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The capitalization effects of school, residential, and commercial impact fees on undeveloped land values

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ABSTRACT

Development impact fees are a controversial and relatively novel method of financing local public infrastructure. While their effects on home values have been examined extensively, very few studies have considered an important potential relationship with the price of undeveloped land. This study uses a 16 year panel of Florida property sales and impact fee rates to investigate the effects of various types of impact fee programs on the value of undeveloped residentially and commercially zoned parcels. Three main findings are obtained. First, school impact fee programs decrease the value of residentially zoned land but increase the value of commercially zoned parcels. Second, fees for water and sewer reduce the price of residentially zoned parcels but have no significant effect on commercially zoned land values. Finally, fees for other traditional categories like roads, police, and fire, seem to have stronger negative effects on commercially zoned land than on residentially zoned parcels.

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1. Introduction

Dating to contributions by Simon (1943) and Oates (1969), the effects of local government policies on the value of real property have often captured the attention of scholars. This study investigates the capitalization effects of development impact fee programs, an innovative fiscal tool now used by over by over 1000 local governments in the US (Nelson et al., 2008). First introduced in the 1970s, impact fees are one time levies a developer pays to a local government, as a condition for obtaining a building permit.[1] Revenues are pooled over time and earmarked for public infrastructure systems including schools, roads, utilities, and police/fire services.

However, even as impact fee programs have established a strong footing in matters of local land use regulation, they remain controversial. Opponents claim they deter economic development and disproportionately burden low-income families.[2] Advocates argue they represent an efficient price-based Coasian bargaining tool, facilitating interactions between communities and developers by reducing uncertainty in the development approval process (Nelson et al., 1992a). Others have focused on the idea that impact fee programs increase allocative efficiency since they move communities away from an average cost approach to financing infrastructure toward a marginal cost based approach (Brueckner, 1997). Both sides of the ongoing debate are armed with evidence to support their claims. Like other local regulations — impact fees lead to tangible costs and benefits, create distinct groups of losers and winners, and can lead to new unintended problems while helping to solve others.[3]

School impact fee programs are perhaps the best example. Unlike most categories of impact fees which are paid by all developers, school fees are levied on residential construction but not commercial developments. As such, they represent a clear shift in the distributional burden of local education finance relative to exclusive property tax reliance that may harm owners of residentially zoned land. At the same time, research demonstrates a systematic bias toward under-providing local educational facilities, suggesting marginally approved projects may carry more benefits than costs (Cellini et al., 2010). Since school impact fees expand educational facilities in areas needing them most, they may carry desirable efficiency properties.

While several existing studies illustrate the effects of impact fee programs on home values, the supply of residential construction, and

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[1] Although impact fee and development fee are the most common labels for this policy, terms such as capacity fee, facility fee, system development fee, excise fee, and capital expansion fee are also used.

[2] For example, the official positions on impact fees of the National Association of Home Builders (http://www.nahb.org) and the National Association of Realtors (http://www.realtor.org) discuss these effects.

[3] Since a detailed review of the broad debate over the merits of development impact fee programs lies beyond the scope of this paper, we point interested readers to Been (2005).

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local employment levels, the underlying relationship between this policy and the price of undeveloped land remains poorly understood. Since impact fees are paid as land moves from vacant to improved, many have argued they would unambiguously cause the price of undeveloped land to fall. However, Yinger (1998) establishes that if the value of infrastructure is high, impact fee programs may not compromise undeveloped land prices, and may be positively capitalized in extreme cases. Others have claimed impact fees may reduce the prevalence and/or stringency of other regulatory barriers to development (Gyourko, 1991; Ladd, 1998), or that the likelihood of obtaining permit approval from development review boards may increase (Burge and Ihlanfeldt, 2006a, 2006b). Altshuler and Gomez-Ibáñez (1993) argue the influence of impact fee programs on land values (or other outcomes) critically depends upon *what they replace and/or stave off*. As such, the relationship between development impact fees and land values is potentially nuanced.

This study builds on three early investigations (Nelson et al., 1992a, 1992b; Skaburskis and Qadeer, 1992) and two recent pieces (Ihlanfeldt and Shaughnessy, 2004; Evans-Cowley et al., 2005). Besides being thin, this literature is conflicting. Early studies found positive capitalization effects, while the more recent papers found the opposite. Also, previous work does not account for the possibility that different categories of impact fees may influence commercially and residentially zoned parcels in different ways — an omission the current study illustrates is important for school and water/sewer impact fees.

We use 1,547,711 sales of residentially zoned undeveloped parcels and 134,610 sales of commercially zoned undeveloped parcels in 61 Florida Counties between 1994 and 2009 to obtain constant quality price indexes for residentially zoned and commercially zoned land. These prices are then examined in panel regressions using different categories of impact fee variables and other covariates. The results suggest that school impact fees lower the value of residentially zoned undeveloped land but increase the value of commercially zoned parcels. Water and sewer impact fees are found to lower selling prices for residentially zoned land but do not significantly affect commercially zoned parcels. Finally, some suggestive evidence indicates impact fees may lower land values in rural environments more significantly than in urban/suburban communities, where previous research has suggested they may be more effective at offsetting other non-pecuniary regulatory barriers to development.

2. Theoretical framework

Discussions of impact fees are often organized into the “traditional” and “new” views. While restrictive if pushed too far, the distinction provides a framework for this study. The traditional view characterizes impact fees as an excise tax on new construction. Examples include Snyder et al. (1986), Huffman et al. (1988), and Delaney and Smith (1989) among others. Under this view, impact fees shift the short-run supply of new development upward by the amount of the fee. This leads to higher prices for improved properties (both new and existing since they are close substitutes), lower values for undeveloped land, smaller profits for developers, and slower rates of new development. The magnitudes of these effects are determined by the corresponding short and long-run elasticities of demand and supply prevailing in the implementing community. Regardless of the short run effects, supply in any given locality is commonly assumed to be highly elastic in the long run, so developer profits must return to normal levels. This means the monetary costs of impact fees must either be passed forward to consumers or shifted backwards to the owners of undeveloped land.

Although the new view has been developed through many contributions, Yinger (1998) is due credit for accelerating this progression. Rather than framing impact fees as a tax on new development, he argues that what happens after impact fees are enacted plays a critical role in determining their causal effects. Instead of ignoring what is done with impact fee revenues, he argues that they create two immediate benefits that stimulate the demand for new facilities. First, they are used to provide valuable infrastructure specifically targeting developing areas within the community. Second, both existing and potential future residents will rationally expect impact fee programs to lower future millage rates.[4] While Yinger acknowledges particularly valuable infrastructure projects may approach (or even exceed) the value needed to eliminate the burden of impact fees on landowners, he concludes that regarding a marginally acceptable construction project (i.e., a project just meeting a standard cost-benefit test), approximately one quarter of the burden of the fee would fall on the owners of undeveloped land.

Brueckner (1997) compares an optimally determined impact fee rate to several alternative mechanisms of funding public infrastructure growth and finds impact fees to be preferred. Although he does not address potential differences between residentially and commercially zoned parcels, the value of undeveloped land plays a critical role in his model. Importantly, he predicts that when switching from traditional approaches to an impact fee regime, the price of undeveloped land could increase, decrease, or remain the same, depending upon whether or not the community has already fully exhausted the economies of scale inherent in the production of local public services. More recently, Turnbull (2004) investigates how alternative development policies – impact fees and growth boundaries – influence the dynamic pace of urban development. Impact fees that fully internalize the external cost associated with new development are found to be efficient in both steady state equilibrium and along the transitional growth path. On the other hand, urban growth boundaries that are efficient in the steady-state generate inefficiently rapid development along the transition path. Burge and Ihlanfeldt (2006b) argue impact fees could lower land prices if they increase the supply of readily developable parcels. This would occur if community planning officials were influenced by the direct monetary payoff from fee revenues, and subsequently zoned more areas ready for right-of-way development.

The effect of any given impact fee on the price of undeveloped land should be largely driven by whether the community is using the impact fee as a policy to control or manage growth. In addressing this question, previous discussions have highlighted the importance of identifying the counterfactual. Altshuler and Gomez-Ibáñez (1993) point out that “exactions look better or worse – in terms of equity, efficiency, or political acceptability – depending on the specific alternatives one considers most relevant analytically or most probable in reality.” While variation in the counterfactual surely exists across communities, several scholars have advanced the position that rapidly growing communities tend to adopt impact fee programs as a growth management strategy, potentially as a substitute for other growth controls that have been routinely shown to lower the market price of undeveloped land.[5] Fischel asks what would happen if a community adopted an impact fee, but the fee was quickly struck down in the state court. He notes that “the question is, would the community go back to its old ways of cheaply accommodating developers, or would it adopt more strict land use regulations that forestalled nearly all development? If prohibition of fees makes the community opt for more stringent regulations, then it seems to me that the impact fee is progrowth (Fischel, 1990).”

