply is perfectly inelastic, the effects of such a tax on prices and volatility are *ex ante* ambiguous. On the one hand, holding signals fixed, imposing a round-trip transaction tax reduces demand for the asset and bids prices down. Yet, if such a tax crowds out traders with erroneous beliefs, then price efficiency improves, and so on net demand for the asset can grow if a sufficiently large fraction of the agents who trade close to fundamental value are not deterred by the tax. As our results in Section 4 highlight, elastic asset supply, especially in a context like the real estate market, means the tax is even less likely to generate a drop in prices.

This logic can be summarized by an empirically implementable version of the optimal tax formula, which says the optimal rate sets aggregate volume equal to fundamental volume:

$$\tau^* \approx \frac{s_{NF}\{\tau = 0\}}{-d \log V\{\tau = 0\}/d\tau} \tag{6.1}$$

Like most optimal tax formulas in public finance, the above formula showcases a tradeoff. There is more scope for a tax to improve price efficiency if the pre-existing share of non-fundamental trading $s_{NF}\{\tau = 0\}$ is large. However, welfare gains to imposing the tax are limited by the extent to which the tax deters fundamental trades, captured by the semi-elasticity of volume with respect to the tax in the denominator. Our bunching analysis in Section 4.2 calibrates this semi-elasticity, but as our five facts about return heterogeneity in Section 5 indicate, relying on observable tags such as non-residency or leverage is not sufficient to identify noise traders.

6.2 Severe Weather Shocks and Speculative Flips

Our strategy for identifying the share of non-fundamental trading in the numerator of (6.1) is inspired by a growing literature documenting the influence of weather on economic activity.[42] The basic intuition is that selling a home generates fixed costs. Individuals who wish to sell a home for job or family-related reasons have a higher threshold fixed cost beyond which they will not sell, compared to owners who are only selling to maximize capital gains (Igan & Kang 2011; Hilber & Kyytikäinen 2017). A persistent and positive shock to the fixed costs of selling should then force out more speculators than non-speculators.

We use spatial and temporal variation in the severity of typhoon seasons in Taiwan during the period (2006-2011) before the transfer tax surcharge to identify shocks to the fixed cost of selling a home. We collect daily data from all 832 meteorological stations managed by the Taiwan Central Weather Bureau. Of these stations, 517 record measures which are used to forecast and classify tropical storms: wind speed, precipitation, humidity, low sea pressure, and temperature. We match each property transacted in our sample to the nearest weather station to exploit the granularity of severe weather paths in the Pacific. We discuss how we construct the weather dataset and provide more scientific context for Pacific storm seasons in Appendix E.

We start by running time series regressions of the following form:

$$Volume_t = \beta \cdot (Weather_t \times Summer_t) + \delta_t + \gamma' \cdot \mathbf{X_t} + \varepsilon_t \tag{6.2}$$

where $Volume_t$ is total transactions in the Taipei-New Taipei greater metro area on date t. $Weather_t$ is a meteorological reading, averaged across the main weather stations which are manned by a person.[43] We use the confidential tax returns to identify buyers and sellers who's transactions coincide with changes in marital or employment status and exclude these sales from $Volume_t$. Such

[42] Papers in this literature include Goetzmann et al. (2014) who show that cloudy days generate pessimistic sentiments in equities markets. Dell et al. (2014) provide an overview of the methods researchers use in economics to identify treatment effects from weather shocks. A common finding is that rain deters economic activities, such as voting (Meier et al. 2019) and stock trading (Cho 2020), which supports our use of accumulated precipitation as our main measure of seasonal storm severity. While much of the new weather literature in finance has focused on weather-induced sentiments, our contribution is to recognize that severe and persistent weather conditions may also increase fixed costs to trading properties. Goetzmann & Zhu (2005) show NYSE spreads widen on cloudy days, which hints that weather conditions generate market frictions.

[43] In Appendix G, we exploit spatial variation in exposure of local real estate markets to typhoon-like conditions by matching all properties in our sample to the nearest of the 832 weather stations in our sample. Our results demonstrate that areas with greater rainfall on a given date experience a larger decline in sales volume. Such cross-sectional results difference out common macroeconomic components to sales volume such as state-recommended business shutdowns. While noisier, we run LPM at the property-level and find that typhoon events result in a 0.002% lower probability that a second home sells.

sales are less likely to be driven by speculative motives.[44]

The typical typhoon season runs from July to September, with 80% of all official typhoon forecast warnings occurring during those months, so we set the dummy $Summer_t$ equal to unity during July, August, or September. The interaction of $Weather_t \times Summer_t$ captures how the effects of weather variables on the real estate market are amplified in the summer months due to the confluence of extreme conditions (e.g. wind gusts + torrential rain + high temperatures and humidity). We control for property damage counts in $\mathbf{X_t}$ to rule out drops in volume due to weather-induced changes in the underlying quality of the housing stock. δ_t includes a full set of day-of-week and 7-day fixed effects to strip out seasonality.

Our results from estimating equation (6.2) in Table 8 show a robust negative effect of accumulated daily rainfall on volume, but no effect of maximum wind gusts conditional on rainfall.[45] These findings make intuitive sense.[46] Severe rainfall increases the costs to commuting, restricts outside activity, and may even result in flooding. While high wind speeds also hinder the process involved in listing a house, given the historical prevalence of typhoons in the southern Pacific, power grids and building materials have evolved to limit damages and service interruptions from downed trees.[47] Notably, even when we control for temperature (column 4), or directly control for high wind speeds that trigger official typhoon and tropical storm warnings (column 6), rainfall continues to exert a stable and statistically significant effect on sales volume.

In terms of magnitude, a one millimeter increase in accumulated daily rainfall lowers volume by about 0.3% relative to its six-month moving average. A three standard deviation shock to rainfall of 66 mm (2.6 inches) produces the average precipitation observed during tropical storms, and results in a 20% drop in sales volume. Under the assumption that sellers who need to move for imperative personal reasons will not be deterred by severe weather from listing houses and closing the deal, this estimate corresponds to the *ex ante* noise trading share s_{NF}.

One concern is that our estimates of $\widehat{\beta}$ in equation (6.2) may not capture a drop in volume from noise trader exits if weather shocks simply delay sales by a few weeks. That is, immediately after a severe storm system subsides there may be pent-up demand for properties, indicating that a large fraction of the original drop in volume was due to short-run intertemporal substitution. We test

[44] Roughly 7% of sales occur within the same tax year as a buyer or seller marriage, and 14% occur within the same tax year as a buyer or seller employer change (20% satisfy at least one condition). We obtain nearly identical estimates in this section regardless of whether we include sales involving either employment or marital status changes, for either counterparty, in our sales volume measure. We therefore conservatively interpret our estimates as upper bound measures of the *ex ante* noise trading share.

[45] We find a marginally statistically significant drop in volume of −0.79% per meter/second increase in maximum wind gusts *averaged* across stations. The effect of rainfall still hovers around a −0.26% drop in volume per one millimeter of average accumulated rainfall, irrespective of any wind speed measures we include on the RHS.

[46] In Appendix E, we provide further support for our focus on rain and wind as proxies for weather shocks by conducting factor analysis using a richer set of atmospheric conditions.

[47] The majority (81%) of property sales in our sample involve units in reinforced concrete buildings.

TABLE 8. Severe Weather Shocks and Real Estate Sales

	(1)	(2)	(3)	(4)	(5)	(6)
Max WS $\times Summer$	-2.27^{**}		-1.16			
	(0.95)		(0.98)			
Rainfall $\times Summer$		-0.32^{***}	-0.26^{***}	-0.31^{***}		-0.24^{**}
		(0.10)	(0.10)	(0.10)		(0.10)
$\mathbb{1}\{T > 32°C\}$				5.14		
				(6.88)		
$\mathbb{1}\{27 < T \leq 32°C\}$				1.51		
				(4.03)		
$\mathbb{1}\{\text{Max WS} \geq 74\text{mph}\}$					-65.98^{***}	-27.49^{**}
					(15.52)	(13.32)
$\mathbb{1}\{55 \leq \text{Max WS} < 74\text{mph}\}$					-10.88	-9.18
					(9.85)	(7.47)
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
Damages controls	✓	✓	✓	✓	✓	✓
N	1,973	1,973	1,973	1,973	1,973	1,973

Notes: The table presents results from estimating time series regressions according to equation (6.2). The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. RHS variables include maximum wind speed and accumulated rainfall interacted with a dummy for the summer typhoon season, dummies for daily high temperature ranges, a dummy for gusts over 74 mph (typhoon), and a dummy for gusts between 55-73 mph (tropical storm). We include daily observations from the pre-reform period during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. All regressions control for daily counts of casualties and properties lost due to flooding and typhoons (see Appendix E for details). Newey-West standard errors with six lags in parentheses adjust for serial correlation. We select the maximum possible lag order such that the estimator for the covariance matrix is consistent (Newey & West 1987). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

for the possibility of pent-up demand using the following time series specification:

$$Volume_t = \beta_1 \cdot (Rain_t \times Summer_t) + \delta_t + \beta_2 \cdot (\overline{Rain}_{t-L,t-1} \times Summer_t) + \gamma' \cdot \mathbf{X_t} + \varepsilon_t \quad (6.3)$$

where, informed by our results in Table 8, we focus on severe rain as a positive shock to costs associated with selling properties.[48] The variable $\overline{Rain}_{t-L,t-1}$ refers to the average accumulated daily rainfall over the previous L days. Therefore, the "true" upper bound drop in volume due to noise trader exits is given by $\widehat{\beta}_1 + \widehat{\beta}_2$.[49]

The point estimates in Table 9 confirm that sales volume does not bounce back after a severe typhoon season ends. We identify a 0.3% drop in sales per one millimeter of rainfall regardless of whether we account for pent-up demand effects at a one, two, four, or eight-week horizon. We also check whether pent-up demand is a consequence of only particularly severe weather shocks by substituting $\overline{Rain}_{t-L,t-1}$ for dummies $\mathbb{1}_{t-L,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$ which are equal to unity when the average accumulated daily rainfall over the previous L days exceeds one-half inches.[50] While the coefficients on $\mathbb{1}_{t-L,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$ are never significant across our specifications, the point estimates remain negative up to four weeks after the initial shock, suggesting severe rainfall over a period of several weeks has a persistently negative effect on speculative volume. Overall, these results support our interpretation of the estimates in Table 8 as upper bound measures of the noise trading share in the Taiwan housing market.

6.3 Discussion

We have now identified in the data the two parameters needed to estimate the optimal transfer tax given by equation (6.1): the semi-elasticity of volume with respect to the tax and the *ex ante* share of non-fundamental trading. Given our estimates of a 75% drop in one-year flips from the bunching analysis, and a 20% non-fundamental trading share based on the results in Section 6.2, we obtain a semi-elasticity of $-75\%/15$ p.p. $= -5$, and an optimal linear tax rate of $\tau^* = 20\%/5 = 4\%$, compared to the actual tax rate of 15% on one-year flips.

It is less straightforward to map our estimate of the 40% overall drop in sales volume into a semi-elasticity due to the multiple holding period thresholds imposed by the policy. The fact that rates in this context discontinuously change along a time dimension means that any market unraveling beyond the two-year threshold cannot be decoupled from the magnitude of the rate changes for short-term sales. An alternative, but conservative estimate of an overall semi-elasticity would be $-40\%/10$ p.p. $= -4$, which supposes the drop from a 10% to 0% rate is the most

[48] The estimated coefficients $\widehat{\beta_1}$ remain unchanged when we include wind speed readings on the RHS.

[49] We provide event study results in Appendix G which show that taxpayers also do not accelerate sales in advance of forecasted severe weather events.

[50] Rainfall of a half inch or more is above the 80th percentile of daily accumulated rainfall, and 40% of such days coincide with official typhoon warnings for the entire island. On average, across days with confirmed typhoon events (i.e. when sustained wind speeds reach 74 mph), accumulated daily rainfall is 73 mm or 2.9 inches.

TABLE 9. Testing for Pent-up Sales after Storm Season

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rain_t \times Summer_t$	-0.33^{***}	-0.33^{***}	-0.32^{***}	-0.32^{***}	-0.33^{***}	-0.33^{***}	-0.32^{***}	-0.31^{***}
	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)
$\overline{Rain}_{t-1w,t-1} \times Summer_t$	-0.57							
	(0.52)							
$\overline{Rain}_{t-2w,t-1} \times Summer_t$		-0.30						
		(0.37)						
$\overline{Rain}_{t-4w,t-1} \times Summer_t$			0.47					
			(0.76)					
$\overline{Rain}_{t-8w,t-1} \times Summer_t$				0.83				
				(1.36)				
$\mathbb{1}_{t-1w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$					-10.33^{*}			
					(6.08)			
$\mathbb{1}_{t-2w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$						-7.34		
						(8.42)		
$\mathbb{1}_{t-4w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$							-3.03	
							(8.32)	
$\mathbb{1}_{t-8w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$								18.85
								(13.46)
7-day FEs	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Damages controls	✓	✓	✓	✓	✓	✓	✓	✓
N	1,973	1,973	1,973	1,973	1,973	1,973	1,973	1,973

Notes: The table presents results from estimating time series regressions according to equation (6.3). The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. The RHS variables are either the moving average of daily accumulated rainfall, or indicators for whether the moving average of daily accumulated rainfall exceeds 0.5 inches over a specific, lagged time horizon (one, two, four, or eight week periods). We include daily observations from the pre-reform period during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. All regressions control for daily counts of casualties and properties lost due to flooding and typhoons (see Appendix E for details). Newey-West standard errors with six lags in parentheses adjust for serial correlation. We select the maximum possible lag order such that the estimator for the covariance matrix is consistent (Newey & West 1987). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

important source of unraveling for longer holding periods. Such an assumption is consistent with the large bunching response at the two-year notch that is absent around the one-year notch. This reasoning yields an optimal transfer tax of $\tau^* = 20\%/4 = 5\%$.

Our estimates generate an extreme upper bound on τ^* for two main reasons. First, as discussed in Section 4.2, the missing mass estimates from our hedonic-logit bunching design underestimate short-term sales volume in the pre-reform period, meaning we also underestimate the amount of trades crowded out by the transfer tax. This biases the semi-elasticity downward, and hence, τ^* is upward biased. Second, although we have excluded sales in which the seller recently changed their marital or employment status, our weather shock estimates of the non-fundamental share are intent-to-treat (ITT) in the sense that we do not know the true fraction of the 20% drop in volume that is due to noisy flippers. By assuming the entire drop in volume due to storm systems is from speculators delaying sales for at least several months after the typhoon season subsides, we focus on a worst-case scenario from the policymaker's perspective.

Still, our upper bound estimate of 4% for the optimal real estate Tobin tax tells us one key lesson: the government taxed too much. The planner's objective function in Dávila (2020) which underlies equation (6.2) does not incorporate price stability, revenue requirements, or macroprudential concerns about leverage. Given the evidence in Section 4.3 and Section 4.4 that housing prices overall increased after the reform, but fell by roughly 20% for bottom-tier apartments, concerns about housing consumption inequality might justify higher optimal tax rates. These issues elevate the need to incorporate prominent features in real estate markets, such as market segmentation and local asset supply elasticities, into standard theories of optimal financial transaction taxes.

7 Conclusion

We exploit a large tax surcharge on short-term sales of second homes in Taiwan to assess the feasibility of real estate transfer taxes towards preventing speculation and promoting housing affordability. The transfer tax crowded out too many transactions relative to the pre-existing volume of speculative flips. Our missing mass estimates indicate the tax generated a 75% drop in one-year flips and a 40% drop in overall sales volume. We leverage spatial and time series variation in severe weather shocks during typhoon season to estimate an upper bound of only 20% for the non-fundamental trading share. We illustrate how our estimates of the drop in volume and the noise trading share provide sufficient statistics for a model of optimal transaction taxes. Calibrating this model, we find support for the low transfer tax rates of less than 4% which are currently in place in many global real estate markets.

In spite of the efficiency losses, the transfer tax did little to improve housing affordability. We find no discontinuity in transaction values or unit prices in either the aggregate housing market or second home market around the implementation date. The tax did induce a negative trend break among property types – namely, smaller apartments – for which the seller's realized capital gain would have been small relative to the transfer tax bill. In the prime property market, prices rose by roughly 10% right around the effective date, implying full pass-through of the tax, as wealthy buyers paid a premium to expedite purchases and offset the seller's tax bill.

We illustrate this inward shift in the supply curve at the high end of the market using taxpayers' differential exposure to the tax, captured by recent and unexpected inheritances as a shock to *ex ante* net worth. In the post-reform period a one standard deviation shock to sellers' housing net worth induced sellers to charge 9.5% more than in the pre-reform period for a comparable property. Ultimately, this inventory reduction channel outweighed the negative shock to demand, putting upward pressure on prices in the prime market segment.

Finally, by linking property records to personal income tax returns and wealth estimates, our setting provides a more complete picture of non-fundamental housing sales volume and the term structure of holding period returns. Our findings largely agree with a narrative frequently told about speculators during the 2000s U.S. boom – that they were primarily low-wealth, out-of-town taxpayers buying lower quality properties. Recent experiments with taxes targeting flips do reduce speculation on the extensive margin and lead investors to adopt longer investment horizons. But our analysis emphasizes the crucial role of market segmentation and local asset supply elasticity in informing the optimal transaction tax rate. We view an extension of the financial transaction tax theory which incorporates these features of property markets as a promising route for future work.

References

Agarwal, S., K. Li, Y. Qin, J. Wu, & J. Yan (2020): "Tax Evasion, Capital Gains Taxes, and the Housing Market," *Journal of Public Economics*, 188: 1-21.

Albanesi, S., G. De Giorgi, & J. Nosal (2017): "Credit Growth and the Financial Crisis: A New Narrative," NBER Working Paper, No. 23740.

Auerbach, A. (1988): "Capital Gains Taxation in the United States: Realizations, Revenue, and Rhetoric," *Brookings Papers on Economic Activity*, 1988(2): 595-637.

Badarinza, C. & T. Ramadorai (2018): "Home Away from Home? Foreign Demand and London House Prices," *Journal of Financial Economics*, 130: 532-555.

Bayer, P., C. Geissler, K. Mangum, & J.W. Roberts (2020): "Speculators and Middlemen: Strategy and Performance of Investors in the Housing Market," *Review of Financial Studies*, 33(11): 5212-5247.

Bernheim, B.D., A. Shleifer, & L.H. Summers (1985): "The Strategic Bequest Motive," *Journal of Political Economy*, 93(6): 1045-1076.

Besley, T., N. Meads, P. Surico (2014): "The Incidence of Transaction Taxes: Evidence from a Stamp Duty Holiday," *Journal of Public Economics*, 119: 61-70.

Best, M.C. & H.J. Kleven (2018): "Housing Market Responses to Transaction Taxes: Evidence from Notches and Stimulus in the U.K.," *Review of Economic Studies*, 85: 157-193.

van Binsbergen, J.H., M. Brandt, & R. Koijen (2012): "On the Timing and Pricing of Dividends," *American Economic Review*, 102(4): 1596-1618.

van Binsbergen, J.H. & R. Koijen (2017): "The Term Structure of Returns: Facts and Theory," *Journal of Financial Economics*, 124(1): 1-21.

Burman, L.E. & W.C. Randolph (1994), "Measuring Permanent Responses to Capital-Gains Tax Changes in Panel Data," *American Economic Review*, 84(4): 794-809.

Cai, J., J. He, W. Jiang, & W. Xiong (2020): "The Whack-A-Mole Game: Tobin Tax and Trading Frenzy," forthcoming *Review of Financial Studies.*

Campbell, J.Y. & K.A. Froot (1994): "International Experiences with Securities Transaction Taxes," in *The Internationalization of Equity Markets*, 277–308, University of Chicago Press.

CBRE Research (2017): "How Much Real Estate? A Global City Analysis," *Global Investment Research.*

Chambers, D., C. Spaenjers, & E. Steiner (2021): "The Rate of Return on Real Estate: Long-Run Micro-Level Evidence," forthcoming *Review of Financial Studies*.

Chetty, R., J. Friedman, T. Olsen, & L. Pistaferri (2011): "Adjustment Costs, Firm Responses, and Micro VS. Macro Labour Supply Elasticities: Evidence from Danish Tax Records," *Quarterly Journal of Economics*, 126(2): 749-804.

Chinco, A. & C. Mayer (2016): "Misinformed Speculators and Mispricing in the Housing Market," *Review of Financial Studies*, 29(2): 486-522.

Cho, T. (2020): "Heat as a Sedative: A Natural Experiment on Noise Trading and Aggregate Stock Market Reversals," *mimeo*, London School of Economics.

Chu, C., M. Lin, & L. Liu (2017): "IGE of Earning, Income, Wealth and Consumption: A Comprehensive Analysis," *mimeo*, National Taiwan University.

Colliard, J. & P. Hoffmann (2017): "Financial Transaction Taxes, Market Composition, and Liquidity," *Journal of Finance*, 72(6): 2685-2716.

Cortés, K., R. Duchin, & D. Sosyura (2016): "Clouded Judgment: The Role of Sentiment in Credit Origination," *Journal of Financial Economics*, 121: 392-413.

Cunningham, C.R. & G.V. Engelhardt (2008): "Housing Capital-Gains Taxation and Homeowner Mobility: Evidence from the Taxpayer Relief Act of 1997," *Journal of Urban Economics*, 63: 803-815.

Cvijanović, D. & C. Spaenjers (2020): ""We'll Always Have Paris": Out-of-Country Buyers in the Housing Market," forthcoming *Management Science*.

Dachis, B., G. Duranton, & M.A. Turner (2012): "The Effects of Land Transfer Taxes on Real Estate Markets: Evidence from a Natural Experiment in Toronto," *Journal of Economic Geography*, 12: 327-354.

Dai, Z., E. Maydew, D.A. Shackelford, & H.H. Zhang (2008): "Capital Gains Taxes and Asset Prices: Capitalization or Lock-In?" *Journal of Finance*, 63(2): 709-742.

Dávila, E. (2020): "Optimal Financial Transaction Taxes," *mimeo*, Yale University.

DeFusco, A.A., C.G. Nathanson, E. Zwick (2017): "Speculative Dynamics of Prices and Volume," NBER Working Paper, No. 23449.

Dehaan, E., J. Madsen, & J.D. Piotroski (2017): "Do Weather-Induced Moods Affect the Processing of Earnings News?" *Journal of Accounting Research*, 55(3): 509-550.

Dell, M., B.F. Jones, B.A. Olken (2014): "What Do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature*, 52(3): 740-798.

Deng, Y., X. Liu, & S. Wei (2018): "One Fundamental and Two Taxes: When Does a Tobin Tax Reduce Financial Price Volatility?" *Journal of Financial Economics*, 130: 663-692.

Deng, Y., Y. Tu, & Y. Zhang (2019): "Explicit Measures of Impacts of Transaction Taxes as Market Cooling Measure: Evidence from the Sellers' Stamp Duty in Singapore Housing Market," *mimeo* Wisconsin-Madison.

Favilukis, J. & S. Van Nieuwerburgh (2021): "Out-of-town Home Buyers and City Welfare," forthcoming *Journal of Finance*.

Foucault, T., D. Sraer, & D. Thesmar (2011): "Individual Investors and Volatility," *Journal of Finance*, 66(4): 1369-1406.

Gao, Z., M. Sockin, W. Xiong (2020): "Economic Consequences of Housing Speculation," *Review of Financial Studies*, 33(11): 5248–5287.

García, D. (2019): "Second Home Buyers and the Housing Boom and Bust," Finance and Economics Discussion Series, No. 2019-029, Federal Reserve Board of Governors.

Garriga, C., P. Gete, & A. Tsouderou (2020): "Investors and Housing Affordability," Federal Reserve Bank of St. Louis Working Paper.

Gelber, A.M., D. Jones, & D.W. Sacks (2020): "Estimating Adjustment Frictions Using Nonlinear Budget Sets: Method and Evidence from the Earnings Test," *American Economic Journal: Applied Economics*, 12(1): 1-31.

Gelman, A. & G. Imbens (2019): Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs, *Journal of Business and Economic Statistics*, 37(3): 447-456.

Giacoletti, M. (2021): "Idiosyncratic Risk in Housing Markets," forthcoming *Review of Financial Studies*.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, & A. Weber (2021): "Climate Change and Long-run Discount Rates: Evidence from Real Estate," forthcoming *Review of Financial Studies*.

Glogowsky, U. (2021): "Behavioral Responses to Inheritance and Gift Taxation: Evidence from Germany," *Journal of Public Economics*, 193: 1-15.

Goetzmann, W.N., D. Kim, A. Kumar, & Q. Wang (2014): "Weather-Induced Mood, Institutional Investors, and Stock Returns," *Review of Financial Studies*, 28(1): 73-111.

Goetzmann, W.N. & M. Spiegel (1995): "Non-Temporal Components of Residential Real Estate Appreciation," *Review of Economics and Statistics*, 77(1): 199-206.

Goetzmann, W.N. & N. Zhu (2005): "Rain or Shine: Where is the Weather Effect?" *European Financial Management*, 11(5): 559-578.

Gorback, C.S. & B.J. Keys (2020): “Global Capital and Local Assets: House Prices, Quantities, and Elasticities,” NBER Working Paper, No. 27370.

Graham, J. (2019): “House Prices, Investors, and Credit in the Great Housing Bust,” NYU Job Market Paper.

Haughwout, A., D. Lee, J. Tracy, & W. van der Klaauw (2011): “Real Estate Investors, the Leverage Cycle, and the Housing Market Crisis,” Federal Reserve Bank of New York Staff Report, No. 514.

Hilber, C.A.L. & T. Kyytikäinen (2017): “Transfer Taxes and Household Mobility: Distortion on the Housing or Labor Market?” *Journal of Urban Economics*, 101: 57-73.

Hirshleifer, D. & T. Shumway (2003): “Good Day Sunshine: Stock Returns and the Weather,” *Journal of Finance*, 58(3): 1009-1032.

Jones, C.M. & P.J. Seguin (1997): “Transaction Costs and Price Volatility: Evidence from Commission Deregulation,” *American Economic Review*, 87(4): 728-737.

Igan, D. & H. Kang (2011): “Do Loan-to-Value and Debt-to-Income Limits Work? Evidence from Korea,” IMF Working Paper, No. 11297.

Kleven, H.J. (2016): “Bunching,” *Annual Review of Economics*, 8: 435-464.

Kleven, H.J. & M. Waseem (2013): “Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan,” *Quarterly Journal of Economics*, 128(2): 669-723.

Kopczuk, W. & D. Munroe (2015): “Mansion Tax: The Effect of Transfer Taxes on the Residential Real Estate Market,” *American Economic Journal: Economic Policy*, 7(2): 214-257.

Kopczuk, W. & J. Slemrod (2003): “Dying to Save Taxes: Evidence from Estate-Tax Returns on the Death Elasticity,” *Review of Economics and Statistics*, 85(2): 256-265.

Kupiec, P.H. (1996): “Noise Traders, Excess Volatility, and a Securities Transactions Tax,” *Journal of Financial Services Research*, 10: 115-129.

Li, Z., L.S. Shen, & C. Zhang (2018): “A “China Shock” on the Finance Side: Evidence from Chinese Housing Investment in the US,” IMF Working Paper.

Lovo, S. & C. Spaenjers (2018): “A Model of Trading in the Art Market,” *American Economic Review*, 108(3): 744-774.

McMillen, D.P. (2012): “Repeat Sales as a Matching Estimator,” *Real Estate Economics*, 40(4): 745-773.

Meier, A.N., L. Schmid, & A. Stutzer (2019): "Rain, Emotions, and Voting for the Status Quo," *European Economic Review*, 119: 434-451.

Newey, W.K. & K.D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrx," *Econometrica*, 55(3): 703-708.

Pavlov, A. & T. Somerville (2020): "Immigration, Capital Flows and Housing Prices," *Real Estate Economics*, 48(3): 915-949.

Piazzesi, M., Schneider, M., & J. Stroebel (2020): "Segmented Housing Search," 110(3): 720-759.

Sá, F. (2016): "The Effect of Foreign Investors on Local Housing Markets: Evidence from the UK," CEPR Discussion Paper, No. 11658.

Sagi, J.S. (2020): "Asset-Level Risk and Return in Real Estate Investments," forthcoming *Review of Financial Studies.*

Scheinkman, J.A. & W. Xiong (2003): "Overconfidence and Speculative Bubbles," *Journal of Political Economy*, 111(6): 1183-1220.

Slemrod, J. (2013): "Buenas Notches: Lines and Notches in Tax System Design," *eJournal of Tax Research*, 11(3): 259-283.

Slemrod, J., C. Weber, & H. Shan (2017): "The Behavioral Response to Housing Transfer Taxes: Evidence from a Notched Change in D.C. Policy," *Journal of Urban Economics*, 100: 137-153.

Suher, M. (2016): "Is Anybody Home? The Impact and Taxation of Non-Resident Buyers," Federal Reserve Board working paper.

Tobin, J. (1978): "A Proposal for International Monetary Reform," *Eastern Economic Journal*, 4(3-4): 153-159.

Umlauf, S.R. (1993): "Transaction Taxes and the Behavior of the Swedish Stock Market," *Journal of Financial Economics*, 33: 227-240.

Online Appendix to

Flip or Flop? Tobin Taxes in the Real Estate Market

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and Ming-Jen Lin (National Taiwan University)

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A Details on Taiwan's Property Tax System

In this appendix, we provide additional details on the administration of Taiwan's property tax system, as outlined in Section 2.1. We focus on the four taxes paid at the time of transaction, of which two (the deed tax and stamp duty tax) are paid by the buyer and two (the land value increment tax and house transfer income tax) are the responsibility of the seller.

From the seller's perspective, there are five main steps required to transfer property ownership.

1. Signing the contract and providing documents to the state to identify parties in the transaction and the new owner. The buyer pays the 0.1% stamp duty tax and a "contract fee" equal to 5-10% of the transaction price (1 to 3 days). The contract fee is then held in escrow until the sale closes.

2. Sellers file a transaction tax return and wait for the official tax document which lists the total payment due. The document usually arrives within 7 to 21 days.

3. Sellers pay transaction taxes and capital gains tax (post-2016), as well as any unpaid building property tax and land value tax. All taxes must be paid within 30 days after signing the contract (step 1).

4. Sellers file the transfer of ownership and pay the stamp duty tax remitted to them by the buyer plus a small flat fee (0.1% + 80 NTD). This process usually takes 3 to 5 days.

5. Buyers pay the remaining balance on the property to the seller and complete the transfer.

Given these steps and approximate timeline, we estimate that finalizing an arms-length property transfer takes 38 days, at maximum.[51]

In addition to the transfer tax surcharge (TTS) we focus on in this paper, all sellers need to pay the land value increment tax and the house transfer income tax. We now illustrate with examples how the TTS amount would typically be much larger than the combined amount of these taxes.[52]

Land value increment tax (LVIT): This tax is applied to the "current land value" (CLV), which is an annually reassessed appraisal value designed to closely track market values. It is a flat 10% rate on the CLV for sales of owner-occupied homes. For sales of non-owner occupied properties, payments are higher if the land quickly appreciates relative to the overall CPI within the period from the last transfer date, or if this is the first sale of the property, from the initial appraisal date. More concretely, the payment amount can be summarized via:

$$\mathcal{T}^{LV} = \tau_1 \cdot X - \tau_2 \cdot Y \tag{A.1}$$

$$X = CLV - P_0 \times \frac{CPI_T}{CPI_0} - B \tag{A.2}$$

$$Y = P_0 \times \frac{CPI_T}{CPI_0} \tag{A.3}$$

[51] H&B Business Group, a leading Taiwanese property sales agency, estimates that from 2016 to 2019 the average time a property spent on the market in the five largest cities in Taiwan was 113.3 days for Taipei, 90 days for New Taipei, 102 days for Tainan, 115.3 days for Taichung, and 107.1 days for Kaohsiung. Hence, for a transaction where the buyer is not predetermined, selling a property within four to five months from listing to closing is feasible.

[52] The examples are based on entries in the Ministry of Finance Tax Manual, available here.

where $\tau_1 \in [20\%, 40\%]$ is levied on X which captures the wedge between land appreciation and CPI inflation. An adjustment is then made for land appreciation according to the CPI, Y, at deduction rate $\tau_2 \in [0\%, 30\%]$. B is the total tax paid during ownership towards local infrastructure benefits. P_0 refers to the initial appraisal or previous transfer value, P_T is the current sale price.

Hence, a more transparent way to express the LVIT payment due is:

$$\mathcal{T}^{LV} = \underbrace{\tau_1 \cdot CLV}_{\text{tax on current value}} - \underbrace{(\tau_1 - \tau_2) \cdot Y}_{\text{deduction for CPI inflation}} - \underbrace{\tau_1 \cdot B}_{\text{deduction for infrastructure}} \tag{A.4}$$

The tax rate pair (τ_1, τ_2) is determined by the holding period length T and the ratio of X/Y (essentially the price growth rate relative to CPI), according to the table below.

Land Value Increment Tax Schedule

	$T < 20$	$20 \leq T < 30$	$30 \leq T < 40$	$T \geq 40$
Level 1: $X/Y < 1$	(20%, 0%)	(20%, 0%)	(20%, 0%)	(20%, 0%)
Level 2: $1 \leq X/Y < 2$	(30%, 10%)	(28%, 8%)	(27%, 7%)	(26%, 6%)
Level 3: $X/Y \geq 2$	(40%, 30%)	(36%, 24%)	(34%, 21%)	(32%, 18%)

House transfer income tax (HTIT): This portion of transfer tax policy applies to the appraised value of buildings (updated once every three years). The HTIT payment can be written as:

$$\mathcal{T}^{HT} = \tau^I \cdot \theta \times P_A \tag{A.5}$$

where P_A is the appraised building value in the most recent appraisal year. The rates τ^I are the same as those that apply to other sources of personal income. Income tax brackets are automatically tied to total CPI inflation, but in 2010 the schedule was:

$$\tau^I = \begin{cases} 5\% & \text{if} \quad I < 500,000 \text{ NTD} \\ 12\% & \text{if} \quad 500,000 < I \leq 1,090,000 \text{ NTD} \\ 20\% & \text{if} \quad 1,090,000 < I \leq 2,180,000 \text{ NTD} \\ 30\% & \text{if} \quad 2,180,000 < I \leq 4,090,000 \text{ NTD} \\ 40\% & \text{if} \quad I > 4,090,000 \text{ NTD} \end{cases} \tag{A.6}$$

where I refers to taxable income, inclusive of income from the building sale (1 NTD $\approx$ 0.03 USD). The scale factor $\theta < 1$ determines the portion of the building sale that is taxable and is set at the municipal level. In 2010, θ was equal to 37% in Taipei, 21% in New Taipei City, 20% in Kaohsiung, 13% in other major cities, 10% in county-administered cities, and 8% in counties.

Example: Computing Total Transfer Tax Liability

Consider the following short-term residential property sale, with features chosen to be representative of appraisal, and sale prices for a single-family home in Taipei in 2012.

Suppose it is January 2012, and Mr. Lee has found a buyer willing to pay 65,000,000 NTD for his second home. The land area is 125 m^2, the current land value (CLV) is 200,000 NTD per m^2, and Mr. Lee originally paid 170,000 NTD per m^2. Suppose he has held the land since July 2010, and the CPI inflation rate over the preceding two years was 1%. Over the holding period, Mr. Lee made a payment of 3,000 NTD towards infrastructure benefits. The land value increment tax Mr. Lee owes is derived as follows:

$$Y = (170,000 \times 125) \times 1.01 = 21,462,500 \text{ NTD}$$

$$X = (200,000 \times 125) - (170,000 \times 125) \cdot 1.01 - 3,000 = 3,534,500 \text{ NTD}$$

$$\implies \mathcal{T}^{LV} = 0.2 \cdot (CLV - Y - B) = 0.2 \cdot (25,000,000 - 21,462,500 - 3,000) = 706,900 \text{ NTD}$$

For the house transfer income tax, suppose the house was recently assessed at 33,600,000 NTD. Since property flippers tend to be very high income, suppose prior to this sale, Mr Lee's taxable income already placed him in the top tax bracket. Given that the house is located in Taipei, the HTIT payment due is $\mathcal{T}^{HT} = 0.4 \times 0.37 \times 33,600,000 = 4,972,800$ NTD.

Thus, if there were no transfer tax surcharge imposed in 2011, Mr. Lee's total transfer tax liability would be 5,679,700 NTD, which is roughly 8.7% of the transaction value of 65,000,000 NTD.[53] With the surcharge in place and 1.5 year holding period, the total transfer tax bill rises by 6,500,000 NTD ($\approx 222,000$ USD) to 18.7% of the sale price.

B Transaction Price Index Construction

As discussed in Section 3.2, we create transaction price indices using newly compiled sales records from local land offices prior to 2012Q3, which we then append to the files available from the government for 2012Q3 to 2019Q4. We describe the index construction methodology in this appendix. The public records offer a rich dataset of property characteristics for sales involving a combination of land parcels and or buildings.[54] Our dataset contains information on the number of floors in the unit and building, floor space, land area, land use/zoning, building materials, front-facing road width, location on the street, construction date, and variables generated from remarks enumerated in the public sale record which we use to identify arms-length transactions.

Yet, while addresses are known up to the block level, one challenge is that unique property identifiers are not included, meaning we cannot directly track sales of the same property over time. This not not necessarily an issue for hedonic indexing methods, which use a set of potentially time-varying observables to price properties in the cross-section. An hedonic approach would, however, require us to make strong assumptions about the underlying functional form for transaction values given the relatively small set of variables available over the full time period (2000Q1 to 2019Q4) and for all properties.

Therefore, we adopt a hybrid repeat sales hedonic-approach in the spirit of McMillen (2012) and Fang et al. (2015) that transforms the time fixed effects in the following regression to estimate a

[53] Note this is a conservative example, as in practice the CLV can be much lower than the market value for the land, and not all properties occur among taxpayers in the highest HTIT county (Taipei) and in the highest income tax bracket.