Gyourko (1991) formalizes the idea that impact fees may represent a price based contract for entry into a community. He argues once

[4] Yinger's prediction that impact fee programs would lower future millage rates was empirically verified by Ihlanfeldt and Shaughnessy (2004). In addition, early analysis in this study verified the same point. [results available upon request] With the exception of water/sewer impact fees, which would not be expected to reduce property taxes, increases in the impact fee variables are negatively correlated with millage rates during the three year period following adoption/increase.

[5] Examples of studies on growth controls and land prices include Brueckner (1990), McMillen and McDonald (2002), and Cunningham (2007). Interested readers should see Cunningham (2007) for a detailed literature review.

impact fees are levied, the stringency of other exclusionary barriers – that are generally far more difficult to observe – may be lessened. Ladd (1998) contends that, without impact fee programs, local officials in rapidly expanding communities may have no effective response when faced with pressure from anti-growth contingencies. With impact fee programs in place, she argues local planning officials have more useful ammunition when trying to appease anti-growth pressures.

Somewhat surprisingly, previous investigations have only considered the effects of impact fees imposed on residential construction on the price of undeveloped residentially zoned parcels. So while existing investigations answer some questions, they motivate others. Most importantly, it is reasonable to expect that impact fees could influence the price of commercially zoned parcels, and that these effects may systematically differ from the residential land market. Because of the way they shift the burden of local education finance, no example is better suited to illustrate this point than school impact fees. For residential parcels, school impact fees bring a direct monetary cost, as well as several potential benefits discussed above. Since at least a portion of the cost-offsetting benefits are difficult to observe, it is hard to make strong a-priori predictions regarding the effect of school fees on residentially zoned land. On the other hand, school fees benefit commercial interests in many of the same ways, but developers of commercial projects pay no direct monetary costs. As such, their predicted effect on undeveloped commercial zoned parcels is unambiguously positive.[6]

Water/sewer utility impact fee programs fund services otherwise paid for through user fees and are not expected to influence the local regulatory environment. Also, residential and commercial developers may not place identical values on the quality and coverage of the existing utility system. Since recent work finds differential effects of water/sewer fees with respect to single family home construction (Burge and Ihlanfeldt, 2006b), multi-family home construction (Burge and Ihlanfeldt, 2006a), and local job growth (Burge and Ihlanfeldt, 2009), we also investigate their effects separately.

The pre-existing regulatory environment should also differ significantly between urban and rural environments. Previous research has consistently found that formal growth controls and other informal regulatory barriers to development are more prevalent in metropolitan areas than in rural communities (Ihlanfeldt, 2004). As such, the present study investigates the possibility that impact fee programs may not have symmetric effects across urban and rural environments.[7] In Florida, where the data for this study are taken, most impact fees (including all school impact fees) operate at the county level. In the empirical analyses that follow, urban counties are defined as those with population densities above 100 persons per square mile according to the 2000 Census. Other counties are designated rural. [8]

3. Previous literature

The empirical literature concerning impact fees and the price of undeveloped land is thin and conflicting. Nelson et al. (1992a, 1992b) use data on sales of undeveloped land from Loveland, CO and Sarasota County, FL. The nature of their identification strategy differs across the two samples. In Sarasota, impact fee levels did not change during their sample (July 1981 through June 1987), but variation was present within different geographic zones across the county. Impact fees in Loveland were applied uniformly across areas, but changed size during their sample. For both cases, they regress logged sale price on the level of total impact fees and other control variables. In the Loveland sample, they find no evidence impact fees influenced land prices. Using the Sarasota data, they find impact fees had a significant positive effect. Skaburskis and Qadeer (1992) use data from three suburban municipalities near Toronto over the period of 1977–1986 to investigate the determinants of residentially zoned land values; finding prices increase by about 1.2 times the size of the impact fee levied.

Ihlanfeldt and Shaughnessy (2004) use time-series data from Dade County, FL. between January 1985 and December 2000. Total impact fees started at $0 and increased eight times during their panel, reaching a level of $5239 for an average sized new home. They find that impact fees lowered the price of land by roughly the size of the fee. In the same paper, they show impact fees increased the price of new and existing homes by considerably more than the size of the impact fee itself. To explain the strong price effects (i.e., fully shifted both backwards and forwards), they propose that even though developers are fully compensated for the costs of impact fees in the form of higher selling prices to homebuyers, they are not certain this will happen at the time they purchase the undeveloped land.

Evans-Cowley et al. (2005) use cross-sectional data from 43 Texas cities. They also find impact fees are negatively capitalized into the price of undeveloped lots, but at only a relatively small percentage of the fee. Specifically, whereas the Ihlanfeldt and Shaughnessy results suggest a $1000 impact fee should lower the price of an average residential lot by approximately $1000; their results indicate the decrease in price would only be $114.

4. Data

The data used in the present study come from 61 of Florida's 67 counties, forming a 16 year panel covering the years 1994 through 2009.[9] The data can be grouped into three categories: 1) selling prices and parcel characteristics for undeveloped land parcels, 2) impact fee levels, and 3) other available covariates that could influence the price of undeveloped land.

Land parcel sales and property characteristics come from the county parcel level tax rolls submitted annually to the Florida Department of Revenue (DOR). They contain the entire population of property sales occurring in Florida over this period. The critical fields from the DOR files are the sale price, time of sale, and land use classification codes. Three additional variables – parcel lot size (*Area*), distance to the central area of economic activity (*CBD*), and distance to the coastline (*Coast*) – were constructed for each sale using parcel level GIS mapping files submitted by each county to the state.[10] *Coast* is calculated only for counties bordering the Atlantic Ocean or Gulf of Mexico, and *CBD* is calculated only for counties classified by the Census as being part of metropolitan statistical areas. For multi-county metropolitan areas, *CBD* is measured from the same central place for parcels in all included counties (e.g., parcels in both Escambia and Santa Rosa Counties are measured from the central area of activity in Pensacola, FL). In the raw data, nearly two million sales of undeveloped land parcels are observed.

[6] Technically, this assumes zoning designations are exogenous to the presence of school fees. If communities adopt school impact fees and then zone more parcels as residential and less as commercial, commercial developers face a reduction in the supply of available parcels. This possibility is acknowledged, but argued to be unlikely.

[7] Besides addressing potential differences in preexisting regulatory environments, supplementary models using urban counties carry two other advantages. First, the available measures are richer for urban areas. Section III outlines how distances to the *CBD* were generally only available for urban counties. Secondly, urban counties have dramatically more sales of undeveloped parcels, such that price indexes constructed in the first stage should be estimated with a greater level of precision, on average, than in rural counties where sales are sparser.

[8] The lone exception was Monroe County. The Everglades National Park makes up a large portion of Monroe. Since the majority of the Park is undevelopable, it should not be in the denominator when measuring density. With this area is excluded, Monroe is well above the population density threshold and, as such, is coded urban.

[9] Hillsborough, Holmes, Lafayette, Liberty, Sumter, and Union are the six omitted counties. Hillsborough and Sumter suffer from data availability problems. The other four were removed using a filter requiring either 500 qualified residential sales or 100 qualified commercial sales for a county to be retained in the sample. The data on impact fee levels and covariates predate 1994 by many years, making the parcel level sales data obtained from the Florida Department of Revenue the limiting factor.

[10] Thanks are due to the Devoe L. Moore Center at Florida State University. Their support led to the generation and dissemination of these variables. Distances are calculated using straight-line approaches. Since lot size is a primary determinant of value, a small number of sales where *Area* could not be constructed were dropped.

Parcels may contribute more than one observation if they sell more than once during the sample period, although the vast majority of parcels sell only once. As some observed sales likely represent simple within-family or within-business transfers, all sale prices of $100 or less are removed. After constructing the selling price per square foot (sales price/lot size), the extreme tails of the distribution are also filtered to mitigate problems associated with original data entry errors. For each county, the default was to drop any sale where the price per square foot fell below $0.03 or above $200. However, undeveloped land in Florida runs the full gamut of legitimate market values, as the state contains everything from isolated rural communities to the 8th largest CMSA in the US (Miami-Fort Lauderdale-Pompano Beach). As such, if either the upper or lower filter removed more than 2% of the sales from the county, it was incrementally adjusted until this was no longer true (e.g., the upper cutoff moved to $500 per square foot in Palm Beach County). After applying these filters, the remaining 1,547,711 residential zoned parcel sales and 134,610 commercially zoned parcel sales are used to measure land prices in hedonic price regressions.