[54] The records also include files related to leases and parking lot transfers, which we exclude from our analysis.

transaction price index:

$$\log P^c_{i,t} = \delta^c_t + \gamma^c_{\tilde{i}} + \beta^{c\prime} \cdot \mathbf{X^c_{i,t}} + \epsilon^c_{i,t} \tag{B.1}$$

$$P^c_t = \exp(\delta^c_t) \tag{B.2}$$

where i indexes a property, t denotes a quarter-year or month-year period, and c refers to a classification based on a combination of the regional market (e.g. Taipei) and property use category (i.e. residential, commercial, industrial). The property type fixed effects $\gamma^c_{\tilde{i}}$ control for all time-invariant observed or unobserved characteristics of the transacted property type.

We make three further restrictions to estimate the model. First, we restrict to transactions involving a single building and drop any transactions with a parking lot or parking space included in the sale. In other words, our sample includes sales of either a land parcel plus structure bundle, or a unit or floor within a building. Second, we drop newly built structures and recently renovated properties. Finally, we identify the $\gamma^c_{\tilde{i}}$ by matching transactions on geolocation information and other features to determine "uniqueness" of a transaction. We consider four variations of this method, with uniqueness defined with increasing stringency as we go down the following list:

1. **Block-level fixed effects:** we assign two transactions the same panel id if they share the same address string (85% of transactions).

2. **Property development fixed effects:** two transactions share a panel id if they have the same latitude and longitude coordinates (18% of transactions).

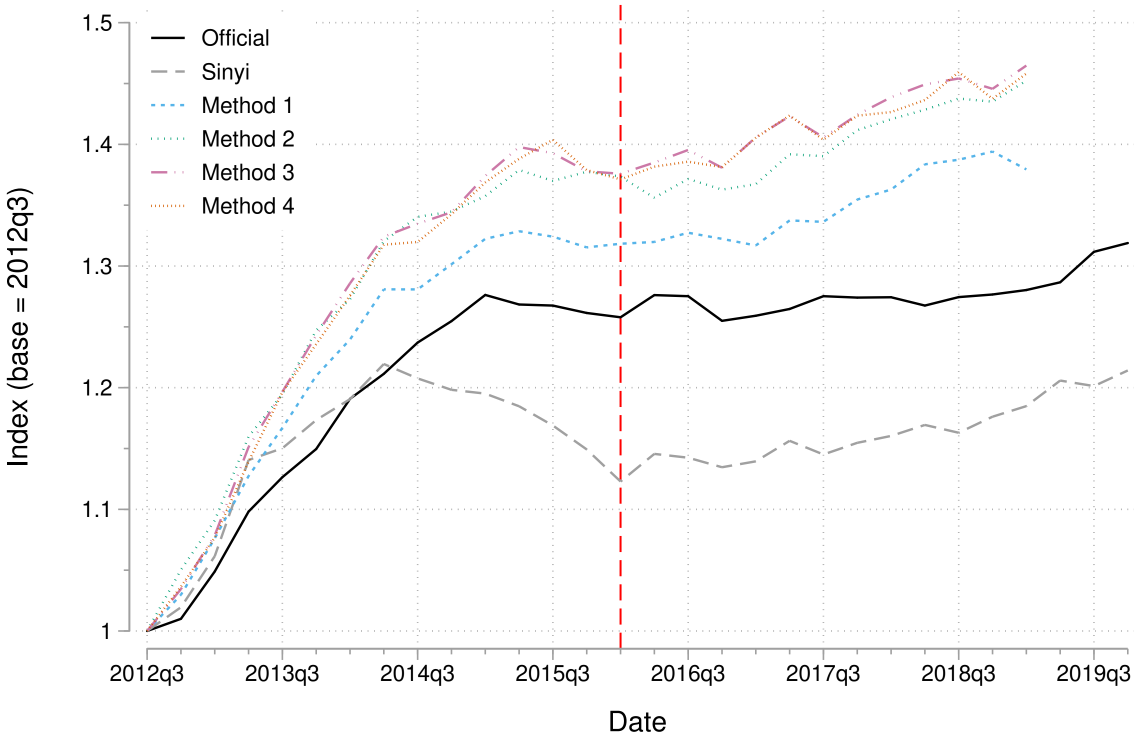
3. **Unique properties up to the nearest 5 m^2 in floor space:** two properties share a panel id if they have the same coordinates and the same building and land area, each rounded to the nearest 5 m^2. This effectively treats two apartments with similar floor space as the same unit, conditional on apartment layout (7% of transactions).

4. **Unique properties up to the nearest 1 m^2 in floor space:** we consider two properties to be the same if they share coordinates and have the same building and land area, each rounded to the nearest 1 m^2. Rounding to the nearest 1 m^2 identifies two units of the same size, accounting for minor typos in the coding of the area variables (5% of transactions).

In the regression, the vector $\mathbf{X_{i,t}}$ includes a polynomial in land area and floor space, the number of floors in the building, and the unit floor (for apartments and office space). To the extent that the above methods may assign two distinct but adjacent properties to the same panel id, controlling for $\mathbf{X_{i,t}}$ accounts for small differences due to the height and size which may be relevant to the transaction value.

When we subset to transactions of pre-existing residential structures, our four indices comove strongly with each other and with two other publicly available indices: the official government index and the Sinyi Residential Property Index. Figure B.1 plots all six indices for the aggregate market over the period 2012Q3 to 2019Q4 when the indices overlap. Notably, the level of the Sinyi index drops below the other indices, including the official index, starting in 2014Q. Since the Sinyi is a hedonic price index, it does not suffer from the positive selection bias on price growth that comes with repeat sales. The official government index is a weighted version of our pricing regression, where the weights are constructed to mitigate the sample selection bias issue inherent in restricting

FIGURE B.1. Comparison of Quarterly Housing Price Indices



Notes: The figure compares the official government price index, constructed using the public transaction records available from 2012Q3, to the Sinyi Residential Property Price Index, and our indices created using four methods for identifying repeat sales. The vertical red dashed line indicates the capital gains tax reform in 2016Q1. All indices normalized to unity in the base period of 2012Q3. See text for details.

to repeat sales.[55] This upward bias is apparent when we compare how the price level increases with the stringency of our criteria for identifying unique properties.[56]

In spite of these differences, the correlation between our index and the official index is 98%, and the correlation between our index and the Sinyi index is 73%. These correlations are stable even when we compare city-level price indices across different methods. We adopt our method 1, which

---

[55]The official indexing procedures, after restricting to arms-length transactions and deleting outliers, can be summarized by a three-step procedure (translated from this website):

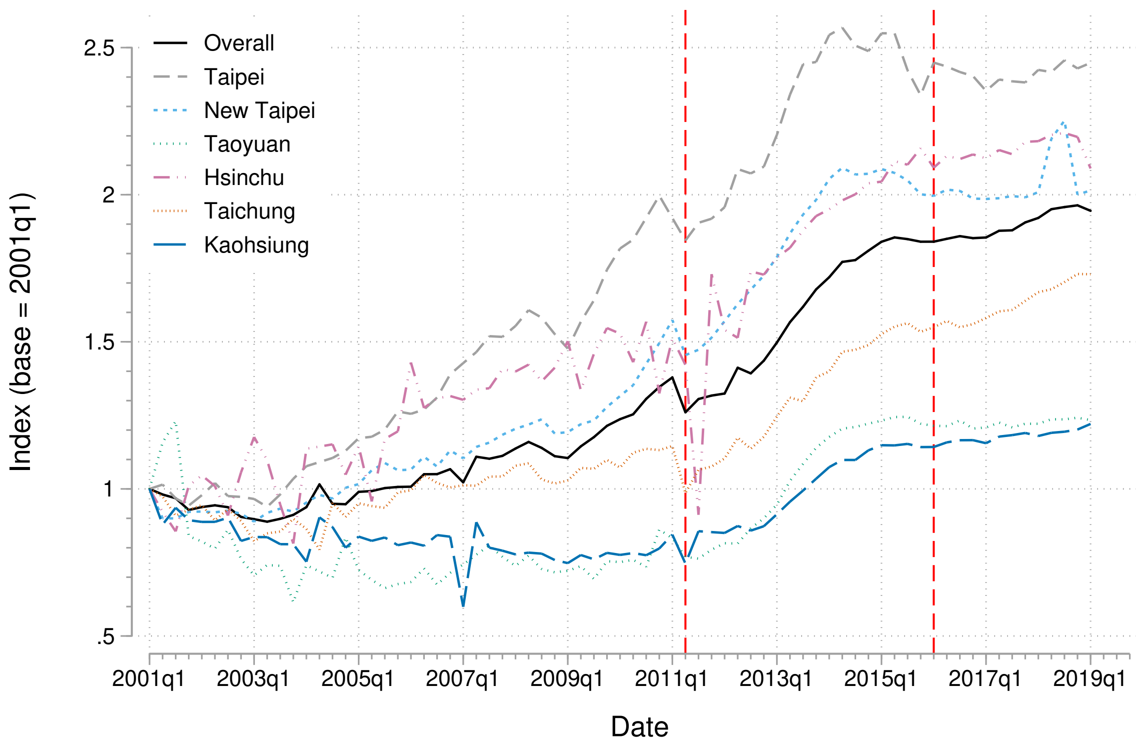
(i) Assign properties to the same panel id if they share the same neighborhood designation or are within 500m of each other, the same type and use categories, they were each constructed within 10 years of each other, there is at least six-month gap in transaction dates between the observations.

(ii) Price matching houses via automated valuation models (AVM), which are trained on the full set of transactions. These models are then used to create adjusted house prices for the repeat sales according to observables.

(iii) Estimate Case-Shiller repeat sales regressions by weighted least squares, where the weights adjust observations according to the length of time elapsed between repeat sales.

[56]Our price levels lie on top of the official ones, in part, because our indices include sales of similar properties occurring within six months. We find in the confidential property records that these extremely short-term sales are very prevalent, particularly in the pre-reform period.

FIGURE B.2. Quarterly Housing Price Indices for Top Six Markets



Notes: The figure plots our indices created using our repeat sales method outlined in the main text (what we call "Method 1"). Overall refers to the model in equation (B.1) estimated for all arms-length transactions. The other lines refer to indices estimated for the six largest housing markets in Taiwan. Vertical red dashed lines indicate the transfer tax reform in 2011Q2 and the capital gains tax reform in 2016Q1. All indices normalized to unity in the base period of 2001Q1.

uses 85% of total transactions, as our preferred index to maximize the precision of our estimates $\widehat{\delta}_t^c$, maximize sample coverage, and limit the repeat sales selection bias.

We plot the time series obtained from our preferred indexing Method 1 in Figure B.2 for the entire housing market and for each of the top six cities by population. In contrast to popularly referenced indices like the Sinyi, our indices show a clear price drop of 7% within the quarter after the reform (2011Q2), with the magnitude of this drop varying between 6% (Taipei and New Taipei) to 28% (Hsinchu). The main difference between our index and publicly available ones is we incorporate short-term property flips which were targeted by the transfer tax surcharge. At the same time, our index generates much smaller price gains between 2001Q1 and 2011Q1 of 40%, compared to the 116% implied by the Sinyi index.

C Additional Results on Return Heterogeneity

This appendix offers additional results on how annualized total returns to housing differ by investors and property type, and for different definitions of non-resident status. To summarize these findings:

- Individual and institutional investors earn statistically identical returns (Table C.1).
- Single family homes earn higher returns than apartments (Table C.2).
- We find no evidence of a local premium in the pre-reform period when we follow the definition of "out-of-town" commonly used in the housing investor literature and define local at the metro area level (Table C.4). In contrast, there is a 4 p.p. premium for local sellers when we define local at the neighborhood level, and this premium widens to 8 p.p. in the post-reform period. We dub owners of properties at an address in distinct district from their permanent address, but potentially within the same metro area, as "out-of-neighborhood" investors (Table C.3).
- We compute rental yields at the taxpayer portfolio level by dividing total rental income reported on the personal income tax return by the sum market value of all properties.[57]. In cases where the property did not transact within the tax year, we use the last observed sale price inflated by the price index value created in Appendix B. In Figure C.1 we find average post-reform rental yields were about 50 bps higher (p-value = 0.034) for taxpayers who had strictly positive rental income in the pre-reform period. This indicates some investors' reaching for rental yields, although this 50 bps increase is economically small relative to the flattening of the yield curve brought about by the tax (Figure 9).

For exposition, we repeat here the taxpayer-level holding period return formula:

$$r^j_{t-1,t} = \frac{\sum_{i=1}^{n}(1-\tau_{i,t}) \cdot \widetilde{V}^j_{i,t} + (1-c^j_{i,t}) \cdot Y^j_{i,t} - T^j_{t-1,t}}{\sum_{i=1}^{n} \widetilde{V}_{i,t-1}} - 1 \tag{C.1}$$

where r^j_t is the holding period return for the set of properties held by taxpayer j between periods $t-1$ and t. $\tau_{i,t}$ is the fraction of the market value $\widetilde{V}$ the seller pays in transfer taxes, $c^j_{i,t}$ is the income tax paid by j on rental income $Y^j_{i,t}$ accumulated between $t-1$ and t, and $T^j_{t-1,t}$ refers to the total property tax bill on land and buildings incurred by j during the holding period. We discuss the schedules underlying all the tax terms in Appendix A. In the event that a property i does not transact in period t, we inflate up from the previous transaction price in $t-1$ using our estimated price index $\widehat{P}$ described in Appendix B, and assuming a linear rate of depreciation that we estimate to be 2% in Appendix F. We annualize returns by computing $(1+r^j_{t-1,t})^{365/n}$, where N is the number of days in the holding period.

[57]We do not observe rental income at the property level since our data are based on annual personal income tax returns

Table C.1. Annualized Holding Period Returns by Investor Type

	N	μ_{HPR}	σ_{HPR}	P^{50}_{HPR}
Non-resident investors	34	30.97	78.16	5.76
Individual investors	$94,099$	14.89	81.62	2.15
Institutional investors	$1,716$	11.96	66.79	3.16

Notes: We define non-resident investors using the flag provided by the tax authority, which only counts taxpayers as non-residents if they report a permanent address outside Taiwan. The true number of non-resident property owners is obviously much higher, but tricky to identify in this context due to surnames common to Taiwan and other property markets in East Asia.

Table C.2. Annualized Holding Period Returns by Property Type

	N	μ_{HPR}	σ_{HPR}	P^{50}_{HPR}
Apartments	$66,720$	13.27	75.08	2.86
Single-family homes	$7,016$	13.75	67.21	5.95
Office space	976	9.03	50.83	2.75
Factories & warehouses	519	10.66	39.50	4.15
Storefronts	$1,037$	24.54	79.17	10.15

Table C.3. Differences in Mean Holding Period Returns across Counterparty Pairs (OON)

A. Difference-in-differences: Local vs. OON Buyers/Sellers

	Local buyer	*OON buyer*	**Difference**
OON seller	9.39%	11.72%	**2.33*****
Local seller	15.72%	18.72%	**3.00*****
Difference	**6.33*****	**7.00*****	**0.67**

B. Difference-in-differences: Local vs. OON Sellers Pre vs. Post-reform

	Pre-reform	*Post-reform*	**Difference**
OON seller	22.06%	8.13%	$-$**13.93*****
Local seller	25.98%	16.30%	$-$**9.68*****
Difference	**3.92****	**8.17*****	**4.25*****

C. Triple Differences: Local Premium Pre vs. Post-reform

Pre-reform

	Local buyer	*OON buyer*	**Difference**
OON seller	21.96%	22.11%	**0.15**
Local seller	26.32%	25.77%	$-$**0.55**
Difference	**4.36***	**3.66****	$-$**0.70**

Post-reform

	Local buyer	*OON buyer*	**Difference**
OON seller	5.74%	9.04%	**3.30*****
Local seller	13.78%	17.63%	**3.85*****
Difference	**8.04*****	**8.59*****	**0.55**

Notes: Each cell in the above tables shows the mean total holding period return for either a buyer-seller pair (Panels A and C), or for sellers in the pre or post-reform period (Panel B). Returns calculated using the procedures described in the text and equations (5.1) and (5.2). In each table, the "difference" column displays the difference between the first two columns. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$ on the t-test for differences in means across the first two columns.

Table C.4. Returns Earned by Out-of-town vs. Local Investors

		N	μ_{HPR}	σ_{HPR}
Local investors sell to OOT buyers:	Pre-reform	$3,865$	24.09	109.87
	Post-reform	$21,348$	15.69	80.32
	Overall	25,213	16.98	85.56
Local investors sell to local buyers:	Pre-reform	$8,092$	23.16	110.61
	Post-reform	$42,053$	13.42	75.35
	Overall	50,145	14.99	82.14
OOT investors sell to OOT buyers:	Pre-reform	$2,492$	25.17	110.71
	Post-reform	$8,684$	9.37	66.74
	Overall	11,176	12.89	78.97
OOT investors sell to local buyers:	Pre-reform	$2,186$	25.06	112.70
	Post-reform	$8,586$	7.96	55.35
	Overall	10,772	11.43	71.17

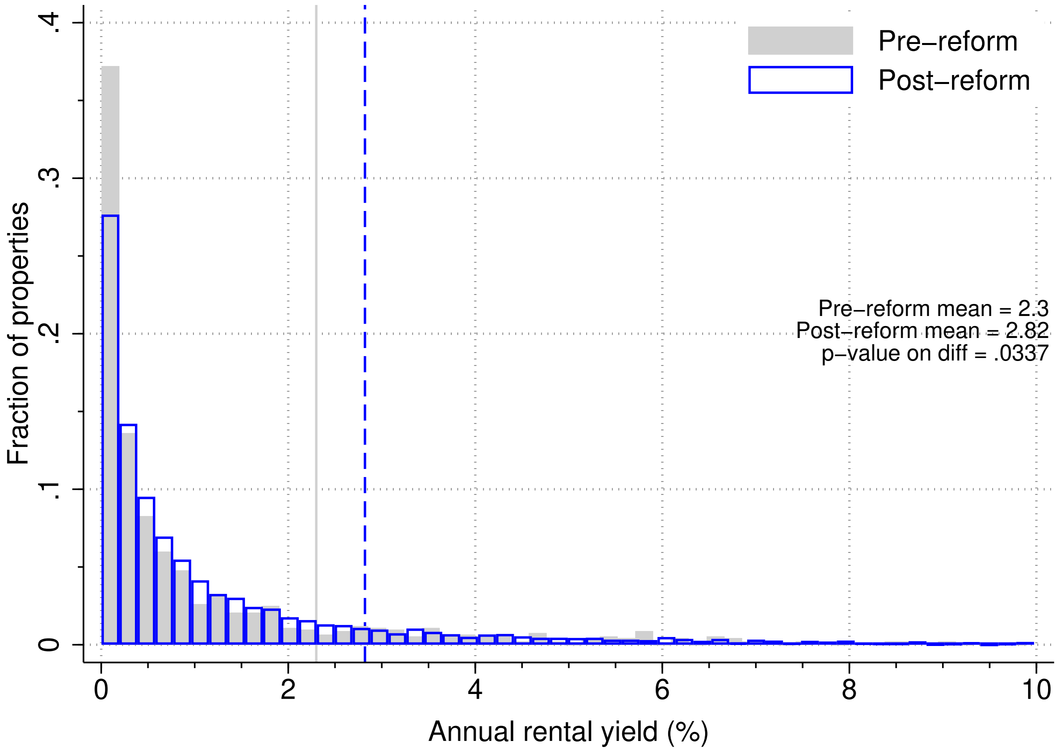
Notes: We define out-of-town (OOT) counterparties as taxpayers involved in the sale of a property located in one of the 22 administrative regions of Taiwan that is different from the region of the permanent address they report on their personal income tax returns. In contrast, out-of-neighborhood (OON) counterparties are involved in the sale of a property located in one of the 368 districts that is distinct from the taxpayer's district of permanent residence.

Table C.5. Breakdown of Returns Earned by Out-of-town (OOT) vs. Local Investors

Year	Investor type	N	μ_{HPR}	$\mu_{capital}$	μ_{rental}	μ_{LTV}
2007	Local	12,066	6.43	6.13	0.84	49.73
	OOT	3,307	3.88	3.99	0.47	513.92
2008	Local	22,266	3.01	2.82	0.60	23.95
	OOT	6,587	3.45	3.45	0.62	61.12
2009	Local	32,242	−0.26	−0.41	0.54	47.86
	OOT	10,006	−0.11	−0.54	1.01	55.45
2010	Local	44,479	7.25	7.00	0.73	201.42
	OOT	13,882	6.59	6.38	0.98	99.88
2011	Local	60,014	8.15	8.51	0.95	114.75
	OOT	19,109	8.05	7.95	0.84	56.34
2012	Local	82,563	6.57	6.24	0.94	50.25
	OOT	27,127	5.89	5.98	0.68	56.03
2013	Local	110,619	11.10	10.79	1.04	364.50
	OOT	36,465	11.22	11.01	0.97	132.59
2014	Local	149,022	8.88	8.54	0.77	51.75
	OOT	45,639	7.33	6.97	0.97	112.35

Notes: The table breaks down the components of annualized holding returns for local and out-of-town (OOT) investors. HPR indicates the overall rate of return, which equals the net of transfer tax capital gain plus the market-value-weighted (across properties in the taxpayer's real estate portfolio) rental income minus the market-value-weighted mortgage interest payment and minus the annual holding tax, divided by the last market value. *capital* indicates the capital gain. *rental* indicates the rental income divided by the last market value. LTV indicates the mortgage-loan-to-value ratio, where loans are derived by the mortgage interest payment and the annual average mortgage interest rates collected by Taiwan National Statistics. Moments of LTV only pertain to investors with mortgage interest payments. The market value is defined as the real transaction price, or, if a sale price is not available, we use the appraisal value times the city-year specific price-appraisal value ratio to proxy for market value. For years during which a property was not transacted, the market value is defined as the last transaction price inflated by the city-year price index, less linear depreciation of 2% per year. We winsorize capital gains at the top and bottom 1%.

FIGURE C.1. Reaching for Rental Yields



Notes: We compute annual rental yields at the taxpayer portfolio level by dividing total rental income reported on the personal income tax return by the sum market value of all properties. In cases where the property did not transact within the tax year, we use the last observed sale price inflated by the price index value created in Appendix B. We winsorize rental yields at the top 1% level. The solid grey vertical line indicates the mean rental yield in the pre-reform period, while the blue dashed line shows the mean in the post-reform period.

D Details on the Inheritance Tax System

Here we discuss the estate planning process and inheritance tax regime in Taiwan and how we compute the inherited wealth measures we use as an instrument for net worth in Section 4.4. The key variable we observe in the tax data is inheritance income *net of any deductions and tax liability incurred by the heirs*, and net of any expenses and outstanding debts of the decedent. Taiwan imposes a flat estate and gift tax rate of 10%, with the following deductions:

- Standard deduction of 73,000 USD for each donor, on top of deductions for the deed and land increment tax associated with bequeathed properties.

- A deduction of 20% on any assets held by the deceased for at least six years, 40% on assets held for seven years, 60% on those held for eight years, up to 80% for those held for nine years or longer.

- Spouses get the largest deduction on inheritances (150,000 USD), followed by parents (37,000 USD), then lineal descendants, siblings, and grandparents (15,000 USD each).

Table D.1. Default Inheritance Shares by Descendant Type

Order of heirs	Default shares	
	Heirs	Spouse
Lineal descendants	Even split	
Parents	1/2	1/2
Siblings	1/2	1/2
Grandparents	1/3	2/3

- Funeral expenses, legal fees, and any outstanding debts, fines, and unpaid taxes incurred by the deceased.
- Conservation easements if inherited land continues to be employed in agriculture.

All these potential deductions are totalled and netted out of our inherited wealth measure IW defined in Section 4.4.[58] Therefore, our first stage measures the extent to which a dollar of net inheritance income passes through the taxpayer net worth on the eve of the tax reform.

Another issue concerns how estates are divided among surviving heirs. Table D.1 summarizes the statutory default inheritance shares for wills or if the decedent dies intestate. There are also minimum legal requirements for inheritance shares of immediate family members. For example, if the deceased is survived by two lineal dependents, parents, and a spouse, then the parents get nothing and the lineal dependents and spouse evenly split the estate. Alternatively, if the deceased is survived by two siblings and a spouse, the spouse gets one-half of the estate and the siblings each get one-fourth. That is, one cannot completely disinherit lineal descendants, parents, spouses, siblings, or grandparents. For lineal descendants, parents, and spouses, the minimum legal share is one-half the default share, while for siblings and grandparents the minimum requirement is one-third of the default share. While we do not observe the status of the will, inheritances rarely deviate from the default proportions. We therefore assign inherited wealth by allocating taxpayers a share of the estate consistent with the ordering of heirs in Table D.1.

Table D.2 summarizes the importance of inheritances for taxpayers' illiquid and total wealth. On average, 15% of sellers' illiquid wealth (land + buildings + vehicles) was inherited, compared to 17% of buyers' illiquid wealth. The average inheritance in the pre-reform period (2007-2010) was about 72,000 USD, of which roughly 70% consisted of illiquid assets. Inherited properties are thus an important component of counterparties' overall net worth.

Finally, our identification strategy relies on the fact that inheritances received as a consequence of untimely deaths represent a component of taxpayer net worth that is unrelated to housing market outcomes. If the probability of family members' untimely death were correlated with the size of the inheritance, then this would be a violation of the exclusion restriction for our instrument. Table D.3 shows no clear relationship between the decedent's age at death and the (net) value of housing inherited by heirs. This bolsters our argument that unanticipated inheritance receipt is unrelated to the pre-existing size of the taxpayer's portfolio.

[58] The total deduction on the estate (i.e. totalled across all heirs, cannot exceed 400,000 USD).

Table D.2. Taxpayer Inheritance Summary Statistics

	N	Wealth	Illiquid wealth	Inheritance	Illiquid inheritance	$\frac{\text{Illiquid inheritance}}{\text{Illiquid wealth}}$
Buyer	103,030	729,458	438,121	72,311	52,579	0.172
		(3,738,570)	(2,764,760)	(573,058)	(244,733)	
Seller	112,843	737,802	487,134	72,655	51,165	0.146
		(3,048,988)	(2,176,712)	(583,536)	(195,098)	

Notes: Includes assessed inheritances net of taxes received in 2007-2010. 198,150 transactions in the post-reform period featured at least one counterparty who received an inheritance. Units in real 2015 USD. Illiquid wealth includes the total estimated liquidation value of land, buildings, and vehicles. See Section 3.1 for more information on how we construct wealth estimates.

Table D.3. Decedent's Age at Death by Quintile of Inherited Housing Wealth

	μ_{age}	σ_{age}
First quintile	74.50	13.43
Second quintile	73.03	13.10
Third quintile	71.96	14.10
Fourth quintile	73.82	13.23
Fifth quintile	71.71	13.35

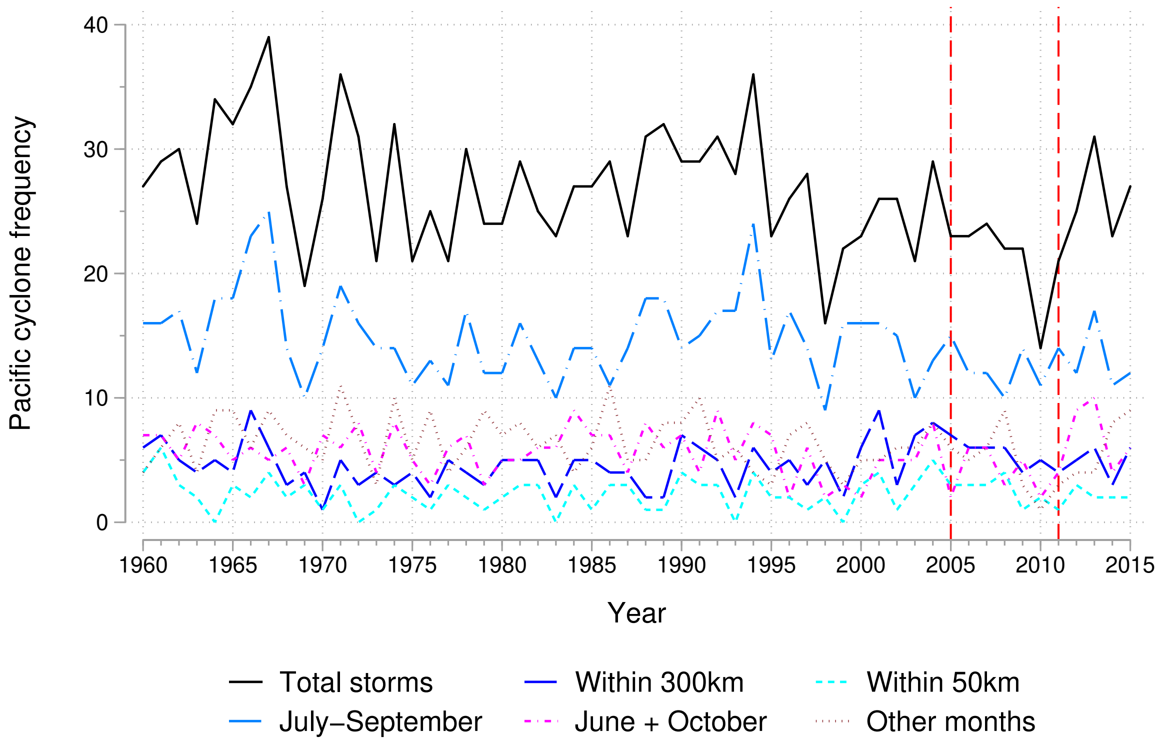
E Constructing Weather Shocks

This appendix provides more details on the meteorological features of Pacific storms, and how we compiled the data used in Section 6.2 to estimate an upper bound limit on the share of non-fundamental trading in the housing market. Figure E.1. shows that over the last 60 years on average 26 tropical cyclones originated in the Pacific each year, with an average of five storms coming within 300km of the main island of Taiwan.[59] In the period 2006-2011, which overlaps with our confidential data and occurs prior to the tax reform, an average of two storms per year made direct landfall in Taiwan. While climate change has led to a increase in the severity of storms, the overall frequency of storms has been on a downward trend, and there is no evidence of the traditional typhoon season (July through September) lengthening for Taiwan, as the number of storms occurring in June and October has consistently hovered between five to seven per year.[60]

[59] Even if a typhoon does not make landfall it often has a noticeable impact on local weather conditions. Typhoons can grow to a diameter of up to 1,000 miles (1,600 km).

[60] The downward trend in frequency is in part due to the increased incidence of two low pressure centers fusing into a larger storm in what is known as the Fujiwara Effect. The time series in Figure E.1. display 10-year cycles due to El Niño effects.

FIGURE E.1. Pacific Storm Incidence and Cyclicality: 1960–2015



Notes: The figure plots the time series of storm frequency by month of occurrence and by the closest the storm comes to making landfall on the main island of Taiwan. Total storms refers to all storms classified as either tropical storms or a more severe storm category. See Table E.1 for the full classification system. Vertical red lines indicate the pre-transfer tax reform period (2005-2011) we use to infer noise trading volume from the weather data. Data on overall Pacific storm frequency are from the Regional Specialized Meteorological Center (RSMC) Tokyo - Typhoon Center. Data on the distance of storms to Taiwan are from the Taiwan Central Weather Bureau.

Hence, in this paper we focus on July, August, and September as the months where severe weather shocks are most likely to occur.

We rely on two main sources for our weather data. We scrape daily weather readings over 2005-2019 from all 832 stations scattered across Taiwan via the CoDiS Database of the Central Weather Bureau (CWB), and merge in the dates when the CWB issued typhoon warnings from the Typhoon Database. According to the official classification system in Table E.1, typhoon warnings are issued whenever winds are expected to reach a sustained speed of at least 74 mph (118 km/h). Meteorological stations are geographically distributed across Taiwan such that each of the 22 administrative regions contains at least two, with more populated regions being serviced by more non-automated stations due to the increased likelihood of property damage should a severe storm arrive.[61]

[61]The total number of stations contained in each region is as follows: Taipei (19), New Taipei (49), Taichung (64), Tainan (65), Kaohsiung (72), Keelung (4), Taoyuan (24), Hsinchu (2), Hsinchu County (20), Miaoli (50), Nantou (85), Changhua (34), Yunlin (35), Chiayi (2), Chiayi County (45), Pingtung (83), Yilan (51), Hualien (69), Taitung (48), Penghu (4), Kinmen (4), Lienchiang (3).

Table E.1. Classification System for Tropical Cyclones

Category	Sustained wind speed
Violent typhoon	$\geq$ 105 knots (121 mph)
Very strong typhoon	85-104 knots (98-120 mph)
Typhoon	64-84 knots (74-97 mph)
Severe tropical storm	48-63 knots (55-73 mph)
Tropical storm	34-47 knots (39-54 mph)
Tropical depression	$\leq$ 33 knots (38 mph)

Source: World Meteorological Organization Technical Document, Typhoon Committee Operational Manual.

There are three types of ground stations which record weather readings:

1. Main stations (N = 32) are staffed by government employees who record all weather variables, including: daily average wind speed, max wind gust, accumulated precipitation, sea surface pressure, air pressure, hours of precipitation and sunlight, cloud coverage, visibility, UVI, dew point, humidity, and average and high/low temperature.

2. Automated stations (N = 485) only record crucial typhoon forecasting variables, including variables related to temperature, station pressure, humidity, wind speed, and accumulated precipitation.

3. Precipitation stations (N = 315) only report accumulated precipitation. Stations in this category are also equipped to provide automated readings.

For each station and each day, we take averages and maxima/minima over hourly readings. Notably, even if a station is equipped to report certain weather variables there can be missing values due to equipment damages or malfunctions, both of which are more likely to occur during severe weather events. Therefore in our analysis we focus on either the manned stations in the first category or a balanced panel of stations within the first two categories.

Table E.2 provides summary statistics for the key weather variables which are related to forecasting Pacific storm severity. To create a consistent sample across variables, in computing these statistics we exclude the 40% of stations which only report automated precipitation readings and create a balanced panel of the remaining stations. Taiwan averages 16 days with active typhoon warnings during the peak season but only four days during non-peak months. Maximum daily precipitation across all stations is 5% higher during typhoon season in the Taipei-New Taipei area,

Table E.2. Summary Statistics for Key Meteorological Station Readings

	Taipei/New Taipei		Other Metros	
	Peak season	Non-peak	Peak season	Non-peak
Avg. # typhoon warning days	15.8	3.9	15.8	3.9
Max daily precipitation (in)	17.5	16.7	37.8	26.7
Cumulative precipitation (in)	38.9	82.4	47.0	48.9
Avg. wind speed (mph)	3.9	4.0	3.8	4.3
Max wind gust (mph)	101.4	88.3	153.9	126.6
Avg. station pressure (hPa)	989.7	997.4	965.4	973.1
Min. station pressure (hPa)	896.5	907.4	627.8	634.0
Avg. daily high temperature (°F)	89.5	73.6	86.3	74.6
Max daily high temperature (°F)	116.6	115.8	112.7	111.5
N	19,944	64,440	74,790	241,650
# Stations	36	36	135	135

Notes: Observations from a balanced panel of stations (N = 171) reporting key typhoon forecasting variables in the pre-reform period. Peak season refers to daily weather readings during the months of July, August, and September, while non-peak consists of readings from all other months. Typhoon warnings are set at the national level, and a full history of announcements going back to 1960 is available from the Central Weather Bureau Typhoon Database.

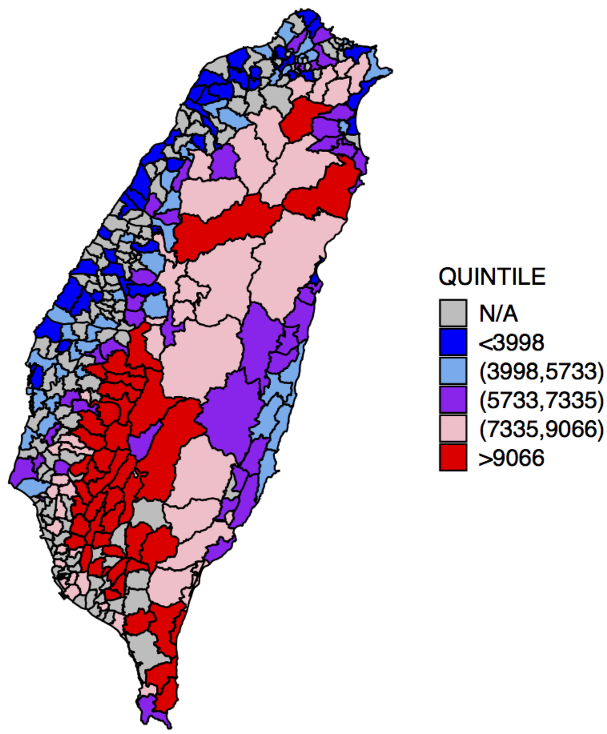
and 42% higher across stations in all other metro areas. The other key metrics which accompany storms are also more pronounced during the peak season and outside the Taipei area: low station pressure readings and high maximum wind gusts. Due to the track patterns of storms in the Pacific, storms are more likely to strike the southern tip of Taiwan or run through the middle of the island, than strike the northern portion where Taipei and New Taipei are located.

Because storm severity can vary at such a granular level, we exploit both time series and spatial variation in weather shocks. Figure E.2 shows how rainfall during typhoon seasons in the pre-reform period is disproportionately concentrated in the center and southern portions of the island of Taiwan (Panel A). However, even within the greater Taipei metro area at the northern tip of the island, where most property sales volume occurs, average accumulated rainfall varies from 157 to 354 inches per typhoon season. In contrast, the spatial pattern of typhoon-force wind incidence appears to be relatively divorced from the distribution of rainfall (Panel B). Yet, we note that our geographic coverage of wind speed readings is incomplete (grey shaded areas) due to a smaller number of stations outfitted with the required technology.