A complete history of impact fees was obtained for each county by contacting their respective planning and building departments.[11] Roughly two-thirds of counties in Florida have impact fees, with the majority changing the rates and scope of their programs several times during the panel. As such, the impact fee data provides considerable within-jurisdiction and cross-jurisdiction variation. The first impact fee variable comes from charges associated with services otherwise funded through recurrent user fees — namely, water/sewer impact fees (*WSIF*). Note that *WSIF* are collected and controlled by utility departments rather than building/planning departments, who would handle all other types of fees. Also, *WSIF* are distinct from traditional tap or connection fees that developers must pay to cover the on-site costs associated with connecting into the existing system. In practice, these fees are based on the number of equivalent residential units (ERUs) associated with a specific project. The baseline ERU for each community depends on the average daily consumption of a single family home, with single family homes paying this amount. Apartment complexes and smaller multifamily structures pay *WSIF* based on the number of residential units contained within their building. While most counties require a full ERU per multifamily unit, some charge a fractional amount. Commercial developers pay *WSIF* as a multiple of the baseline residential ERU, according to the specific physical characteristics and intended use of their facilities, following predetermined schedules. The baseline ERU rate is used presently for *WSIF*.

All other categories of impact fees fund services otherwise paid for primarily through property taxes. Roads, schools, parks, libraries, police, fire, EMS and public buildings represent the most frequently observed programs. The second impact fee variable, *CIF*, measures all commercial impact fees associated with these services. Most counties have very nuanced systems concerning commercial property. For example, a newly developed fast food restaurant may pay different fees than a clothing store, even if they occupy similar buildings. Since developers use commercially zoned land for a variety of substitutable outcomes, using an aggregate/average measure of these complicated schedules is appropriate. Fortunately, a unifying theme across all county programs is that each document the fees charged per 1000 square feet of interior space for 'general retail', 'general office', and 'general industrial'. *CIF* is calculated as the average across these three rates.

The third impact fee variable, *RIF*, measures all residential impact fees collected by planning departments, except those from school fee programs. This includes fees for roads, police, fire, EMS, parks, public buildings, and other less frequently observed types. Counties generally fall into one of two categories regarding *RIF*. The common approach is to charge an entirely fixed/flat fee, such that large and small homes pay the exact same rate. However, a handful of counties introduce variability based on the interior square footage or number of bedrooms in the home. In these select cases, the difference in charges between small and large homes is generally only a small fraction of the overall cost. When applicable, *RIF* always references an average sized (1800 square foot, 3 bedroom) home.

The final impact fee variable, *SIF*, measures school impact fees. As outlined above, most types of impact fees are paid by both residential and commercial developers. The exceptions to uniform applicability are school, park, and library impact fees, which are only paid by residential developers. Library fees are rare and, where observed, are quite small in magnitude. Park fees are slightly more common, and can be non-trivial in size. Unfortunately, the data reveals that park impact fees almost always change at the precise time communities change other major categories, which are paid by both residential and commercial developers. Planning departments typically administer all of these programs, and may simply have a preference for revising their levels concurrently. As such, identification strategies that rely on first-differenced data (which are later described as the preferred approach in the present context) are not equipped to estimate independent effects of park fees on commercial land (i.e., even though commercial developers do not pay them, they pay other fees which change at the same time). Fortunately, *SIF* is by far the largest and most important of the three residential fees only; creating a unique opportunity. Investigation reveals that, while the levels of *SIF* and *CIF* are positively correlated over the long run, their first-differenced values are not significantly correlated. That is to say, communities with high school impact fees do tend to have higher levels of other fees, but the timing of rate increases to reach those higher levels is independent. *SIF* references the same 1800 square foot, 3 bedroom home used for *RIF*.

The dynamics governing the timing of the relationship between impact fees and land sales merit attention. Impact fees are paid prior to the approval of the eventual building permit, not at the sale of the undeveloped land. When land sells, the factor influencing its price should be the discounted present value of any expected future liabilities/benefits associated with the impact fee program. If a builder purchases land and quickly moves into the permitting stage, their impact fees will likely be those in place when the land was purchased. However, as the time between the land purchase and date of permit approval increases, this becomes less likely. Previous research verifies that the stages of the development process occur quickly, meaning the average length of time between these events should be just a few months (Somerville, 2001). A further complication is that changes in impact fees may be anticipated several months in advance, as they originate from ordinances or updated administrative fee schedules. Following exploration regarding various lag structures for the data, a simple and intuitive convention was adopted. Fig. 1 illustrates the timing over which impact fee rates and land sales are observed. [Insert Fig. 1 about here] Although impact fee rates can change at any time, a common practice among Florida counties is to update rates on January 1st. Since the panel is annual, all impact fee variables reflect the rates a developer would pay on January 1st of each year. Constant quality land prices for the corresponding county/year observation in the panel come from sales occurring over the next twelve months.

The covariates come from a variety of sources. Population and per capita income come from the Bureau of Economic Analysis, millage rates come from the Florida Department of Revenue, student–teacher ratios come from the Florida Department of Education, and the Florida Statistical Abstract is used to obtain crime rates. The panel nature of these overlapping data sources enables the first-differenced and random-trends estimation strategies that are described below. An advantage of estimating panel models using changes in the values of

[11] Impact fees in Florida are primarily imposed by county governments and are generally countywide in their application. While cities can charge impact fees for services not provided by the county, this is rare, and city fees are small relative to county levels. Where they are used, a common pattern is for cities to mimic county levels for services like parks, libraries, or police, if they have their own program. The inclusion/exclusion of the small number of counties where city level impact fees play a non-trivial role did not significantly impact the results.

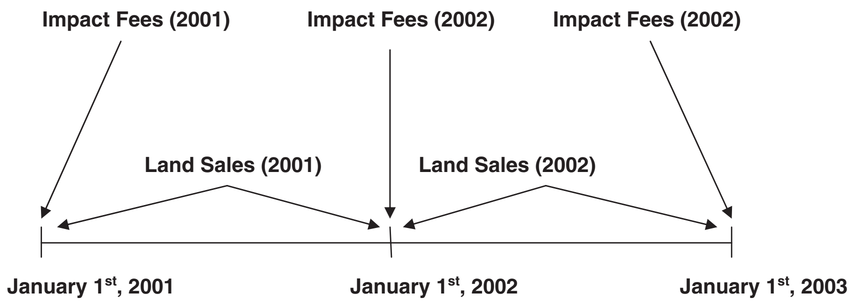

Fig. 1. Timing of observation for impact fee variables and land sales prices.

explanatory variables is that exogeneity tests reveal that it mitigates bias from the suspected endogeneity of impact fee programs with respect to changes in land prices. Regressions using variables in levels all fail strict exogeneity tests, while estimations using first-differenced data consistently pass. The downside of using first-differenced data is that variables changing smoothly over time are poorly suited to display causal effects in models with area fixed effects. However, since the performance of these variables is not of primary interest to this study, this limitation is acknowledged and willingly accepted. Finally, the Consumer Price Index for the Urban South was obtained from the Bureau of Labor and Statistics, and is used it to transform monetary variables (per capita income, estimated constant quality land prices, and all impact fee variables) into real price series using 2009 as the base year.

Table 1 presents the variables along with their descriptions and sources. Tables 2 and 3 give summary statistics for the variables in the first and second stage regressions, respectively. [Insert Tables 1, 2 & 3 about here] The trends in impact fee levels are interesting. While inflation adjusted averages rise over the panel for all four impact fee variables, they do so in different ways. For *WSIF*, there was a small increase in the number of counties with programs, but little change in the average size of charges. Although *RIF* and *CIF*, also experience only moderate growth in the number of counties with programs, the size of the average fee (in real terms) more than doubles over the panel in both cases. Finally, *SIF* increases the most rapidly, both in terms of county coverage and fee magnitude. In 1994, only twelve counties collected school impact fees, displaying an average rate of $1442 for an average sized new home. By 2009, the average school impact fee was over $4650, and 32 counties had programs in place.

5. Empirical methodology

A two stage procedure is used to examine the effects of impact fees on the price of undeveloped land. In the first stage, nearly 1.7 million observed sales from 61 Florida Counties are used to estimate the annual constant quality price of residentially zoned and commercially zoned parcels within each county between 1994 and 2009. The resulting county level price indexes then serve as the dependent variable for the second stage, where variation in the constant quality price of land over time are regressed on impact fee variables, control variables, and fixed effects controlling for unobservable factors that vary by time and place.