A natural question is whether precipitation and wind gusts are sufficient to characterize the severity of weather conditions. We test the validity of our interpretation of the meteorological data by using factor analysis to identify the four factors with eigenvalues above one, which together capture 88% of variation in weather patterns. Table E.3 reports the factor loadings for the eleven variables which are common to all main stations and automated stations in our sample. The first factor loads on fair weather characteristics: high atmospheric pressure, high temperature, low humidity, limited wind and precipitation. The second loads negatively on pressure and positively on temperatures. Since, these two characteristics precede tropical storm systems, this factor identifies a

FIGURE E.2. Spatial Distribution of Cumulative Rainfall and Severe Wind (2005-2011Q2)

A. Accumulated Rainfall (mm) during Typhoon Seasons



B. Total Number of Days with Strong Winds (≥ 74 mph) during Typhoon Seasons

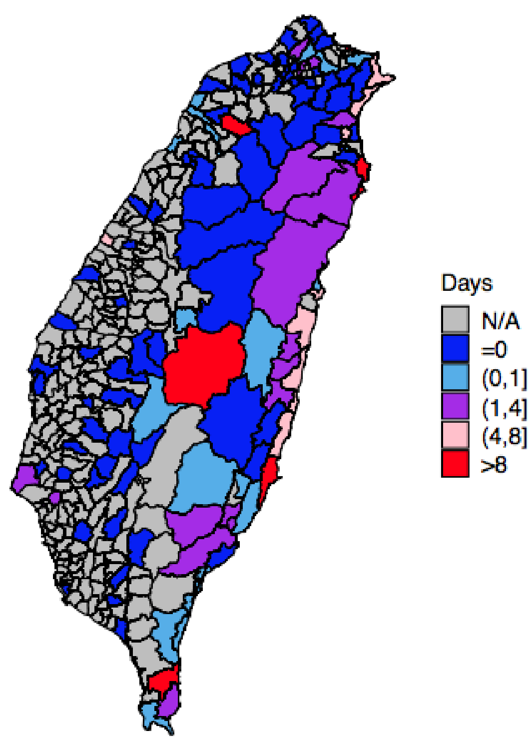


Table E.3. Factor Loadings for Key Weather Variables

	Factor 1	Factor 2	Factor 3	Factor 4
Avg. station pressure	0.37	−0.38	0.01	0.21
Max station pressure	0.37	−0.38	0.02	0.21
Min station pressure	0.37	−0.37	0.01	0.21
Avg. temperature	0.33	0.43	−0.01	0.19
Max temperature	0.33	0.44	−0.04	0.08
Min temperature	0.31	0.42	0.00	0.28
Avg. relative humidity	−0.34	0.04	−0.32	0.38
Min relative humidity	−0.33	−0.07	−0.19	0.46
Avg. wind speed	−0.13	−0.01	0.65	0.14
Max wind gust	−0.13	0.06	0.66	0.17
Cumulative precipitation	−0.14	0.02	0.00	0.58

Notes: The table reports the factor loadings for each variable recorded by the main and automated weather stations in our sample. We restrict attention to the four factors (columns) with eigenvalues greater than one.

storm forecast component. The third factor loads prominently on average and maximum wind speed, while the fourth factor loads on humidity and accumulated rainfall. Hence, we loosely interpret factor 1 as a "fair weather" factor, factor 2 as a low pressure system, factor 3 as high wind, and factor 4 as heavy rainfall.[62]

In Table E.4 we replace the $Weather$ shocks in our baseline volume regression (6.2) with the four factors identified in Table E.3. Consistent with our interpretation, the four factors have the expected sign on property sales. Fair weather (factor 1) is positively associated with volume, while wind (factor 3) and rain (factor 4) are negatively associated with volume. There is no obvious economic reason why low atmospheric pressure conditional on other weather conditions (factor 2) would influence selling behavior, and consequently the association of this factor with volume is statistically insignificant. When we run a "horserace" regression with all four factors in column 6, the wind factor (factor 3) is the only one with an effect on volume. This suggests what we interpret as a rainfall effect on noise trading in our main results may in fact be due to wind once we condition on a richer set of atmospheric conditions. However, wind is not a substitute for rain, as both factors have a significantly negative effect on volume when we exclude the fair weather and low pressure factors (column 5).

We match each property sale in our dataset to the nearest station – according to Haversine distance – as of the transaction date. Since the government periodically retires and relocates weather stations during our sample period (mainly due to equipment depreciation). The average property

[62]We obtain similar results when we restrict to main stations, which offer a larger set of meteorological variables, including visibility, sunshine, cloud coverage, dew point, and duration of rain vs. sunshine. The main difference is we identify a fifth factor with an eigenvalue greater than one, which we interpret as an "overcast" factor.

Table E.4. Principal Weather Factors and Real Estate Sales

	(1)	(2)	(3)	(4)	(5)	(6)
$Factor1 \times Summer$	17.54^{***}					6.35
	(3.34)					(6.69)
$Factor2 \times Summer$		-4.46				5.63
		(6.90)				(7.27)
$Factor3 \times Summer$			-17.67^{***}		-13.66^{***}	-14.29^{***}
			(2.89)		(2.74)	(2.93)
$Factor4 \times Summer$				-13.24^{***}	-8.02^{***}	-3.42
				(2.60)	(2.32)	(5.00)
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
Damages Controls	✓	✓	✓	✓	✓	✓
N	4,681	4,681	4,681	4,681	4,681	4,681

Notes: The table presents results from estimating time series regressions according to equation (6.2) using the principal components from Table E.3 instead of the usual rainfall and maximum wind speed shocks. The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. We include daily observations over the period 2006-2016, which encompasses a full El Niño cycle. All regressions control for daily counts of casualties and properties lost due to flooding and typhoons. Newey-West standard errors with eight lags in parentheses adjust for serial correlation. We select the maximum possible lag order such that the estimator for the covariance matrix is consistent (Newey & West 1987). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

in our sample is located within 10.2 km of one of the first two types of weather stations (median of 7.4 km). To account for the fact that readings may be a less precise measure of local storm severity in more rural areas where CBDs are further from weather stations, we also check robustness of our property-level specifications to including polynomial functions of distance to the nearest station on the RHS.

Finally, we recognize that strong storms may entail property damage which alter sales volume by either lowering the quality of the available housing stock or inducing owners to engage in costly and time-consuming renovations. We downloaded official statistics from the National Fire Agency, Ministry of Interior going back to 1960 on reported fatalities, injuries, full and partial property losses, and disaster crews and equipment deployed. This information is itemized by the date and type of disaster, allowing us to match the damages to the typhoon warnings and other weather variables in our dataset. Over our pre-reform window of 2005-2011, the average flood or typhoon event during the regular typhoon season generated 70 casualties – most of which were minor injuries – completely destroyed 20 houses, and partially destroyed eight houses. Excluding damages from Typhoon Morakot in August 2009, which was the most destructive typhoon hitting Taiwan in the last 60 years, the average flood or typhoon event was responsible for 12 casualties, 4 completely destroyed homes, and 3 partially destroyed homes. Overall, the typical severe weather event was more of a nuisance than a substantial shock to the quality of investable real estate.

F Estimating Property Depreciation Rates

Our methods follow LaPoint (2020) and Yoshida (2020), who estimate depreciation rates for the Japanese commercial and residential markets, respectively. Two main assumptions underlie our estimation of real estate depreciation (Epple et al. 2010). First, real estate production is a generalized CES function of building and land quantities. Second, property owners are assumed to maximize profits subject to paying shadow prices for structure and land. Under these assumptions one can show that the overall property depreciation rate is the building depreciation rate δ_a times the building value share $s_{t,a}$ in real estate production:

$$-\frac{\partial \log P_{t,a}}{\partial a} = \delta_a \cdot s_{t,a} \equiv \delta \tag{F.1}$$

where δ_a is a function of the age a of the building at time t, the production inputs (i.e. floor area and plot size), and any factors that augment the productivity of the inputs.

This motivates estimating hedonic regression models with the following translog form:

$$\begin{aligned}
\log P_{i,j,t} &= \alpha_0 + f(A,S,L,D) + \beta_1 \log S_i + \beta_2 (\log S_i)^2 \\
&+ \beta_3 \log L_i + \beta_4 (\log L_i)^2 + \beta_5 D_i + \beta_6 D_i^2 + \beta_7 D_i^3 \\
&+ \beta_8 \log S_i \times \log L_i + \beta_9 \log S_i \times D_i + \beta_{10} \log L_i \times D_i \\
&+ \psi X_{i,j,t} + \gamma_j + \delta_t + \epsilon_{i,j,t} \\
f(A,S,L,D) &= \alpha_1 A_i + \alpha_2 A_i \times \log S_i + \alpha_3 A_i \times \log L_i + \alpha_4 A_i \times \log D_i
\end{aligned} \tag{F.2}$$

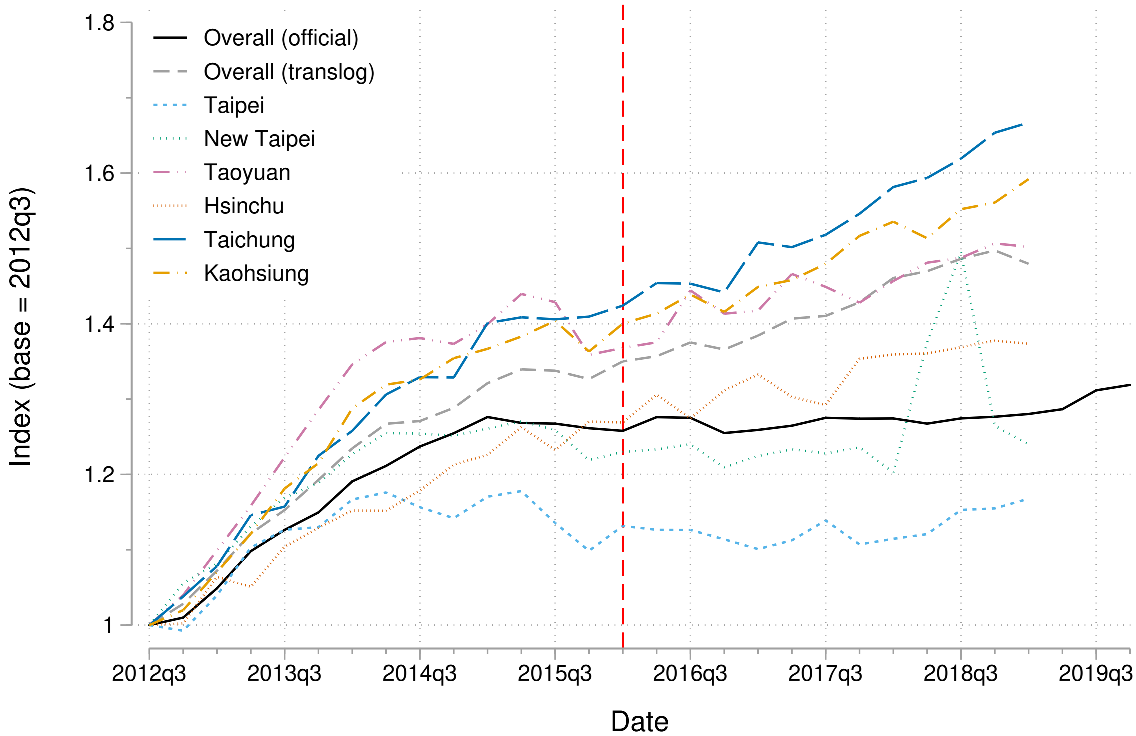
where $P_{i,j,t}$ denotes the price of property i located in district j traded in time t, $\log S_i$ is log floor area, $\log L_i$ is log plot size, and D_i is distance to the nearest transport hub, which we define as the minimum among the distances to a metro stop, commuter rail, or high speed rail station.[63] The function $f(A,S,L,D)$ captures how prices vary with building age A_i and interactions of age with building size, plot size, and distance. The vector $X_{i,j,t}$ includes a full set of indicators for land use designation, building material, the number of floors, and the floor of the apartment unit (if applicable). γ_j and δ_t are a full set of location and quarter-year fixed effects, respectively.[64]

The quarter-year dummies in equation (F.2) form an alternative index to the matching estimator index we use to compute holding period returns. Figure F.1. compares the translog indices for the overall market and top six metros to the official government index for the overall market. Notably, the translog index continues to grow beyond 2014, while the official government index stagnates. The translog index includes a rich set of interactions between size, age, and distance, and therefore accounts for changes in sample composition in ways that the official index, which is a type of matching estimator, does not. The overall translog index grew by 48% between 2012 and 2019, while our matching estimator index for the overall market (see Method 1 in Figure B.2. grew by 38% over the same period.

[63] A district here refers to a neighborhood within one of the 22 administrative regions of Taiwan. There are 368 districts in total which appear in the transactions data.

[64] We restrict to transactions involving either apartments or single-family homes, which are land plus building bundles. Land-only transactions typically pertain to agricultural land and do not have an age.

FIGURE F.1. Quarterly Translog Housing Price Indices for Top Six Markets



Notes: The figure plots indices created by transforming the estimated quarter-year dummies in equation (F.2) via $P_t = \exp(\widehat{\delta_t})$. Overall refers to the translog model estimated for all arms-length transactions. The other lines refer to indices estimated for the six largest housing markets in Taiwan. We compare the translog indices to the official government price index which uses the public transaction records available from 2012Q3. The vertical red dashed line indicates the capital gains tax reform in 2016Q1. All indices normalized to unity in the base period of 2012Q3. See text for details.

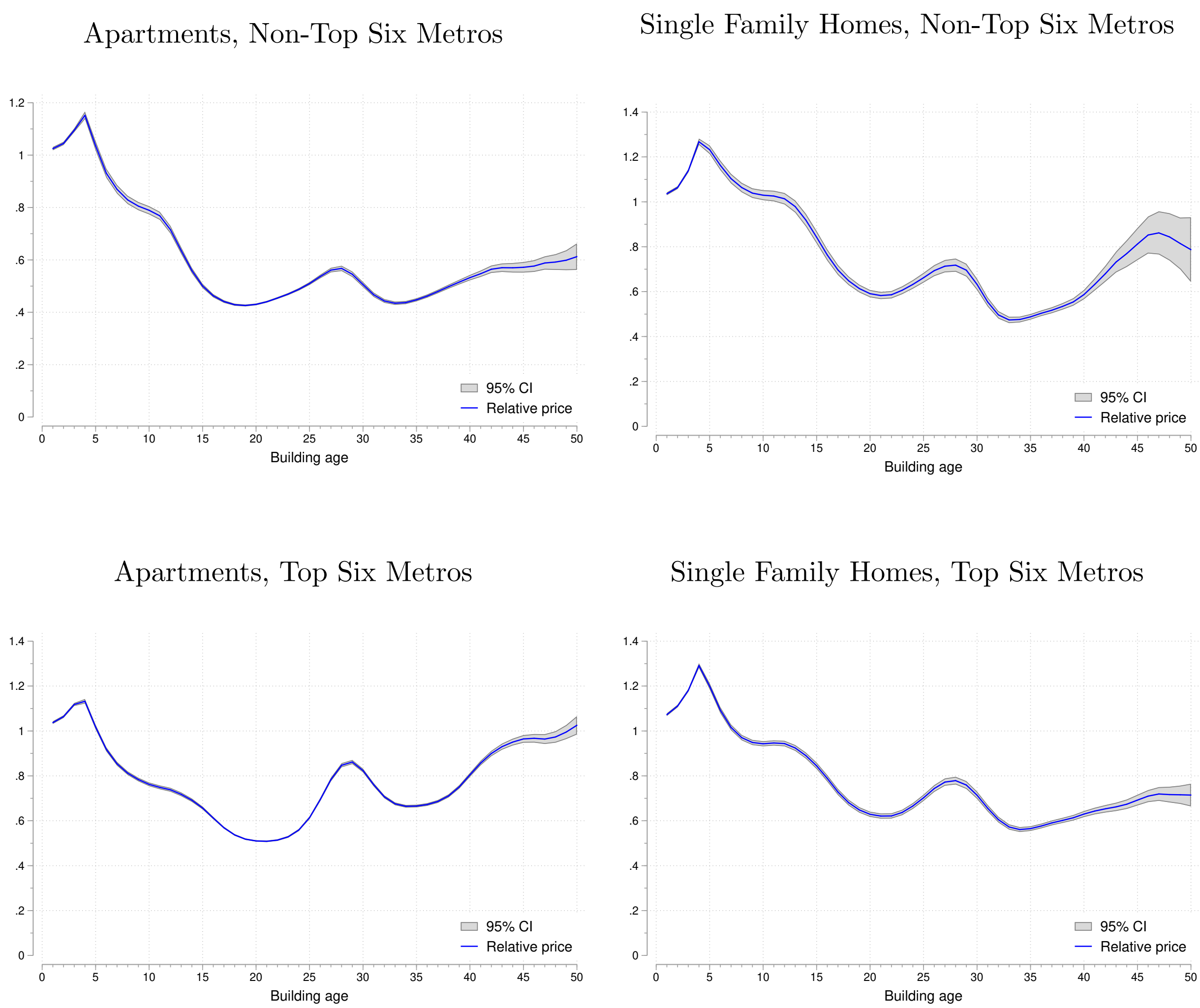
We also estimate versions of equation (F.2) where the function $f(A, S, L, D)$ is stepwise in age:

$$f(A, S, L, D) = \sum_g \Big[\alpha_{1,g}\mathbb{1}_g + \alpha_{2,g}\mathbb{1}_g \times \log S_i + \alpha_{3,g}\mathbb{1}_g \times \log L_i + \alpha_{4,g}\mathbb{1}_g \times D_i\Big] \qquad \text{(F.3)}$$

The stepwise function allows us to parametrically estimate how the depreciation rate varies at different age groups g, which we create by taking five year intervals of age. Figure F.2. plots prices relative to the price of a new property (of age equal to one year or less) as a function of building age. For single family homes, there is a roughly linear relationship between prices and building age for the first 20 years in the property life cycle. Overall, apartments tend to depreciate faster than single-family homes, and beyond age 20 apartments in the top six metros and single family homes outside the top six metros actually begin to appreciate, perhaps reflecting historic value or selection on building durability with respect to adverse weather events.

Table F.1 provides the linear depreciation rates implied by estimating the average marginal effect (AME) of age from the continuous hedonic model (odd columns) and the stepwise model (even columns). Consistent with the non-parametric results, apartments and properties located in

FIGURE F.2. Non-parametric Estimates of Prices by Building Age



Notes: Each panel in the figure plots the non-parametric local linear functions of the transaction price relative to the price of a new property of age one year or less with respect to age. Top six metros refers to properties located in Taipei, New Taipei, Kaohsiung, Taoyuan, Taichung, or Hsinchu. Building age is defined as the transaction year minus the build year plus one.

the most populated markets depreciate the fastest. There is little difference in depreciation rates over the property life cycle between the top six and non-top six metros. Yet, single family homes depreciate more slowly outside the top six metros.

The estimates in Table F.1 capture the overall real estate depreciation rate δ given by equation (F.1). While there is no accounting depreciation associated with land, the economic value of a parcel of land might depreciate independently of the building for a variety of reasons, including the introduction of new commuting patterns or demographic changes. To isolate building depreciation for single family homes, we compute $\delta_a = \delta/s_{t,a}$. Under the two assumptions on real estate production described above the building value ratio is equal to $\partial \log P_{t,a}/\partial \log S = s_{t,a}$. The ratio of the AME with respect to age divided by the AME with respect to floor area from estimating equation (F.2) thus isolates the building depreciation rate. For single family homes, we estimate an average building value share of 0.66, implying an annual building depreciation rate of 0.013/0.66 = 2% in the top six areas. We therefore apply a 2% linear depreciation rate to both single family homes and apartments to compute market values in between sale years.

Table F.1. Translog Hedonic Estimates of Property Depreciation

	Top Six Metros				Outside Top Six Metros			
	Single family		Apartment		Single family		Apartment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Building age	0.013***		0.017***		0.010***		0.016***	
	(0.000)		(0.000)		(0.000)		(0.000)	
𝟙(1-5 years)		0.000		−0.002**		−0.012***		−0.009***
		(0.000)		(0.001)		(0.001)		(0.001)
𝟙(6-10 years)		0.025***		0.022***		0.010***		0.025***
		(0.001)		(0.001)		(0.002)		(0.001)
𝟙(11-15 years)		0.036***		0.042***		0.025***		0.060***
		(0.001)		(0.001)		(0.001)		(0.001)
𝟙(16-20 years)		0.062***		0.067***		0.059***		0.078***
		(0.001)		(0.000)		(0.001)		(0.001)
𝟙(21-25 years)		0.068***		0.072***		0.062***		0.077***
		(0.001)		(0.000)		(0.001)		(0.000)
𝟙(26-30 years)		0.057***		0.077***		0.040***		0.076***
		(0.001)		(0.000)		(0.002)		(0.001)
𝟙(31-35 years)		0.060***		0.085***		0.049***		0.087***
		(0.001)		(0.000)		(0.002)		(0.001)
𝟙(36-40 years)		0.055***		0.087***		0.038***		0.086***
		(0.001)		(0.001)		(0.002)		(0.001)
𝟙(41-45 years)		0.041***		0.092***		0.023***		0.078***
		(0.003)		(0.001)		(0.005)		(0.002)
𝟙(46-50 years)		0.045***		0.095***		−0.006		0.083***
		(0.005)		(0.002)		(0.010)		(0.003)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Location FEs	✓	✓	✓	✓	✓	✓	✓	✓
N	81,434	81,434	356,386	356,386	47,126	47,126	141,617	141,617
Adj. R^2	0.761	0.773	0.846	0.852	0.759	0.775	0.788	0.801

Notes: Each column in the table provides estimates of annual property depreciation rates from the Actual Price Registration data (2012-2019). Specifications in odd columns show the average marginal effect with respect to age from estimating equation (F.2), while even columns show the average marginal effect at different 5-year age bins from estimating the stepwise hedonic model in equation (F.3). Controls include the set of variables in the $X_{i,j,t}$ vector described in the text. Top six metros refers to properties located in Taipei, New Taipei, Kaohsiung, Taoyuan, Taichung, or Hsinchu. Building age is defined as the transaction year minus the build year plus one.

G Robustness and Additional Results

This appendix presents several robustness checks for the main results presented in Section 4, Section 5, and Section 6. We summarize these supplemental findings as follows:

1. **Kolmogorov-Smirnov tests of hedonic-logit model fit.** Our ability to match the empirical distribution of housing sales in the pre-reform period via our hedonic-logit model in Section 4.2 is not affected by skewed outcomes in various subsample populations. Table G.1 provides the test statistics and the associated p-value for Kolomogorov-Smirnov tests of the difference in the empirical and model-implied sales distributions by holding period. We fail to reject the null of no difference when we restrict to older properties, out-of-town sellers, or sellers with different *ex ante* levels of net worth.

2. **Local vs. non-local investor responses.** Behavioral responses to the transfer tax reform are concentrated among non-local investors who decide to delay sales to avoid paying the tax. Figure G.1 computes the missing mass implied by comparing the empirical distribution to the counterfactual distribution of sales made by out-of-town (OOT) investors (Panel A) or local investors (Panel B). In spite of the fact that OOT investors account for only one-third of observed sales, the missing mass generated by OOT investors is 2.5 times as large as that generated by local investors.

3. **Old vs. new properties.** We examine the sensitivity of our bunching results to the exclusion of properties which were built within the five years prior to sale. Figure G.2 uncovers similar bunching patterns to our baseline analysis in Figure 6 when we exclude newly built properties (Panel A). Bunching patterns are less pronounced for units which are ten or more years old (Panel B), reflecting that depreciated properties are less attractive short-term investments.

4. **Sudden death inheritances.** Our results on inheritance shocks presented in Section 4.4 are robust to defining the inheritance shock as wealth derived from "sudden deaths," or cases where the decedent's age at death was two standard deviations or more below the average age at death. For our preferred specification, which uses shocks to the seller's overall net worth, we find 0.56 cents of every dollar of inherited wealth passes through to taxpayer net worth (Table G.2), implying a 1 million NTD (approx. 35,000 USD) exogenous increase in net worth leads sellers to charge 1.3% higher sale prices (Table G.3). In other results (untabulated) we obtain similar point estimates from our 2SLS model when we instead define sudden deaths as those where the cause of death is due to an accident or non-chronic conditions (e.g. heart attack or stroke).

5. **Weather shock event studies.** Figure G.3 shows that for the aggregate greater Taipei metro area there is no clear pre-trend in housing sales volume in the week prior to either a rain shock (Panel A), or a confirmed typhoon event where maximum wind gusts exceed 74 mph (Panel B). Thus, taxpayers do not accelerate sales in advance of bad weather.[65] Sales volume contemporaneously declines by 0.52%, relative to the six month moving average, for every one millimeter of rainfall, and this effect persists for about a week. For a severe weather shock like a confirmed typhoon event, volume precipitously falls by 60% and immediately reverts to trend after the storm passes.

[65] In other results (untabulated) we find no noticeable increase in sales volume around days where the government has issued an official typhoon warning.

6. **District-level weather shock results.** One potential issue with interpreting the estimates from equation (6.2) is that weather shocks may coincide with other factors which deter property sales, even after stripping out high and low frequency calendar variation. For instance, if severe weather forecasts induce the state or local governments to recommend businesses and transport services to shutdown, then sales volume may decline regardless of whether forecasts turn out to be true at the local level. We difference out common daily factors influencing aggregate sales volume by considering district-level panel regressions, where we define the weather shock $Weather_{j,t}$ as the average reading across stations located within district j on date t. Table G.4 shows that rain continues to have a negative and statistically significant effect on sales volume in the cross-section of districts. In the pre-reform period, a district experiencing a one millimeter greater amount of accumulated rainfall sees sales volume decline by 0.04% more than other districts. This effect increases to 0.08% in the post-reform period when typhoon seasons were on average more severe and generated more spatial variation in rainfall. As in the main results in Section 6, wind is negatively associated with volume in the geographical cross-section, but the point estimates are not statistically significant.

7. **Seller's permanent address as shock location.** Given that our analysis focuses on second homeowners, a natural question is whether the effects of rainfall on property sales differ depending on whether the weather event occurs at the seller's location, measured by their permanent address (i.e. where they receive tax bills), instead of the property location. We obtain similar district-level results when we measure $Volume_{j,t}$ as sales volume in district j using the seller's address instead of the property address. In the pre-reform (post-reform) period a one millimeter greater amount of accumulated rainfall implies a 0.03% (0.08%) greater decline in sales initiated by sellers in that district.

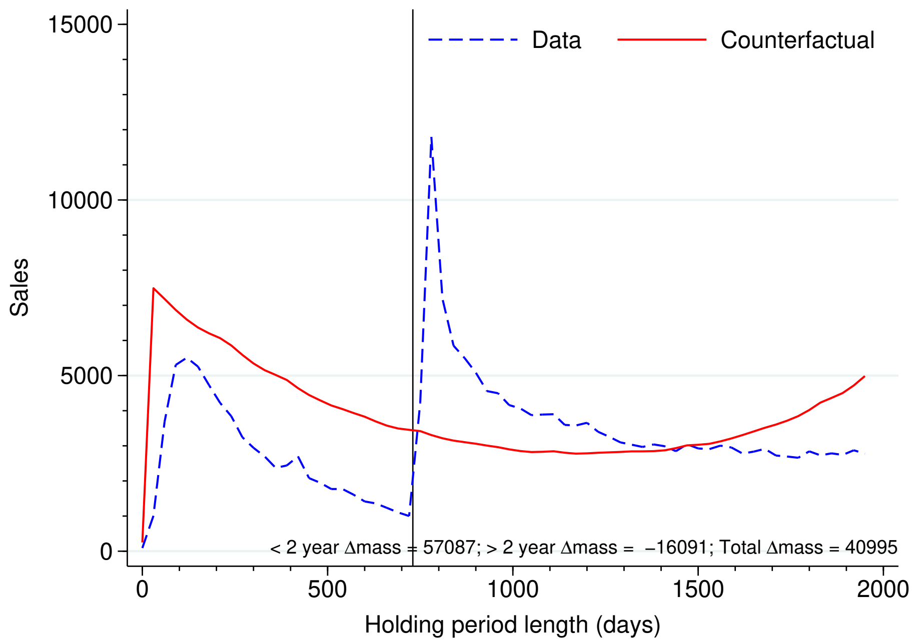
Table G.1. Kolmogorov-Smirnov Tests: Empirical vs. Counterfactual Distributions

	Baseline	Age < 5	Age 5-10	Age > 10	OOT	non-OOT	$Q_1(NW_s)$	$Q_3(NW_s)$	$Q_5(NW_s)$
K-S stat	0.105	0.149	0.090	0.149	0.105	0.119	0.149	0.119	0.075
p-value	0.858	0.444	0.951	0.444	0.858	0.726	0.444	0.726	0.992

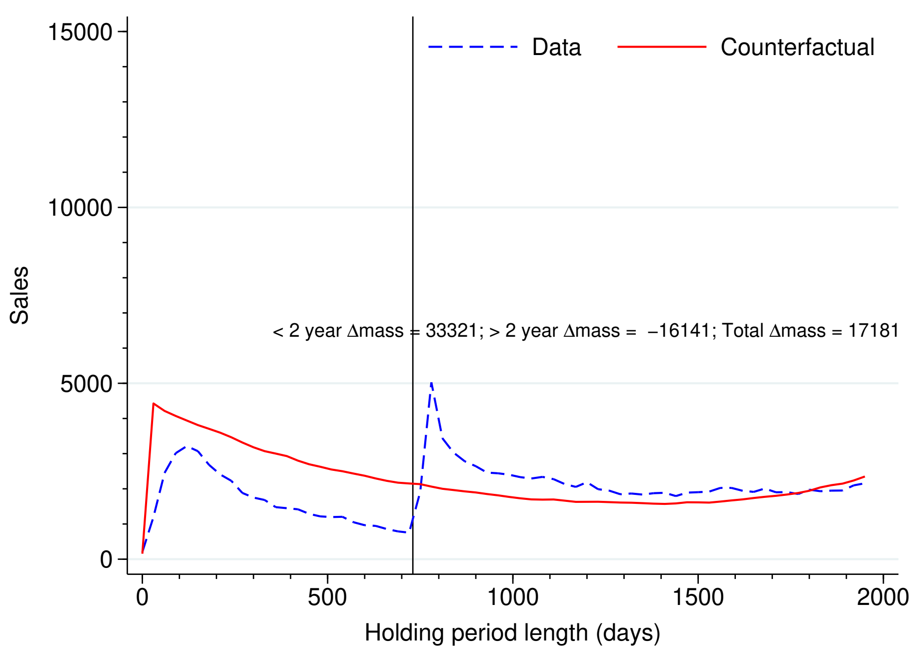
Notes: This table provides the test statistics and the associated p-value for Kolmogorov-Smirnov tests of the null that the empirical and counterfactual distributions of sales by holding period are identical. We conduct tests for several property subsample groups: baseline refers to estimating the hedonic-logit model on the full sample, as pictured in Figure 5 in the main text; age $<$ 5, 5-10, and $>$ 10 refer to buildings contructed for less than 5 years, more than five but less than ten years and more than ten years prior to sale; OOT focuses on sales involving an out-of-town counterparty; the last three columns refer to sales where the seller is in either the first, third, or fifth quintile of the taxpayer net worth distribution.

FIGURE G.1. Empirical and Counterfactual Sales: the Role of OOT Investors

A. OOT Investors: Distribution by Holding Period Length



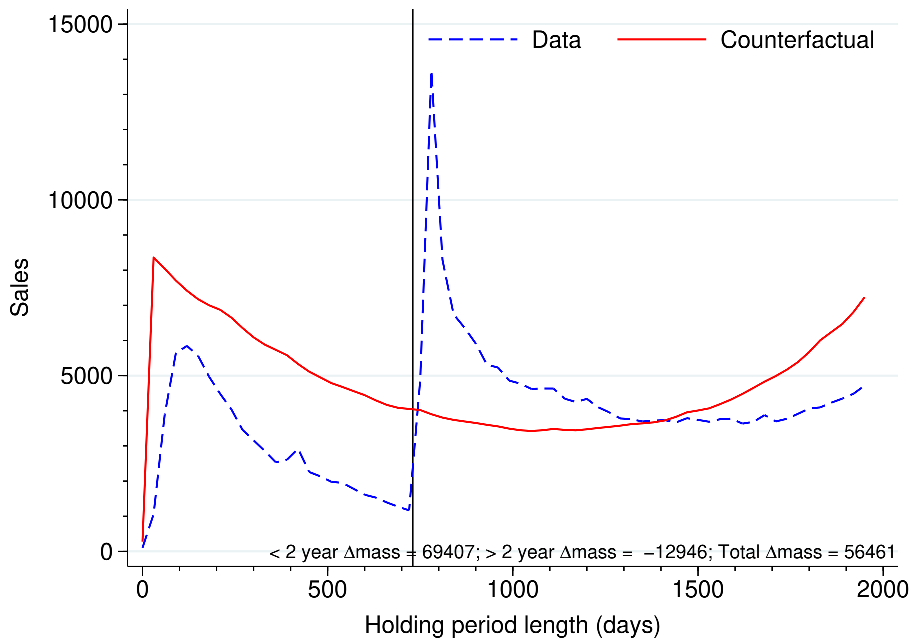
B. Local Investors: Distribution by Holding Period Length



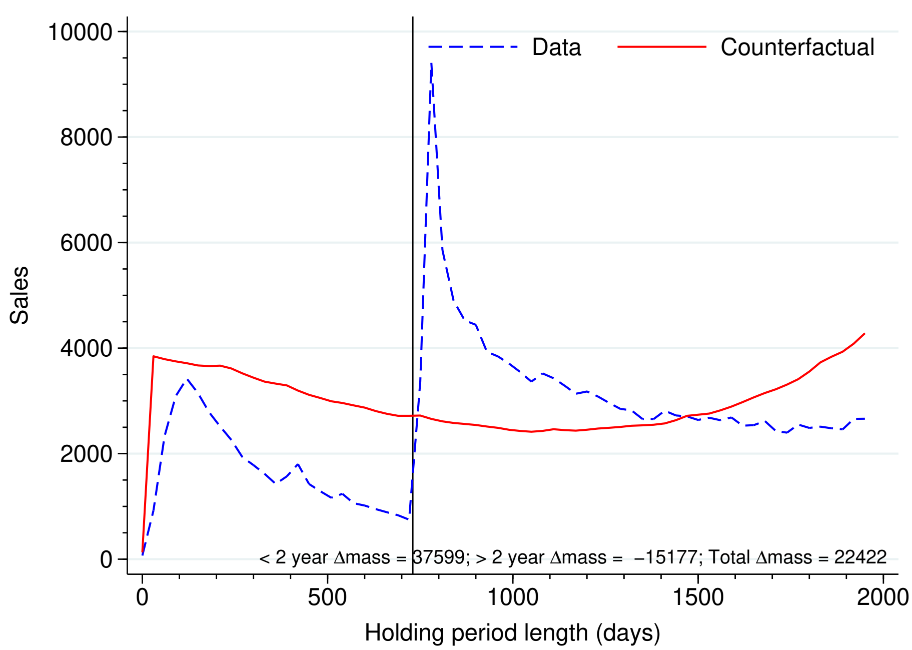
Notes: The figure plots the distribution of second home sales volume by holding period length estimated via the system of equations in (4.2)–(4.4) in red for either out-of-town (OOT) investors in Panel A, or local (non-OOT) investors in Panel B. The empirical post-reform distribution appears in the blue dashed line. The full logit model includes month-year, week-of-month, day-of-week fixed effects, a holiday dummy, a quadratic in property age (measured using the construction date), dummies for the structure material, dummies for the use category (e.g. apartment vs. single family home), floor space, land area, holding period length, number of floors and building floor dummies.

FIGURE G.2. Empirical and Counterfactual Sales: Older vs. Newer Properties

A. Properties Built > 5 Years Prior to Sale



B. Properties Built > 10 Years Prior to Sale



Notes: The figure plots the distribution of second home sales volume by holding period length estimated via the system of equations in (4.2)–(4.4) in red for either housing units older than 5 years (Panel A) or older than 10 years (Panel B). The empirical post-reform distribution appears in the blue dashed line. The full logit model includes month-year, week-of-month, day-of-week fixed effects, a holiday dummy, a quadratic in property age (measured using the construction date), dummies for the structure material, dummies for the use category (e.g. apartment vs. single family home), floor space, land area, holding period length, number of floors and building floor dummies.