5.1. First stage: estimating constant quality land prices

The goal of the first stage is to obtain unbiased estimates of the constant quality price of undeveloped land over the panel, for parcels with residential and commercial zoning designations. Hedonic and repeat-sales regression techniques are both commonly used to obtain estimates of this nature. The repeat-sales approach is based on the early work of Bailey et al. (1963) and has since been advanced through contributions by Case and Shiller (1987, 1989), Gatzlaff and Haurin (1997, 1998), and many others. Repeat-sales regressions only use data from properties that sell two or more times during the observed period. The advantage of the approach is that it requires only the sale price and time of sale, since property characteristics are assumed to remain constant. The main criticisms of the repeat-sales methodology are: 1) that it reduces the sample size by discarding information from parcels selling only once, 2) that it introduces selection bias if the subset of properties selling multiple times differs systematically from the full population,

Table 1
Variable descriptions and data sources.

Variable name	Variable description	Source
1st stage: estimating land prices		
Sales price	Nominal sales price in dollars	Florida Department of Revenue
Sales date	Date of sale, used to generate the set of year specific dummies	Florida Department of Revenue
Land use code	Classification codes for sorting zoning designation	Florida Department of Revenue
Area	Parcel size (in square feet)	Florida Department of Revenue
CBD	Straight-line distance to the CBD of the respective MSA	Florida Department of Revenue
Coast	Straight-line distance to the nearest point of coastline	Florida Department of Revenue
2nd stage: explaining land prices		
Population	Annual county population	Bureau of Economic Analysis
PC income	Annual county real per capita income	Bureau of Economic Analysis
Millage rate	Annual county millage rate for unincorporated areas	Florida Department of Revenue
Crime	Annual county index crime rate per 100,000 persons	Florida Statistical Abstract
Teacher ratio	Annual county student/teacher ratio for all public schools	Florida Department of Education
WSIF	Real water/sewer impact fee January 1st, per ERU	Florida county governments
CIF	Real commercial impact fee January 1st, per 1,000 square feet.	Florida county governments
RIF	Real residential impact fee January 1st, per single family home	Florida county governments
SIF	Real school impact fee January 1st, per single family home	Florida county governments
PLR_{it}	Real constant quality selling price for residential land	1st Stage regression results
PLC_{it}	Real constant quality selling price for commercial land	1st Stage regression results

Table 2
Summary statistics by county — 1st stage variables; median values.

County	Residentially zoned parcels					Commercially zoned parcels				
	#Obs	*Area*	*CBD*	*Coast*	*Sales price*	#Obs	*Area*	*CBD*	*Coast*	*Sales price*
Alachua	10,443	26,482	48,029	N/A	40,000	1047	43,878	33,328	N/A	108,650
Baker	1215	43,970	N/A	N/A	18,000	172	440,203	N/A	N/A	133,750
Bay	17,139	14,639	53,378	2825	36,000	2341	99,393	56,182	7125	87,500
Bradford	2049	41,778	N/A	N/A	15,500	287	550,636	N/A	N/A	75,000
Brevard	85,807	10,228	55,647	29,482	28,000	4614	51,426	76,968	9376	139,000
Broward	16,574	7907	57,261	50,650	325,000	4128	8627	43,169	24,204	434,200
Calhoun	978	26,432	N/A	N/A	6000	280	386,157	N/A	N/A	16,400
Charlotte	124,833	10,001	54,609	10,411	19,500	4440	12,507	48,483	12,227	80,000
Citrus	33,601	12,304	N/A	51,375	18,900	829	52,346	N/A	46,576	63,200
Clay	12,658	23,509	120,800	N/A	25,000	533	92,304	120,271	N/A	125,000
Collier	41,071	26,902	74,148	35,268	63,000	4610	109,891	57,512	35,694	125,000
Columbia	4289	45,721	N/A	N/A	20,500	3097	276,297	N/A	N/A	30,000
Dade	15,712	7877	69,890	22,243	210,000	10,939	30,414	82,263	37,841	220,000
DeSoto	3783	43,661	N/A	N/A	23,300	679	219,314	N/A	N/A	70,000
Dixie	3727	44,264	N/A	96,197	12,140	995	113,831	N/A	105,863	12,500
Duval	23,482	10,537	51,676	62,976	49,800	5243	37,892	41,342	66,263	85,000
Escambia	14,137	12,570	46,085	8416	34,900	2070	43,034	32,935	12,541	112,000
Flagler	46,132	10,120	N/A	22,405	22,900	1049	217,867	N/A	28,216	200,000
Franklin	5687	21,018	N/A	679	84,000	576	12,128	N/A	693	35,000
Gadsden	3269	42,022	98,872	N/A	16,000	384	515,751	97,315	N/A	116,750
Gilchrist	3847	54,374	173,122	N/A	16,900	94	436,014	170,027	N/A	45,000
Glades	2491	11,738	N/A	N/A	18,000	242	371,860	N/A	N/A	57,200
Gulf	4563	20,483	N/A	1040	54,000	203	173,208	N/A	26,131	40,000
Hamilton	4091	57,740	N/A	N/A	11,800	141	888,629	N/A	N/A	85,000
Hardee	1747	19,267	N/A	N/A	25,000	657	316,098	N/A	N/A	60,000
Hendry	17,406	13,630	N/A	N/A	22,500	847	130,553	N/A	N/A	105,000
Hernando	37,517	16,288	211,132	39,548	19,900	5125	117,084	218,408	76,492	55,000
Highlands	34,723	10,800	N/A	N/A	17,000	1246	164,116	N/A	N/A	75,000
Indian River	22,970	10,587	51,986	13,653	39,000	1613	31,294	36,738	7846	160,000
Jackson	8139	4802	N/A	N/A	8500	232	12,948	N/A	N/A	38,750
Jefferson	470	83,119	132,885	155,501	10,000	1214	219,154	129,223	146,526	25,000
Lake	10,570	21,142	148,411	N/A	36,000	1659	206,408	157,069	N/A	68,500
Lee	244,647	10,890	72,044	38,265	24,900	7969	13,106	53,499	18,024	125,000
Leon	17,538	22,932	41,679	N/A	44,700	1736	45,996	22,211	N/A	140,000
Levy	17,112	43,441	N/A	107,506	10,000	1825	442,613	N/A	103,687	50,000
Madison	2403	45,809	N/A	N/A	13,000	1066	436,033	N/A	N/A	49,995
Manatee	18,152	10,898	60,768	13,623	87,600	3089	215,363	77,294	16,407	115,900
Marion	98,012	12,736	71,081	N/A	14,500	7158	230,290	64,373	N/A	70,000
Martin	1137	13,750	26,588	3658	70,000	128	121,971	25,048	5076	185,000
Monroe	7460	7506	N/A	649	55,000	463	8117	N/A	695	75,000
Nassau	8985	24,159	118,770	9937	60,000	458	34,875	125,610	5603	130,650
Okaloosa	18,208	14,527	67,175	7319	66,900	2068	64,099	112,784	73,817	150,000
Okeechobee	12,779	49,304	N/A	N/A	12,500	884	207,928	N/A	N/A	48,000
Orange	39,136	10,953	62,382	N/A	35,000	5840	86,431	49,395	N/A	177,000
Osceola	19,697	11,108	118,922	N/A	40,650	1030	62,166	97,654	N/A	315,800
Palm beach	34,887	47,406	77,255	52,236	57,000	3242	32,825	52,185	10,938	350,000
Pasco	18,258	15,396	138,673	41,497	32,200	1688	65,587	143,330	42,585	115,000
Pinellas	17,123	9652	104,191	4974	79,000	4116	13,319	96,176	5898	250,000
Polk	32,732	10,905	74,241	N/A	28,900	8195	141,263	68,266	N/A	95,000
Putnam	43,915	10,205	N/A	N/A	10,000	4855	64,378	N/A	N/A	19,900
St. Johns	20,910	17,019	189,375	16,518	58,000	636	120,930	199,197	14,918	260,000
St. Lucie	58,847	10,014	49,653	18,383	24,000	4083	57,366	92,658	13,956	165,000
Santa Rosa	28,793	19,906	87,226	3885	28,500	1849	32,746	85,331	3467	115,000
Sarasota	79,849	10,095	148,623	26,720	30,000	1575	42,519	82,424	12,871	335,000
Seminole	13,366	13,327	81,105	N/A	92,000	3451	85,390	85,793	N/A	210,000
Suwannee	7828	88,200	N/A	N/A	14,500	783	581,078	N/A	N/A	52,000
Taylor	4075	43,664	N/A	10,770	12,390	264	404,846	N/A	62,668	35,950
Volusia	29,084	13,576	106,863	88,892	30,000	2922	24,774	86,809	16,774	125,000
Wakulla	6152	10,000	101,649	21,999	18,000	125	174,812	102,227	22,584	126,000
Walton	13,662	13,334	N/A	1544	86,000	385	428,544	N/A	4817	175,000
Washington	17,844	13,098	N/A	N/A	25,000	1141	218,922	N/A	N/A	21,500

and 3) that property characteristics may change between sales. In considering undeveloped land, the two most important characteristics of the property – size and location – are fixed. As such, the third assumption is reasonable. However, the first two present serious (and related) problems. It is unlikely that parcels selling twice in the same form represent a random sample. A common transition pathway for undeveloped land is for a developer (or other intermediary) to purchase a large plot of land, carry out the necessary steps for its subdivision, and to then sell the subdivided parcels to various builders. As such, land frequently sells twice — but not in the same form. To enter a repeat-sales regression, the land must sell twice in the initial aggregated stage or twice as an already subdivided parcel. Not only is this rare, where it does occur but also there are likely systematic differences from the underlying population of undeveloped parcels.