Table G.2. First and Second Stage Results for Sudden Death Inheritances

	(1)	(2)	(3)	(4)	(5)	(6)
$NWShock$ (β_1)	1.923***	0.562***	0.829***	−0.009	0.936***	0.929***
	(0.225)	(0.171)	(0.187)	(0.263)	(0.003)	(0.009)
First stage $Y \times Post$ (β_2)	0.018***	0.013***	0.031***	0.030***	0.020***	0.020***
	(0.003)	(0.004)	(0.008)	(0.002)	(0.001)	(0.001)
First stage Y	HNW^S	NW^S	HNW^B	NW^B	$ln(HNW^S)$	$ln(NW^S)$
IV	IHW^S	IW^S	IHW^B	IW^B	$ln(IHW^S)$	$ln(IW^S)$
Montiel Olea & Pflueger F-test	14.67	125.08	3.60	0.60	10,209.35	8,827.90
First stage F-test (Kleibergen-Paap)	14.63	124.68	3.59	0.60	10,240.52	8,843.33
First stage F-test (Cragg-Donald)	438.87	1186.07	130.43	522.18	59,306.86	52,301.89
Property controls	✓	✓	✓	✓	✓	✓
Time & district FEs	✓	✓	✓	✓	✓	✓
Adj R^2	0.697	0.698	0.700	0.711	0.706	0.711
N	182,646	182,646	182,646	182,646	22,914	27,078

Notes: The table provides first stage and 2SLS estimates from the model specified in equations (4.5) and (4.6), considering only inheritances from decedents who died at an age two standard deviations younger (i.e. 47.35 years old or younger) than the average age at death. $NWShock$ refers to the estimated pass-through of inheritance shocks over 2007-2010 to overall taxpayer net worth as of the 2010 filing year. First stage $Y \times Post$ refers to the 2SLS estimate of the premium charged by a seller or buyer). We check how inheritance shocks differentially influence the behavior of sellers and buyers, and how the pass-through to net worth changes depending on whether we restrict to housing inheritances (IHW) or all inheritances (IW). All inheritance measures are net of estate tax liability and applicable deductions. The last two columns provide estimates in logs, and therefore only include taxpayers with strictly positive inheritance receipts (intensive margin). There are $N = 368$ districts in total, and in some specifications we include district fixed effects as well as month-year, week-of-month, day-of-week fixed effects, and a holiday dummy. Property controls include a polynomial in age, area, floor space, use category, structure type, unit floor number (for apartments), and number of floors (for single family homes). Robust standard errors in the second stage regression clustered at the district of the property. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table G.3. Seller Pass-through of Transfer Tax to Buyers: Sudden Death Inheritance Shocks

A. Overall Responses: Sale Price Response to Changes in Seller's Wealth

	(1)	(2)	(3)	(4)	(5)	(6)
$NW^S \times Post$	0.0003**	0.0090**	0.0097**	0.0130**	0.0129**	0.0129**
	(0.0001)	(0.0031)	(0.0032)	(0.0043)	(0.0043)	(0.0047)
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
Montiel Olea & Pflueger F-test	–	127.56	125.37	125.08	336.06	177.51
First stage F-test (Kleibergen-Paap)	–	127.03	124.84	124.68	335.16	177.03
First stage F-test (Cragg-Donald)	–	1214.45	1,190.53	1,186.07	1,170.81	1,172.06
Property controls	✓		✓	✓	✓	✓
Time & district FEs	✓			✓	✓	✓
Clustering	$district^P$	$district^P$	$district^P$	$district^P$	$district^S$	$district^B$
Adj. R^2	0.672	0.009	0.085	0.690	0.689	0.690
N	182,646	183,007	182,660	182,646	180,256	179,634

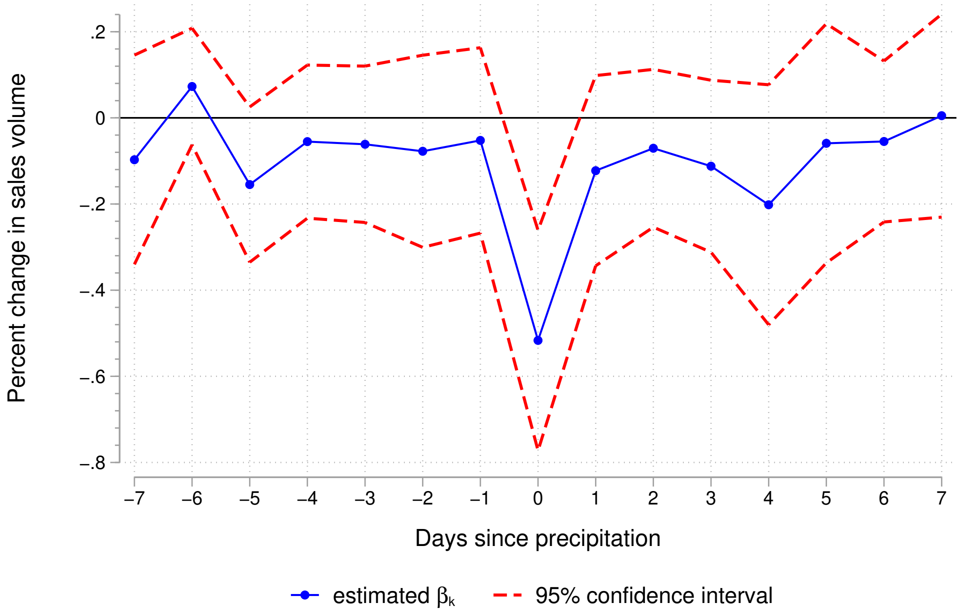
B. Intensive Margin Responses: Change in Price-wealth Elasticity across Reform

	(1)	(2)	(3)	(4)	(5)	(6)
$\log NW^S \times Post$	0.022***	0.015***	0.016***	0.020***	0.020***	0.020***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Estimation	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
Montiel Olea & Pflueger F-test	–	8,332	8,709	8,828	12,593	17,572
First stage F-test (Kleibergen-Paap)	–	8,292	8,666	8,843	12,571	17,543
First stage F-test (Cragg-Donald)	–	51,538	52,029	52,302	51,253	51,116
Property controls	✓		✓	✓	✓	✓
Time & district FEs	✓			✓	✓	✓
Clustering	$district^P$	$district^P$	$district^P$	$district^P$	$district^S$	$district^B$
Adj. R^2	0.705	0.018	0.108	0.702	0.702	0.702
N	161,126	27,187	27,125	27,095	26,726	26,644

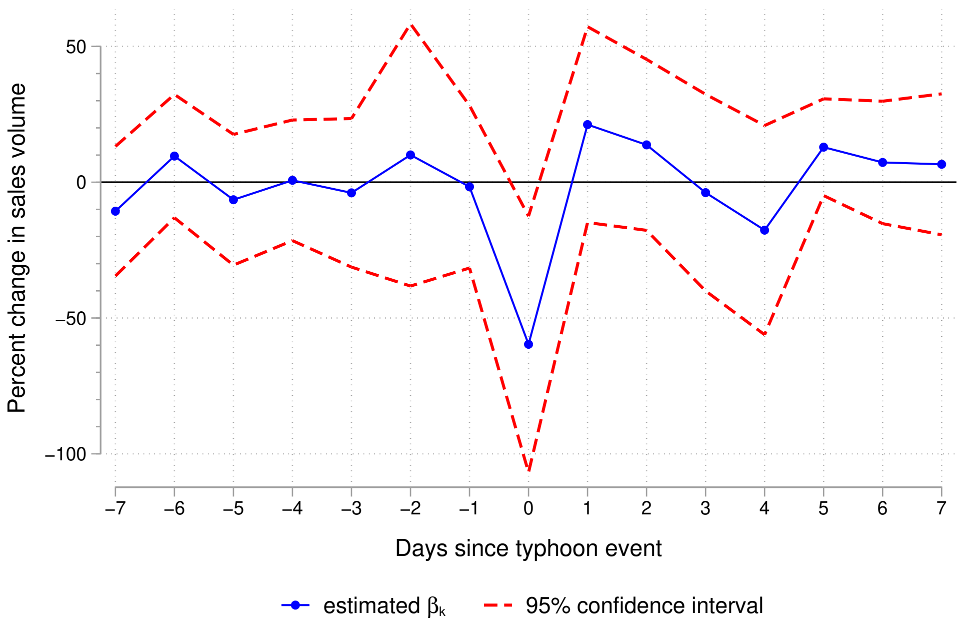
Notes: The dependent variable in each regression is the log transaction value. In all 2SLS specifications we only consider inheritances from decedents who died at an age two standard deviations younger (i.e. 47.35 years or younger) than the average age at death. In panel A, for 2SLS specifications we instrument overall seller net worth with $NWShock$ as in equation (4.6). In Panel B, we estimate the change in the elasticity of prices with respect to exogenous wealth by regressing log seller net worth with log inherited wealth in the first stage. Regressions in Panel B only include transactions involving sellers who received a strictly positive amount of inheritances in the pre-reform period. There are $N = 368$ districts in total, and in some specifications we include district fixed effects as well as month-year, week-of-month, day-of-week fixed effects, and a holiday dummy. Property controls include a polynomial in age, area, floor space, use category, structure type, unit floor number (for apartments), and number of floors (for single family homes). Robust standard errors in the second stage regression clustered at either the district of the property, of the buyer, or of the seller. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

FIGURE G.3. Sales Volume around Severe Weather Shocks

A. Rainfall Shocks to Sales Volume



B. Strong Wind (≥ 74 mph) Shocks to Sales Volume



Notes: The figure plots the estimated $\widehat{\beta}_k$ from regressions of the form: $Volume_t = \sum_{k=-7}^{+7} \beta_k \cdot Weather_{t-k} + \delta_t + \gamma' \cdot \mathbf{X_t} + \varepsilon_t$. $Weather$ is a continuous variable equal to the average daily accumulated rainfall across weather stations in the Taipei-New Taipei metro area (Panel A), or a dummy equal to unity if date t features a confirmed typhoon event in which maximum wind gusts exceed 74 mph (the meteorological definition of a typhoon). $Volume$ is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. We control for reported damages, holiday effects, and day-of-week and 7-day fixed effects in each panel. 95% confidence intervals for the point estimates pictured in red dashed lines from Newey-West standard errors with six lags to adjust for serial correlation.

Table G.4. District-level Results: Weather Shocks and Real Estate Sales

A. Pre-reform Period (2006-2011Q2)

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall $\times Summer$	-0.037^{**}	-0.038^{**}			-0.030^{**}	-0.037^{**}
	(0.015)	(0.015)			(0.015)	(0.014)
Max WS $\times Summer$			0.043		0.116	
			(0.140)		(0.142)	
Avg. WS $\times Summer$				-0.138		-0.012
				(0.383)		(0.382)
Damages controls		✓	✓	✓	✓	✓
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
N	101,141	101,141	88,078	98,666	88,076	98,627

B. Post-reform Period (2011Q3-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall $\times Summer$	-0.074^{***}	-0.077^{***}			-0.074^{***}	-0.077^{***}
	(0.015)	(0.016)			(0.016)	(0.016)
Max WS $\times Summer$			-0.223		-0.106	
			(0.163)		(0.163)	
Avg. WS $\times Summer$				-0.399		-0.291
				(0.412)		(0.410)
Damages controls		✓	✓	✓	✓	✓
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
N	89,656	89,656	88,078	88,603	88,076	88,601

Notes: The table presents results from estimating district-level panel regressions of the form: $Volume_{j,t} = \beta \cdot (Weather_{j,t} \times Summer_t) + \delta_t + \psi_j + \gamma' \cdot \mathbf{X_t} + \varepsilon_{j,t}$. The outcome variable in each column is 100 times the deviation of log sales volume in district j from its 6-month symmetric moving average. RHS variables include maximum or average wind speed and accumulated rainfall interacted with a dummy for the summer typhoon season. We include daily observations from the pre-reform period (Panel A) during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. For the post-reform period (Panel B), we include observations during the transfer tax regime which laster from June 1, 2011 through December 31, 2015. All regressions except the first column control for daily counts of casualties and properties lost due to flooding and typhoons (see Appendix E for details). Conley (2008) standard errors in parentheses adjust for spatial autocorrelation according to the distance between the midpoint coordinates of each district. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

H Property Flip Tax and time on market

In this appendix we present additional evidence from listings data that the transfer tax negatively impacted liquidity of investment properties based on time on market (TOM). We obtained residential listings data for the Greater Taipei metro area covering a symmetric one-year period on either side of our reform date of June 1, 2011 from a large, anonymous brokerage firm.[66] The data include the start and end date of the listing and basic property characteristics such as the block-level address, last listed price, and floor space and land area. Our sample includes listings which were removed due to a sale *closing* within our sample period.

We use the address and closing date to merge these listings to the confidential tax returns, which allows us to assess whether the sale was subject to the tax based on owner-occupied status. Since the listing removal date is the contract date (what we observe in the tax data) plus any delays in taking down the listing, merging on the block-level address and listing removal date produces very few exact matches. Hence, we use a two-step procedure to match properties across the listings and tax data:

1. For each property in the listing data, we find the set of properties in the tax records which (i) match on the address and (ii) for which the listing removal date is equal to the contract date $\pm$ 7 days.
2. From the set obtained via step 1, we compute Euclidean distance with respect to the prices and floor space of the sale listing for each potential match and then select the sold property which minimizes the distance. Or, in symbols:

$$\min_i \left\{ (x_\ell - x_i)^2 + (p_\ell - p_i)^2 \right\} \tag{H.1}$$

where ℓ indicates a listing, i is a potential matched transaction, x is floor space, p_i is the contract price, and p_ℓ is the last observed listed price.

Applying this procedure we obtain a matched sample with owner-occupier flags and non-missing building characteristics for 4,605 transactions out of a full sample of 17,685 listings closed between June 1, 2010 and June 1, 2012.

Our main bunching results in Section 4 support the notion that liquidity declined in the medium-run, as the holding period nearly doubled and after the transfer tax and the missing mass of sales was positive for very long holding periods ($>$ 5 years). The results in this appendix based on TOM suggest that liquidity also declined in the *very short-run* after the reform. We summarize our TOM results as follows:

- We start by comparing TOM for the pre-reform vs. post-reform period for all transactions and by price tier. Figure H.1 shows an average post-reform increase in TOM of 6.9 days in the full set of listings, compared to a difference in means of 6.2 for the matched sample of listings. This suggests that there may be a slight selection bias in our two-step matching procedure which skews towards propeties which are more liquid in both the pre-reform and post-reform period. Mirroring the heterogeneity in the high-frequency analysis of Section 4.3,

[66] While, unfortunately, we were only able to obtain a short window around the reform, the symmetric nature of this window means seasonality can play only a minimal role in our results.

mean time on market increases by 7.5 days in the bottom quintile (p-value = 0.001) and by 9.5 days in the top quintile (p-value = 0.002), but only by 4 to 5 days in the middle of the price distribution.

- Figure H.2 indicates that the reduction in short-run liquidity in the housing market was driven by an increase in TOM among the non-owner occupied properties subject to the tax. TOM increased by 7.3 days for non-owner occupied properties (Panel A) but, if anything, declined by a statistically insignificant 4.5 days (p-value = 0.3445). Given that 76% of the sales in our matched listings sample are non-owner occupied compared to 75% in the full sample of transactions in the tax data, our matching procedure is not inadvertently selecting on properties which are more or less likely to be subject to the tax on investment homes.

- Finally, we adjust the means in Figure H.2 for property covariates and sales seasonality by estimating standard differences-in-differences regressions of the form:

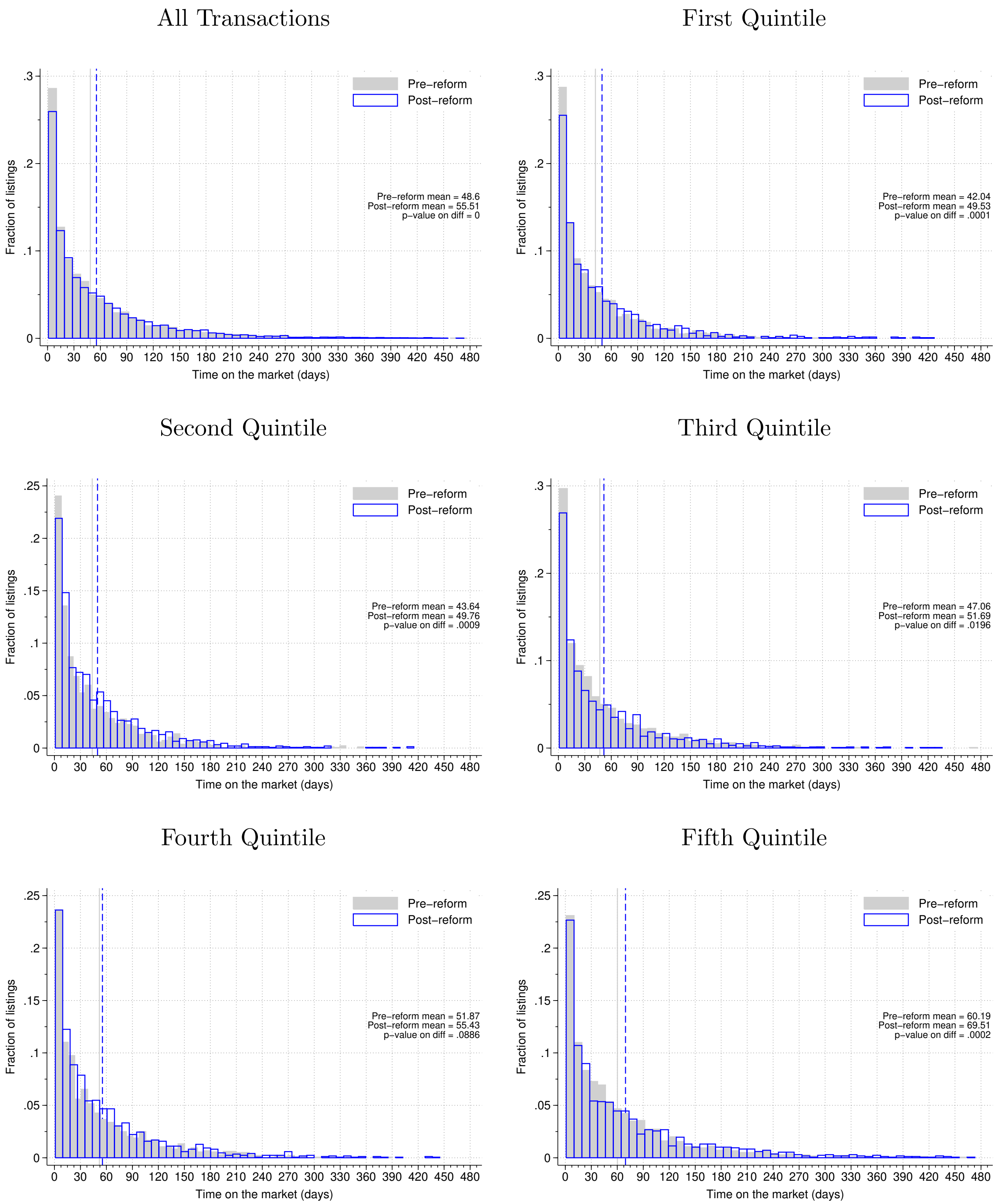
$$TOM_{i,t} = \alpha + \beta_1 \cdot Post_t + \beta_2 \cdot SelfOcc_{i,t} + \beta_3 \cdot Post_t \times SelfOcc_{i,t} + \gamma' \cdot \mathbf{X_{i,t}} + \varepsilon_{i,t} \quad \text{(H.2)}$$

  where $TOM_{i,t}$ is time on the market, $Post_t$ is a dummy for the post-reform period, $SelfOcc_{i,t}$ is a dummy for whether the property is owner-occupied, and $\mathbf{X_{i,t}}$ includes covariates such as day-of-week and month-year fixed effects, property age, previous transaction value, land area, floor space, total number of floors (for single-family homes), and floor number (for apartments). Our coefficient of interest is the β_3, which captures by how much TOM differed in the post-reform period for owner-occupied (control) vs. non-owner occupied (treated) properties.

The first three columns of Table H.1 show the results from estimating equation (H.2). Average TOM increased by around 7.5 days after the reform, but this increase in TOM was 15 days less for self-occupied properties which were not subject to the tax.

The last three columns of Table H.1 replace $SelfOcc_{i,t}$ in equation (H.1) with $Second_{i,t}$, a dummy for whether the listed property was acquired by the seller after their first property. $Second_{i,t}$ is a temporal ordering of homes within the seller's portfolio. Since homes which were acquired later by the seller may still be owner-occupied, and therefore not subject to this tax, the interaction $Post \times Second$ captures the extent to which the tax may have influenced sellers' reservation prices for all but the first property in their portfolio. While we find average TOM for second homes was higher (statistically insignificant) than for first homes, we do not observe any meaningful difference across the tax reform with respect to the temporal ordering of home acquisitions. Overall, we conclude it is unlikely that the liquidity crunch spilled over to segments of the housing market which were not subject to the flip tax.