Fortunately, the hedonic approach is well suited to measure the constant quality price of undeveloped land. Popularized by Rosen (1974), the technique assumes prices are determined by a bundle of attributes associated with the parcel. OLS regressions obtain the value of each

Table 3
Summary statistics — 2nd stage variables.

Variable name	Full panel (61 counties)		Urban (34 counties)	
	Mean (st.dev)	#Obs	Mean (st.dev)	#Obs
Population	252,316 (404,997)*	976	427,483 (474,075)	544
PC income	31,062 (9499)	976	36,418 (9139)	544
Millage rate	16.56 (3.15)	976	15.75 (3.18)	544
Crime	4298 (1785)	976	4865 (1808)	544
Teacher ratio	16.72 (1.43)	976	16.90 (1.36)	544
WSIF	2342 (2061)	956	3576 (1416)	524
CIF	1494 (2134)	976	2377 (2348)	544
RIF	2464 (3654)	976	3923 (3995)	544
SIF	901 (1832)	976	1448 (2157)	544
PLR_{it}	79,783 (237,897)	953	117,050 (311,492)	531
PLC_{it}	169,141 (405,156)	944	225,968 (212,193)	530

* The reduction in the number of observations for PLR_{it} and PLC_{it} stems from data related issues that prevented the estimation of constant quality land prices for a small number of county/year observations. The twenty missing observations for *WSIF* come from two cases where utility impact fee programs were in place, but early rates have proven unobtainable after intensive interactions with county officials.

attribute, including the time period of sale. The estimated first stage models follow the form[12]:

$$\ln\left(P_{i,t}/Area_i\right) = \beta_0 + \beta_1 Area_i +_2 Area_i^{\,2} + \beta_3 Area_i^{\,3} + \beta_4 CBD_i + \beta_5 CBD_i^{\,2} + \beta_6 Coast_i + \beta_7 Coast_i^{\,2} + \beta_8 T_t + \mu_{i,t} \tag{1}$$

where

$P_{i,t}$ = the selling price of parcel i at time t.
$Area_i$ = the size, in square feet, of parcel i.
CBD_i = the distance, in feet, between parcel i and the central place of economic activity (only available for parcels in census defined metropolitan statistical areas).
$Coast_i$ = the distance, in feet, between parcel i and the nearest contact with the Atlantic Ocean or Gulf of Mexico (only available for coastal counties).
T_t = a vector of annual dummy variables.
$\mu_{i,t}$ = a randomly distributed regression error term.

Eq. (1) is estimated separately for residentially and commercially zoned parcels in the 61 counties. The results of interest come from the point estimates of ß$_8$, which are transformed using standard techniques to construct the second stage constant quality measures of land prices described below, PLR_{it} and PLC_{it}. For consistency, this baseline functional form was used for all 122 estimations. While the generated distance measures CBD_i and $Coast_i$ effectively control for the location of parcels for the vast majority of sales, there are 16 counties that are both inland and rural. In these cases, since both distance measures are missing, an alternative procedure was developed to account for the role of location. The DOR tax rolls contain a field (*range*) that places the parcel into a set of contiguous geographic zones. Unless a range contained less than 5% of the sales data, a dummy variable for the range was included in the regression. Parcels in omitted ranges serve as the reference group.

5.2. Second stage: explaining land prices

The equilibrium price of undeveloped residentially zoned land (PLR_{it}) and commercially zoned land (PLC_{it}) in county *i* at time *t* depends on a wide range of factors. Conceptually, these determinants can be split into those that change little (or not at all) over time within a county, and those that do change over time. We denote the area specific time invariant factors in the former category to be vector X_i. Regardless of whether the factors in X_i are observable or not, their influence on land prices can be accounted for by including area specific fixed effects. In the latter category are impact fees and all other time variant influences. For ease, let the four impact fee variables described above be denoted IF_{it} and let all other factors be contained in vector Y_{it}. Observable covariates found in Y_{it} are student–teacher ratio, population, income, millage rates, and crime. Reduced form models explaining logged equilibrium constant quality prices for residential and commercial land in county *i* at time *t* can then be expressed as:

$$\ln(PLR_{it}) = a + bX_i + cIF_{it} + dY_{it} + e_{it} \tag{2}$$

and

$$\ln(PLC_{it}) = a + bX_i + cIF_{it} + dY_{it} + e_{it}. \tag{3}$$

After first differencing the data, the vector of area specific fixed effects (X_i) drops out leaving:

$$\Delta\ln(PLR_{it}) = a + c\Delta IF_{it} + d\Delta Y_{it} + e_{it} \tag{4}$$

and

$$\Delta\ln(PLC_{it}) = a + c\Delta IF_{it} + d\Delta Y_{it} + e_{it}. \tag{5}$$

Inevitably, many of the variables in Y_{it} are not directly observable. However, time varying unobservable influences will fall into one of two groups: 1) those that change uniformly over time across all counties, and 2) those that change non-uniformly across counties over time. Note that the first group can be effectively controlled for by including time fixed effects. The second includes factors following a trend over time within a specific county. These factors should effectively be controlled for by allowing each county to posses its own area specific growth trend. This is accomplished by re-introducing the set of county dummy variables into the already first-differenced models. After adding both time (γ) and county (α) fixed effect vectors to (4) and (5), the estimating equations become:

$$\Delta\ln(PLR_{it}) = a + \alpha_i + \gamma_t + c\Delta IF_{it} + d\Delta Y_{it} + e_{it} \tag{6}$$

and

$$\Delta\ln(PLC_{it}) = a + \alpha_i + \gamma_t + c\Delta IF_{it} + d\Delta Y_{it} + e_{it}. \tag{7}$$

Often referred to as random trends models, (6) and (7) utilize first-differencing to control for heterogeneity in *levels*, and area fixed effects to control for heterogeneity in *changes*. Omitted variable bias will now only occur if changes in unobservable factors influencing undeveloped land prices are also commonly correlated with the time counties implement and/or update their impact fee programs. Other than the stringency of the local regulatory environment and the probability of receiving development approval from local authorities (which have both been identified and discussed above), it is hard to imagine other unobserved factors meeting this requirement. Still, standard strict exogeneity tests recommended for verifying consistency in panel data estimations were carried out and are discussed in Section V.

Heteroskedasticity and serial correlation were both consistently detected in the residuals of early estimations. Consequently, standard errors that are robust to both arbitrary serial correlation and heteroskedasticity are used (Wooldridge, 2002, p. 282).[13] Also, to mitigate data errors and issues with prohibitively thin sales counts in specific county-years, the extreme tails of the estimated

[12] Logged price, as opposed to logged price per square foot, is also a commonly used dependent variable. The estimated constant quality prices coming from models using each were found to be highly similar.

[13] The preferred test for serial correlation involves regressing Δe_{it} on $\Delta e_{i,t-1}$, for various time periods, as suggested by Wooldridge (2002, p. 283). The fully robust standard errors are obtained using the "cluster" option in Stata, specifying that standard errors be clustered as the county level.

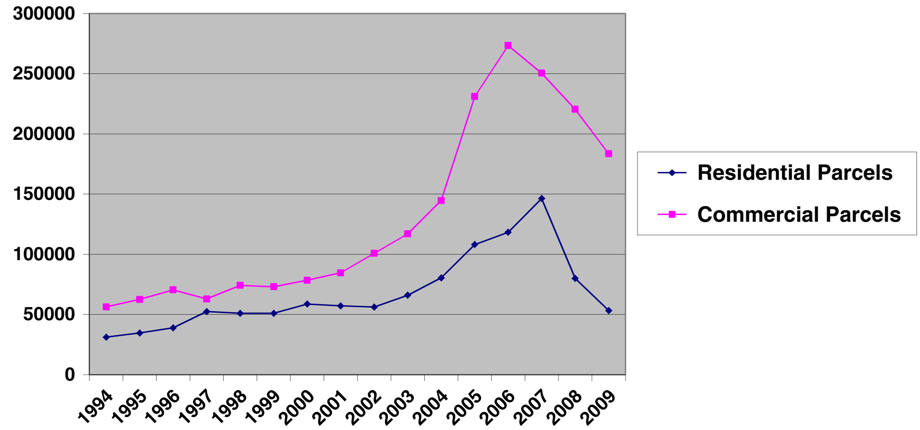

Fig. 2. Median constant-quality land parcel prices: nominal dollars, 1994–2009.

distribution of changes in land prices were filtered for both the residential and commercial models. Any year-over-year price change exceeding a factor of four, in either direction, was removed. So for example, if $10 was a given years estimated constant quality selling price per square foot, next year's observation was removed if the price exceeded $40 per square foot or fell below $2.50. This affected an extremely small number of cases, but does represent the small difference between the number of observations later reported in results of tables and the raw number of initial observations shown in Table 3.

Since previous literature suggests the relationship between development impact fees and the price of land may differ across metropolitan and rural environments, and because first stage land price indexes are estimated with more precision in areas with more observable sales, Eqs. (4)–(7) are estimated for the full sample of 61 counties and, as a robustness check, for the subsample of urban (34 counties) following the criteria presented in Section II.

6. Results

In total, 122 different hedonic price regressions (61 counties across 2 land use categories) are estimated to obtain the constant quality land prices needed for the second stage dependent variable. Fig. 2, as well as Tables 4 and 5, summarize the most important information from this large set of results. [Insert Fig. 2, Table 4, and Table 5 about here] Averaging across the estimates for all 61 counties, Fig. 2 shows the nominal median constant quality price of residential and commercial land in Florida between 1994 and 2009. For both residential and commercial land, moderate price appreciation occurs over the first ten years of the panel. Investigation reveals price appreciation over this early period closely tracks inflation, such that real values are essentially flat. Around 2002, interesting changes in those dynamics begin to surface. Price appreciation for residentially zoned parcels increases significantly, with a pronounced acceleration around 2003. Quality adjusted prices more than double between 2003 and 2007, the year in which the value of residentially zoned land peaked. However, the recent well-documented real estate crash led to the years of 2008 and 2009 removing nearly all of these gains, retuning prices to early 2000s levels. In terms of inflation adjusted real prices, the average 1994 and 2009 prices for residential land are nearly identical. Turning to commercially zoned parcels, the rapid price run-up is even larger, with constant quality prices more than tripling between 2001 and their peak in 2006. Interestingly, the appreciation during 2004–2006 is even stronger than 2001–2003, suggesting the strength of the bubble may have actually increased as it approached the point of bursting. Finally, the value of undeveloped commercial land loses most, but not all, of the run-up gains during 2008 and 2009, staying considerably above early 2000s price levels, even after adjusting for inflation.

Although the first stage hedonic regression results are not the primary focus of this paper, it is worth noting that the overall constant quality price trends presently obtained are strikingly consistent with the land price movements reported by Nichols et al. (2012). Using undeveloped land sale price data from 23 large MSAs in the United States, they find residential and commercial land prices rose slowly between the mid 1990s through the early 2000s, experienced a dramatic acceleration around 2002–2003 that led to a peak in the late 2006-early 2007 range, and then lost the majority of these gains during the latter portions of 2007 through 2009. All told, the two distinct sets of estimated constant quality land price trends show highly similar patterns. Also, where both studies consider the same market (i.e., the Florida MSAs in their study); the county-specific price indexes they obtain are remarkably similar to the price trends we obtain. This provides some external validation that the first stage regressions accurately measure their intended target.

While aggregate price movements are interesting, attention to the considerable variation across counties is also merited. Price appreciation was minimal in several counties, and even negative for a few extreme cases. Note that a 44% nominal appreciation rate was required just to keep pace with inflation. 43 counties met or exceeded this mark for residential land values, while 18 did not. Turning to commercially zoned parcels, 49 counties met or exceeded this mark and 12 did not. A better indicator of whether undeveloped land in Florida was a good or bad investment over this period comes from comparing the estimated appreciation rates to those of other common financial investments. Between January 1st 1994 and December 31st 2009, both the Dow Jones Industrial Average and the price of gold experienced roughly 175% nominal price appreciation. 21 counties beat this benchmark performance for residential land, while 40 fell short. For commercial land, 39 counties exceeded the benchmark and 22 fell short. Interestingly then, although economic development in Florida was intense over this period, the rate of return on undeveloped land across the state was, on average, no better or worse than other common investments.[14]

Tables 4 and 5 contain the summarized results of the 122 land price regressions. Columns 2 and 3 show the number of observations and R^2 from each regression, respectively. While possessing high levels of explanatory power within these regressions is not necessary for estimating accurate price movements over time, the reasonable R^2 values are reassuring. In the residential regressions they range from a high value of 0.68 to a low of 0.15. For commercial, the highest R^2 value is 0.65 (seen thrice), while the lowest value is 0.20. Note the estimated

[14] In fairness, this comparison ignores two important considerations. Property tax liabilities reduce the net rate of return on land, but not the other two investments. On the other hand, it can be argued that undeveloped land produces at least some direct benefits if the land has useful pre-development purposes (i.e., hunting/recreation).

Table 4
First stage results summary — hedonic price regressions for residentially zoned parcels.

County	#Obs	R^2	Area	Area^2	Area^3	*CBD*	*CBD*^{2}	Coast	Coast^2	Δ price 94-09
Alachua	10,443	0.38	Negative[a]	Positive[a]	Negative[a]	Negative	Negative[a]	N/A	N/A	22.13%
Baker	1215	0.34	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	665.46%
Bay	17,139	0.45	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	161.01%
Bradford	2049	0.32	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	312.60%
Brevard	85,807	0.16	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	273.15%
Broward	16,574	0.36	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Positive[a]	Negative[a]	349.20%
Calhoun	978	0.33	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	319.88%
Charlotte	124,833	0.22	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	74.58%
Citrus	33,601	0.30	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Positive[a]	Negative[a]	37.41%
Clay	12,658	0.55	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	163.21%
Collier	41,071	0.68	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	354.31%
Columbia	4289	0.56	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	91.31%
Dade	15,712	0.21	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	−75.79%
DeSoto	3783	0.27	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	95.38%
Dixie	3727	0.57	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	340.70%
Duval	23,482	0.16	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	−2.34%
Escambia	14,137	0.25	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	21.46%
Flagler	46,132	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	181.45%
Franklin	5687	0.50	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	411.92%
Gadsden	3269	0.32	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	207.19%
Gilchrist	3847	0.42	Negative[a]	Positive[a]	Negative[a]	Positive	Negative	N/A	N/A	219.25%
Glades	2491	0.32	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	57.08%
Gulf	4563	0.63	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	275.94%
Hamilton	4091	0.28	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	71.82%
Hardee	1747	0.65	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	376.79%
Hendry	17,406	0.43	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	64.33%
Hernando	37,517	0.29	Negative[a]	Positive[a]	Negative[a]	Positive	Negative[a]	Positive	Negative[a]	11.46%
Highlands	34,723	0.20	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	−31.65%
Indian river	22,970	0.27	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	104.54%
Jackson	8139	0.31	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	51.77%
Jefferson	470	0.44	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative	Positive[a]	21.73%
Lake	10,570	0.28	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	108.59%
Lee	244,647	0.17	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	60.11%
Leon	17,538	0.17	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative	N/A	N/A	1.59%
Levy	17,112	0.29	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	149.08%
Madison	2403	0.40	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	23.50%
Manatee	18,152	0.36	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Positive[a]	Negative[a]	46.05%
Marion	98,012	0.31	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	138.57%
Martin	1137	0.39	Negative[a]	Positive[a]	Negative[a]	Positive	Positive	Negative[a]	Positive[a]	102.01%
Monroe	7460	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	362.83%
Nassau	8985	0.30	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	158.91%
Okaloosa	18,208	0.40	Negative[a]	Positive[a]	Negative[a]	Positive	Positive	Negative[a]	Negative[a]	266.45%
Okeechobee	12,779	0.60	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	150.70%
Orange	39,136	0.37	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	34.55%
Osceola	19,697	0.35	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	−45.25%
Palm beach	34,887	0.34	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	57.27%
Pasco	18,258	0.46	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	155.74%
Pinellas	17,123	0.15	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	41.52%
Polk	32,732	0.25	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	208.79%
Putnam	43,915	0.22	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	−21.60%
St. Johns	20,910	0.54	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	30.30%
St. Lucie	58,847	0.23	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Negative[a]	Positive[a]	99.49%
Santa Rosa	28,793	0.21	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	47.58%
Sarasota	79,849	0.20	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	30.58%
Seminole	13,366	0.25	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	−59.30%
Suwannee	7828	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	199.76%
Taylor	4075	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	174.75%
Volusia	29,084	0.30	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative	Negative[a]	Positive[a]	−86.56%
Wakulla	6152	0.30	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	227.30%
Walton	13,662	0.46	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	208.98%
Washington	17,844	0.45	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	418.62%

[a] Statistically significant at the 95% confidence level.