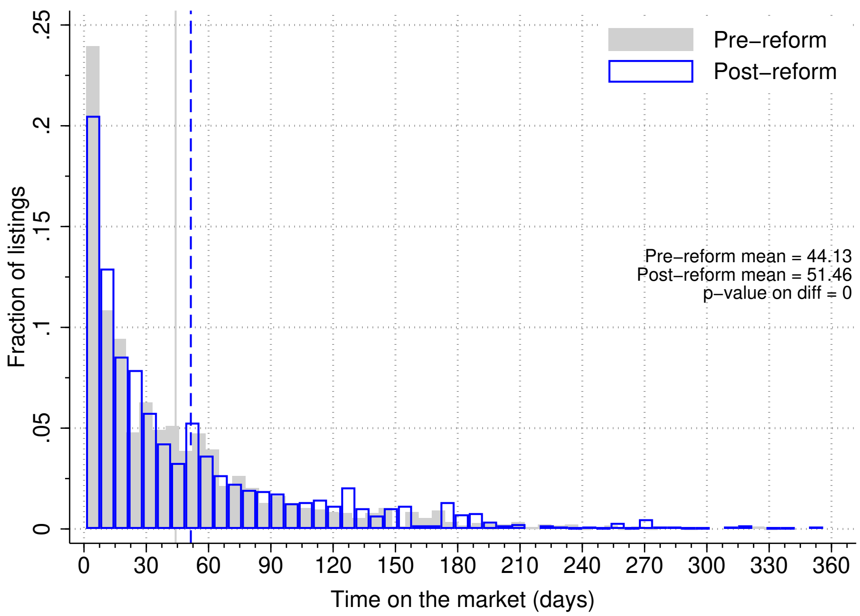
FIGURE H.1. Time on Market by Price Tier



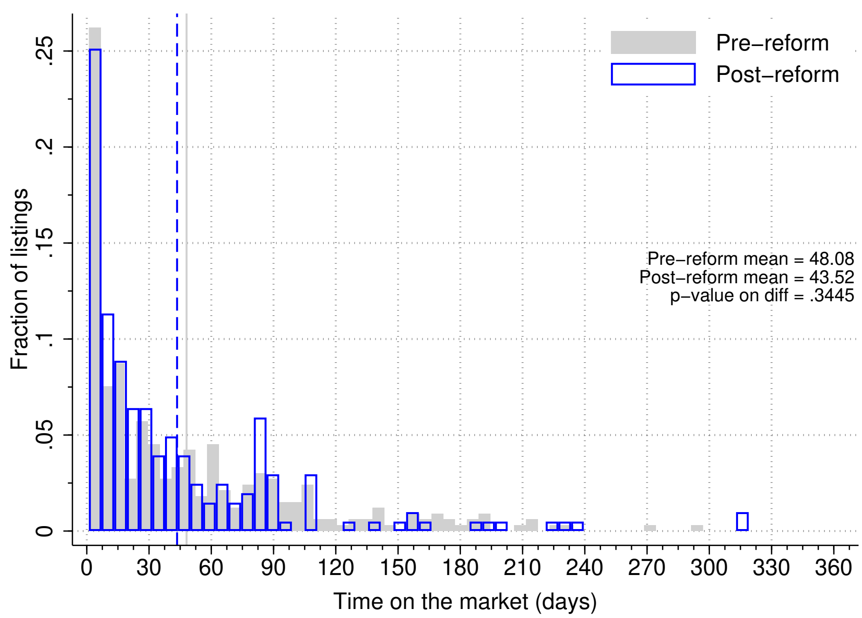
Notes: Each panel compares the distribution of pre-reform and post-reform residential listings in the greater Taipei metro area by time on market. Data from a large, but anonymous, brokerage firm. We define time on market as the number of days between the initial listing date and the day the listing was removed due to a sale closing. Pre-reform includes listings removed within the year prior to the June 1, 2011 Tobin tax reform, while post-reform includes listings posted and removed within the year after the reform. The first panel pools all transactions, while the remaining five panels divide the universe of transactions into sale price quintiles computed over the entire sample period. Solid grey vertical lines indicate the mean time on market in the pre-reform period, while blue dashed lines show the mean in the post-reform period.

FIGURE H.2. Time on Market by Occupancy Status

A. Non-owner Occupied Properties (Treatment Group)



B. Owner-occupied Properties (Control Group)



Notes: Each panel compares the distribution of pre-reform and post-reform residential listings in the greater Taipei metro area by time on market. Data from a large, but anonymous, brokerage firm. We define time on market as the number of days between the initial listing date and the day the listing was removed due to a sale closing. Pre-reform includes listings removed within the year prior to the June 1, 2011 Tobin tax reform, while post-reform includes listings posted and removed within the year after the reform. Panel A includes listings we match to the tax data which are non-owner occupied (subject to the transfer tax) at the time of sale, while Panel B includes listings which are owner-occupied at the time of sale and therefore not subject to the surcharge. Solid grey vertical lines indicate the mean time on market in the pre-reform period, while blue dashed lines show the mean in the post-reform period.

Table H.1. Time on Market and Occupancy Status: DiD Results

	(1)	(2)	(3)	(4)	(5)	(6)
$Post$	7.59***	7.39***	7.52***	7.71**	6.88*	6.92*
	(1.87)	(1.89)	(1.90)	(3.51)	(3.54)	(3.57)
$SelfOcc$	1.14	2.21	2.31			
	(3.60)	(3.82)	(3.82)			
$Post \times SelfOcc$	−15.01***	−14.62***	−14.82***			
	(5.52)	(5.62)	(5.62)			
$Second$				2.88	2.76	2.70
				(2.39)	(2.38)	(2.38)
$Post \times Second$				−2.31	−1.44	−1.36
				(4.06)	(4.10)	(4.11)
District × month-year FEs	✓	✓	✓	✓	✓	✓
Property controls		✓	✓		✓	✓
Day-of-week FEs			✓			✓
N	4,605	4,553	4,553	4,605	4,553	4,553
Adj. R^2	0.021	0.033	0.033	0.019	0.031	0.031

Notes: The table displays regression results from estimating differences-in-differences specifications of the form in equation (H.2), with time on market (TOM) in days as the outcome variable. The first three columns include a dummy for whether the listing is for an owner-occupied property ($SelfOcc$), while the last three columns instead include a dummy for whether the listing is for the seller's second (or later) home. We define a "second home" here as one that was acquired after the seller's original home purchase. Property controls include building age, previous transaction value, floor space and land area, the number of floors on the property, or the floor of the unit if it is in an apartment building. Standard errors in parentheses clustered at the property panel id level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

I Checking for Pre-trends in Property Characteristics

Our bunching analysis of the transfer tax reform in Section 4.2 relies on a key identifying assumption: that the market would have valued property amenities in the same fashion as in the pre-reform period in the absence of the new tax. In this appendix we provide two tests of this assumption for each of the covariates we include in our baseline hedonic-logit model.

1. **Non-parametric test using sales shares.** We compute the 2010Q4 quartiles of candidate covariates used in our hedonic-logit models, including building age (years), distance to the nearest train station (kilometers), floor space (square meters), and the plot size for the land underlying the building. We then compute for each quarter the fraction of sales sorted into four bins based on the 2010Q4 covariate quartiles. We choose 2010Q4 as our base period, as it is the last quarter of sales data before the announcement of the flip tax at the end of January 2011. Therefore, this test is analogous to an event study design where we normalize the time dummies to the last pre-reform period, except that we are not imposing functional

form assumptions.

Figure I.1 plots the results of this exercise. We find little evidence of any selection prior to the reform on age, commuting distance, or floor space for the unit. However, we do find evidence of selection in favor of sales of units in smaller land plot buildings, which is consistent with the evidence on heterogeneity in Section 4.2 that the incidence of the tax disproportionately fell on lower-quality apartments favored by flippers in the pre-reform period. Hence, in our hedonic-logit models we interact land area with a dummy for whether the transaction involves a detached single-family home ($< 5\%$ of sales in the greater Taipei metro area).

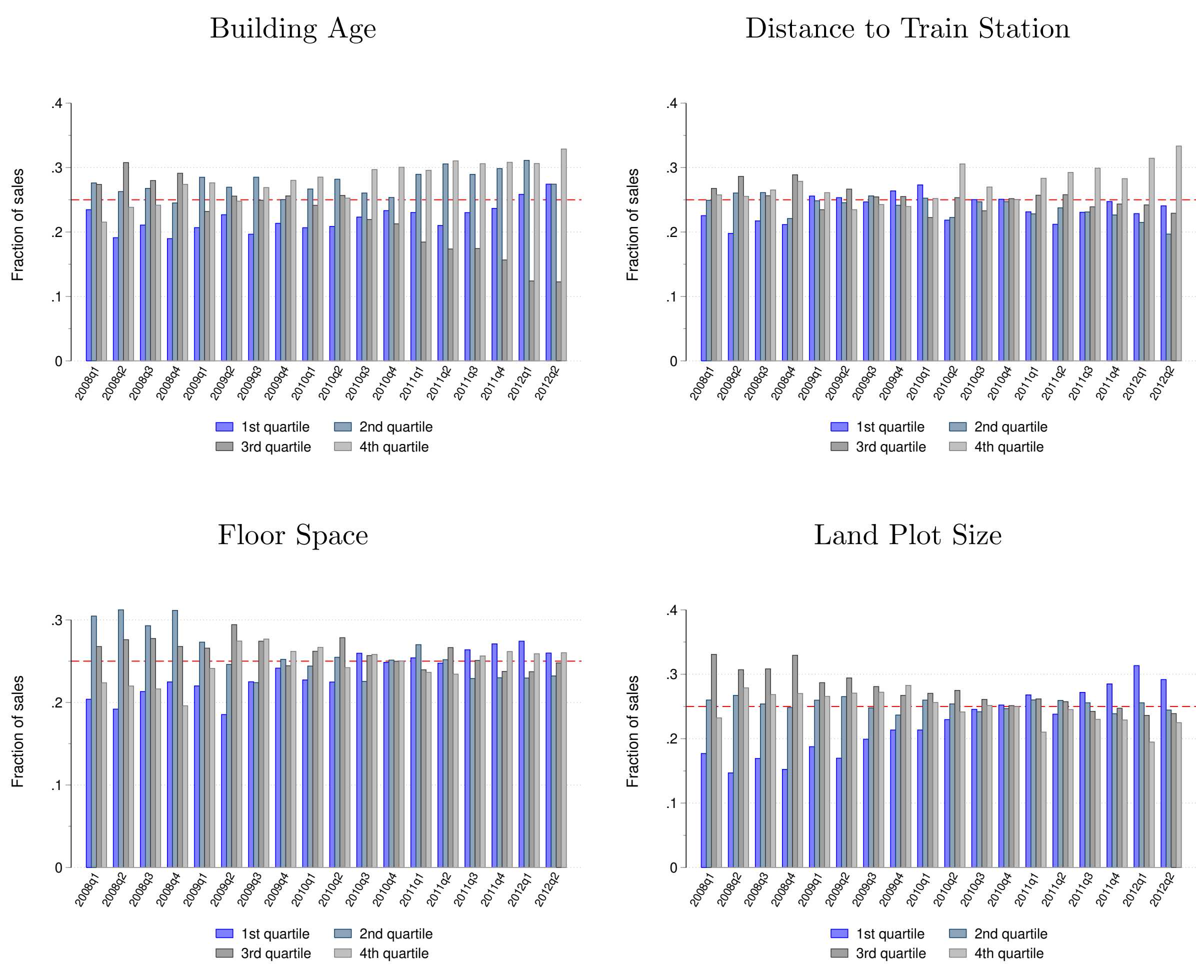
2. **Factor loadings in matching estimator regressions.** Our second test is an event study design where we estimate matching estimator regressions of the form outlined in Appendix B:

$$\log P_{i,t} = \sum_{t=2008Q1}^{2012Q2} \sum_{k=1}^{N} \beta_{t,k} \cdot X_{i,t}^{k} + \gamma_{\tilde{i}} + \epsilon_{i,t} \tag{I.1}$$

We allow prices to be a polynomial of order N for each continuous covariate $X_{i,t}$ to account for well-documented non-linear relationships with prices. The match-level fixed effects $\gamma_{\tilde{i}}$ strip out all time-invariant property characteristics common to a six decimal point latitude-longitude area (roughly half a street block). As discussed in Appendix B, this type of pricing model allows us to create a quality-adjusted index without the extreme selection bias of standard repeat sales.

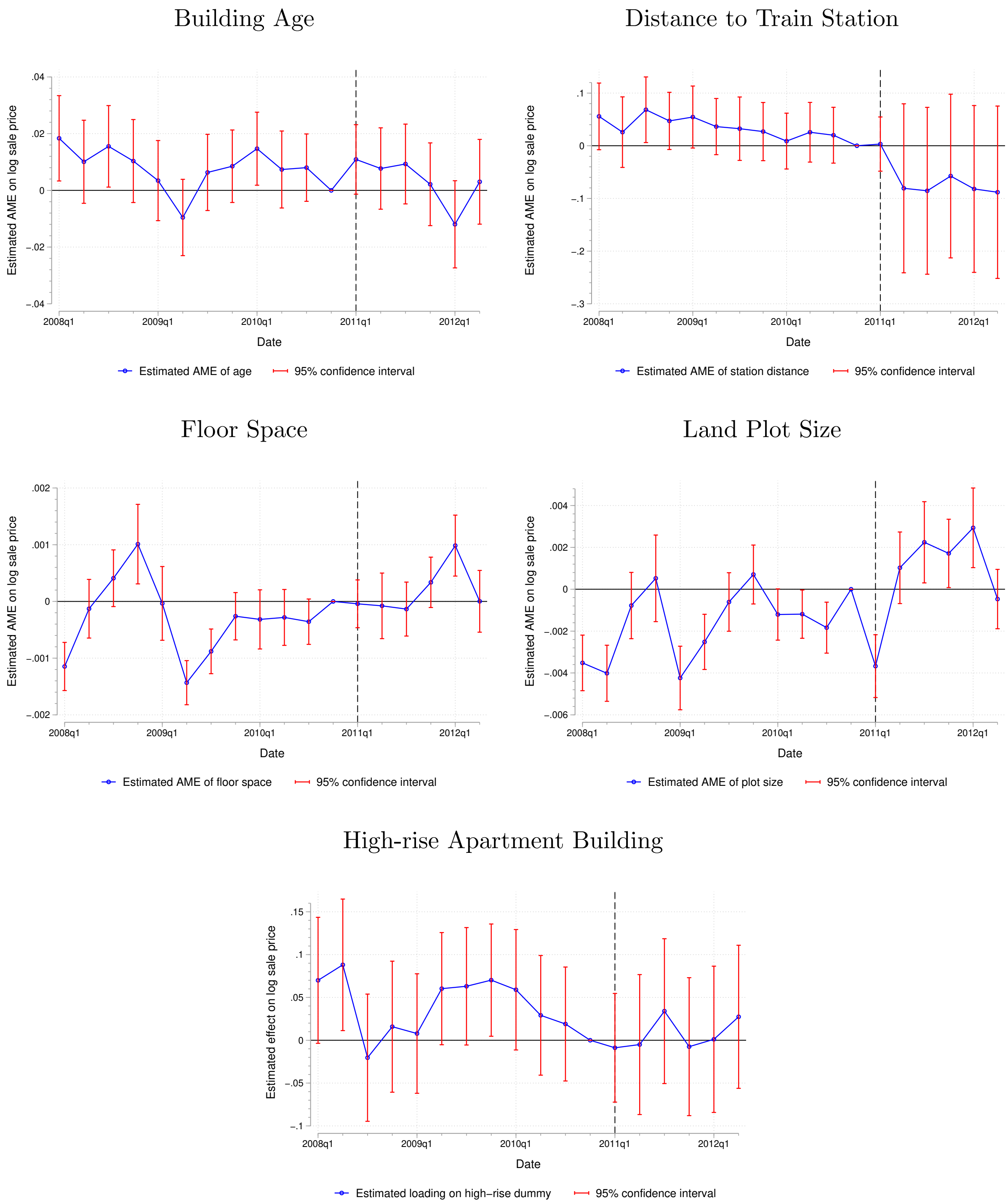
Figure I.2 plots the average marginal effects (again, normalized to zero in 2010Q4) for a quadratic function of age, station distance, floor space, and land plot size, as well as the time-varying loading on a dummy for whether the sale involves a unit in a high-rise apartment building (i.e. a building with > 10 floors). We again find no systematic evidence of pre-trends in pricing of housing characteristics, with the exception of a statistically insignificant negative trend in station distance. Thus, in our baseline hedonic-logit specifications we exclude station distance as a predictor of sale probability.

FIGURE I.1. Non-parametric Pre-trend Test: Sales by Covariate Quartile Bin



Notes: Each panel shows the fraction of sales in each quarter from 2008Q1 to 2012Q2 split into four bins corresponding to a 2010Q4 covariate quartile. The transfer tax surcharge on second home flips was announced at the beginning of 2011Q1 and implemented at the end of 2011Q2. Note that since each variable is not entirely continuous, the sales fractions in each bin are not exactly 0.25 in the base period of 2010Q4. For this exercise, we pool all residential sales in the greater Taipei metro area, and exclude newly built properties with age < 1 year. We define train station distance as the minimum among the distances to a metro stop, commuter rail, or high speed rail station.

FIGURE I.2. Parametric Pre-trend Test: Average Marginal Effects on Housing Prices



Notes: Each panel plots the average marginal effects (AMEs) from a matching regression of the form in equation (I.1), estimated separately for each covariate. For the continuous variables (building age, distance, floor space, land plot size), we plot marginal effects from a quadratic specification ($\beta_{t,1} + 2\beta_{t,2}$) and standard errors computed via the delta method. The transfer tax surcharge on second home flips was announced at the beginning of 2011Q1 (vertical dashed black line). We normalize all coefficients relative to the value in the base period of 2010Q4. We pool all residential sales in the greater Taipei metro area, and exclude newly built properties with age < 1 year. We define train station distance as the minimum among the distances to a metro stop, commuter rail, or high speed rail station.

Appendix References

Conley T.G. (2008): "Spatial Econometrics," in *The New Palgrave Dictionary of Economics*, Palgrave Macmillan, London.

Epple, D., B. Gordon, H. Sieg (2010): "A New Approach to Estimating the Production Function for Housing," *American Economic Review*, 100(3): 905-924.

Fang, H., Q. Gu, W. Xiong, L. Zhou (2015): "Demystifying the Chinese Housing Boom," NBER Macroeconomics Annual, 30: 105-166.

LaPoint, C. (2020): "You Only Lend Twice: Corporate Borrowing and Land Values in Real Estate Cycles", *mimeo*, Yale University.

McMillen, D.P. (2012): "Repeat Sales as a Matching Estimator," *Real Estate Economics*, 40(4): 745-773.

Newey, W.K. & K.D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrx," *Econometrica*, 55(3): 703-708.

Yoshida, J. (2020): "The Economic Depreciation of Real Estate: Cross-Sectional Variations and their Return," forthcoming, *Pacific-Basin Finance Journal.*