ß$_8$ coefficients provide the critical information needed to conduct the second stage estimations. However, they are not included, as their presentation would be cumbersome (16 coefficients times each of the 122 estimations).[15] The final column of each table reports the estimated cumulative 1994–2009 price appreciation for each county.

As expected, larger lot size leads to higher selling prices. Columns 4 through 6 show the sign and significance of the *Area*, *Area*^{2}, and *Area*^{3} variables. Note the typical expectation would be for *Area* to be positive, then finding alternating signs on higher order terms. However, the employed dependent variable is already specified as price per square foot, such that it makes sense for the alternating sign pattern to begin negative. The alternating sign pattern is seen uniformly in all estimated regressions (for residential and commercial land), with all three exponential terms significant in the vast majority of cases. The next four columns in Tables 4 and 5 summarize the results concerning distance to the central place of economic activity (*CBD*) and to the coast (*Coast*). Consistent with traditional models of urban location theory,

[15] Full results are available upon request.

Table 5
First stage results summary — hedonic price regressions for commercially zoned parcels.

County	#OBS	R^2	Area	Area^2	Area^3	*CBD*	*CBD*^{2}	Coast	Coast^2	Δ price 94-09
Alachua	1047	0.48	Negative[a]	Positive[a]	Negative[a]	Negative	Negative	N/A	N/A	47.59%
Baker	172	0.57	Negative[a]	Positive	Negative	N/A	N/A	N/A	N/A	1275.94%
Bay	2341	0.65	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	200.57%
Bradford	287	0.23	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	71.29%
Brevard	4614	0.30	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative	Negative[a]	Positive[a]	211.37%
Broward	4128	0.26	Negative[a]	Positive[a]	Negative[a]	Positive	Negative	Positive	Positive	601.46%
Calhoun	280	0.40	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	151.73%
Charlotte	4440	0.41	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	−39.67%
Citrus	829	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative	Negative	511.47%
Clay	533	0.55	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	−51.54%
Collier	4610	0.51	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative[a]	Negative[a]	Positive[a]	483.28%
Columbia	3097	0.28	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	740.65%
Dade	10939	0.56	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Positive[a]	Negative[a]	196.06%
DeSoto	679	0.38	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	1332.20%
Dixie	995	0.40	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	347.05%
Duval	5243	0.20	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	17.34%
Escambia	2070	0.47	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Negative[a]	Positive	53.90%
Flagler	1049	0.49	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	243.36%
Franklin	576	0.42	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive	728.21%
Gadsden	384	0.41	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	−53.33%
Gilchrist	94	0.59	Negative[a]	Positive[a]	Negative[a]	Negative	Positive	N/A	N/A	180.89%
Glades	242	0.61	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	−47.86%
Gulf	203	0.65	Negative[a]	Positive[a]	Negative	N/A	N/A	Negative[a]	Positive[a]	13.28%
Hamilton	141	0.61	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	412.64%
Hardee	657	0.38	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	1185.97%
Hendry	847	0.37	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	27.19%
Hernando	5125	0.35	Negative[a]	Positive[a]	Negative[a]	Positive	Negative[a]	Negative[a]	Positive[a]	522.14%
Highlands	1246	0.44	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	66.03%
Indian river	1613	0.35	Negative[a]	Positive[a]	Negative[a]	Positive	Negative[a]	Negative[a]	Positive[a]	3.62%
Jackson	232	0.58	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	9.74%
Jefferson	1214	0.35	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative	Positive[a]	655.34%
Lake	1659	0.22	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	N/A	N/A	1366.99%
Lee	7969	0.32	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Positive	Negative[a]	12.93%
Leon	1736	0.46	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	104.01%
Levy	1825	0.54	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Positive[a]	Negative[a]	430.36%
Madison	1066	0.35	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	551.30%
Manatee	3089	0.62	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Negative[a]	Positive[a]	16.87%
Marion	7158	0.37	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	N/A	N/A	300.32%
Martin	128	0.38	Negative[a]	Positive	Negative	Positive	Negative	Negative[a]	Positive	340.44%
Monroe	463	0.37	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	44.72%
Nassau	458	0.50	Negative[a]	Positive[a]	Negative[a]	Positive	Negative[a]	Negative[a]	Positive[a]	831.57%
Okaloosa	2068	0.65	Negative[a]	Positive[a]	Negative[a]	Positive	Positive	Negative[a]	Positive[a]	467.80%
Okeechobee	884	0.32	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	257.87%
Orange	5840	0.38	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative	N/A	N/A	365.48%
Osceola	1030	0.37	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	N/A	N/A	21.23%
Palm beach	3242	0.38	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	397.04%
Pasco	1688	0.58	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Negative[a]	Positive[a]	409.88%
Pinellas	4116	0.24	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	133.36%
Polk	8195	0.25	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	N/A	N/A	918.08%
Putnam	4855	0.29	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	197.96%
St. Johns	636	0.50	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive[a]	Negative[a]	Positive[a]	172.13%
St. Lucie	4083	0.29	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Negative	Positive	Negative[a]	713.52%
Santa Rosa	1849	0.41	Negative[a]	Positive[a]	Negative[a]	Negative	Positive	Negative[a]	Positive[a]	407.39%
Sarasota	1575	0.39	Negative[a]	Positive[a]	Negative[a]	Negative[a]	Positive	Negative[a]	Negative	69.62%
Seminole	3451	0.35	Negative[a]	Positive[a]	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	388.17%
Suwannee	783	0.37	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	990.26%
Taylor	264	0.23	Negative[a]	Positive[a]	Negative	N/A	N/A	Negative[a]	Positive	240.59%
Volusia	2922	0.43	Negative[a]	Positive[a]	Negative[a]	Negative	Negative[a]	Negative[a]	Positive[a]	277.19%
Wakulla	125	0.35	Negative	Positive	Negative	Positive[a]	Negative[a]	Negative[a]	Positive[a]	185.11%
Walton	385	0.60	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	Negative[a]	Positive[a]	682.64%
Washington	1141	0.25	Negative[a]	Positive[a]	Negative[a]	N/A	N/A	N/A	N/A	309.51%

[a] Statistically significant at the 95% confidence level.

we generally see negative and significant effects of the linear terms and positive and significant effects of the squared terms when *CBD* and *Coast* are present.[16] Collectively, there seems to be evidence that the first stage builds accurate measures of constant quality residential and commercial land prices over time at a level of geography that aligns with the application of impact fee programs.

Tables 6 and 7 report the second stage results for the residentially zoned and commercially zoned models, respectively. [Insert Tables 6 and 7 about here] Before discussing the performance of the impact fee variables, a few comments on the covariates are merited. The standard urban land use model suggests faster population growth and higher per capita income should increase land values. However, this conclusion is linked to the idea that higher levels of these variables increase bid-rent premiums for land located in central/interior locations. These

[16] The rare exception is that in some counties with *CBDs* located near the coastline both variables are so strongly correlated that each significantly influences the performance of the other. In these cases, the inclusion of one, but not the other, always strengthens the significance of the included variable and leads to the expected pattern of signs. Across several exploratory exercises, inclusion/exclusion had little effect on the estimated price indexes.

Table 6
Second stage results — residential land price regressions.

Model	(4) First-differenced		(6) Random trends		(4) First-differenced		(6) Random trends	
Sample	Full sample		Full sample		Urban sample		Urban sample	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
RIF	−0.0013	1.01	−0.0020	1.31	−0.0008	0.57	−0.0016	0.96
SIF	−0.0026	2.34**	−0.0027	1.99**	−0.0014	1.08	−0.0015	0.97
WSIF	−0.0072	2.79**	−0.0094	2.65**	−0.0060	2.08**	−0.0061	2.12**
Teacher ratio	0.8685	0.27	1.4939	0.42	−2.2477	0.67	−1.8809	0.51
Population	−0.0006	3.83**	−0.0007	1.29	−0.0005	2.61**	−0.0008	1.27
PC income	−0.0007	0.57	−0.0009	0.57	0.0015	0.80	0.0010	0.48
Millage rate	0.7958	1.09	0.6868	0.96	0.2643	0.34	0.1823	0.23
Crime	−0.0044	1.96*	−0.0048	1.96**	−0.0051	1.70*	−0.0059	1.86*
Year dummies	Yes		Yes		Yes		Yes	
Area dummies	No		Yes		No		Yes	
R^2	0.15		0.19		0.17		0.20	
Observations	838		838		464		464	

* and ** denote statistical significance at the 10% and 5% level, respectively, using a two-tailed test.

relationships will be fundamentally different near the urban fringe, since land is typically converted over time from its previous agricultural uses. Both variables, but particularly population, should influence the rate of development more than the equilibrium selling price at the point of conversion. This nuance, along with the previously mentioned complication of using first-differenced demographic data in fixed effects panel regressions, inhibits making any strong conclusions based on the estimated effects of these variables.

Student–teacher ratios are uniformly found to have insignificant effects in both residential and commercial models. While population and per capita income are generally insignificant, the cases where they do register significance show negative influences on land price, a result likely related to the two previously outlined challenges in interpreting results on the control variables. For millage rates, point estimates are positive in all four residential regressions and negative in all four commercial regressions, but never come close to achieving statistical significance. This is not surprising as changes in property tax rates should only be capitalized into land prices if the expected future marginal costs and benefits of greater taxation/spending are significantly different from one another. If anything, a significant negative effect of property taxes on land values would be surprising in this setting, since undeveloped land is more likely to be located in areas where the collected tax revenues will be spent. Finally, the results suggest higher crime rates may influence residential and commercial parcels in different ways — with negative and generally statistically significant effects on residential land prices, but positive and statistically insignificant effects on commercial prices.

It is worth noting that models utilizing the data in levels are found to have greater explanatory power than otherwise similar regressions using first-differenced data. This difference is not surprising, as area specific fixed effects carry far more explanatory power in models explaining price levels than they do in models explaining price changes. A natural question is then, why are first-differenced and random-trends models preferred? Since the panel estimations include time period fixed effects; achieving consistency for the estimated coefficients requires meeting the standard of strict exogeneity (Wooldridge, 2002). This requires the explanatory variables in each time period be uncorrelated with the idiosyncratic error term (e_{it}) in future time periods. Standard tests investigating this property are generally not passed when the models are run in levels, but are passed when estimations use first-differenced data.[17] As such, the first-differenced and random trend models presented are more appropriate for estimating the causal effects of impact fees on undeveloped land prices.

The most important finding of the study comes from the school impact fee variable, *SIF*. *SIF* is found to significantly decrease the value of residentially zoned undeveloped land, but to increase the value of commercially zoned parcels, confirming a suspected possibility regarding fees of this nature. Recall that Section II argued residential developers experience benefits associated with fee adoption, but also pay the fees as a direct cost. No such direct costs are faced by commercial developers who still enjoy important benefits. In the absence of school impact fee programs, communities in Florida rely almost entirely on property tax revenues (educational bond financing) to fund education related infrastructure expansions. This alternative places the financing burden on both residential and commercial property owners. On the other hand, school impact fee programs place the entire burden of educational infrastructure finance squarely upon residential interests. Table 8 reports the estimated price effects of a $1000 increase in *SIF* on parcels of both zoning designations. On a per acre basis, the predicted decline in residential value is $643; while the predicted price increase for an acre zoned commercial is $375. The commercial result represents a novel finding that carries implications for those interested in local education finance.

The residential result suggests a $1000 school fee would lower the price of a commonly sized quarter-acre lot by about $161. This is very close to the Evans-Cowley et al. (2005) findings and falls far short of full negative capitalization. Note the shifts that can be seen when moving from the full sample to the urban sample. In the full model, the *SIF* slope coefficients are larger in absolute value and produce larger t-statistics than their urban model counterparts. There, the estimated effect of $1000 of additional fees drops to well below $100 and is not significantly different from zero. Since land price trends should be estimated more accurately in urban areas than rural, the only explanation we see for this result is that school impact fee programs actually create more substantial indirect benefits for developers in urban areas than they do in rural areas. Given the previous literature that suggests impact fees may lessen other unobservable regulatory barriers to development, and the commonly argued idea that preexisting regulatory barriers are very low in rural areas, but pose a significant challenge in urban and suburban communities, this shift in effects seems reasonable.

To our knowledge, this study is the first to consider school impact fees independently from other fee categories and the first to show they influence the values of residentially zoned and commercially zoned undeveloped parcels in opposite directions. Note that for residential developers, school impact fee programs create a critical tradeoff between one direct cost (the monetary cost of the fee itself) and three indirect benefits: 1) lower future property tax burdens, 2) valuable new educational facilities, and 3) a potential reduction in other regulatory barriers to development. The results suggest that while these

[17] A test for strict exogeneity in panel models comes from Wooldridge (2002). This involves regressing ΔPLR_{it} and ΔPLC_{it} on future as well as contemporaneous values of the impact fee change variables. If future changes are significant, then the null hypothesis of strict exogeneity is rejected. The presented first-differenced and random-trend models meet these tests when the first and second lead values of impact fee variables are included. In all cases the joint significance tests are based on *F-statistics* robust to heteroskedasticity and serial correlation.

Table 7
Second stage results — commercial land price regressions.

Model	(5) First-differenced		(7) Random trends		(5) First-differenced		(7) Random trends	
Sample	Full sample		Full sample		Urban sample		Urban sample	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CIF	−0.0035	1.97*	−0.0044	2.16**	−0.0016	0.75	−0.0023	0.95
SIF	0.0049	2.52**	0.0057	2.74**	0.0043	1.96*	0.0047	2.05**
WSIF	−0.0003	0.10	−0.0005	0.13	0.0011	0.47	0.0011	0.33
Teacher ratio	−2.4756	0.55	−3.6721	0.74	−3.7142	1.21	−4.3574	1.32
Population	−0.0002	1.31	−0.0006	1.64	0.0001	0.54	0.0002	0.60
PC income	−0.0038	1.72*	−0.0021	0.86	−0.0024	0.96	−0.0013	0.49
Millage rate	−0.4121	0.45	−0.3278	0.35	−0.4096	0.39	−0.5379	0.50
Crime	0.0048	1.51	0.0035	1.05	0.0002	0.33	0.0005	0.09
Year dummies	Yes		Yes		Yes		Yes	
Area dummies	No		Yes		No		Yes	
R^2	0.07		0.11		0.15		0.20	
Observations	823		823		465		465	

* and ** denote statistical significance at the 10% and 5% level, respectively, using a two-tailed test.

benefits are important, they are not large enough to overcome the size of the school fee itself. On the other hand, commercial interests benefit from at least the first and second associated benefits, but pay no monetary costs. Hence, it is not surprising that the value of undeveloped commercial land increases in the presence of school impact fee programs.

The results for *WSIF* are also nuanced. Table 6 indicates that residential land prices are affected in a negative and significant way by *WSIF*, in both the first-differenced and random trend models, and across the full and urban samples. This suggests the monetary costs of water and sewer impact fees are not fully offset by other benefits to residential developers, such that a portion of the burden of the fee is shifted backwards to land owners. Table 8 shows how, on average, a $1000 increase in *WSIF* would lead to a $662 reduction in the predicted value of a representative residentially zoned parcel. This seems plausible, as the average parcel in the data is roughly one-third of an acre. Since most improved residential lots in Florida are smaller than this, $662 may actually overstate the predicted per-residence effect. For example, the predicted decline in value for a quarter-acre lot would be just over $500, roughly half the magnitude of the impact fee. This estimate falls squarely between $114 and $1000; the estimated price effects from the two most recent studies considering this question (Ihlanfeldt and Shaughnessy, 2004; Evans-Cowley et al., 2005).

Turning to the commercial models, *WSIF* is not found to have a significant relationship with the price of commercially zoned parcels, providing at least some evidence that the additional monetary costs of *WSIF* in this case are largely (or even fully) offset by other benefits to commercial developers associated with their implementation. Two possibilities may help explain the divergence of the *WSIF* effects between the residential and commercial models. First, if enhanced water/sewer services are more highly valued by commercial development than by residential development and *WSIF* programs improve the coverage and quality of service, both results make sense. Additionally, the relative burden (i.e., across commercial and residential interests) of financing water/sewer infrastructure expansions may more heavily fall upon commercial users when an impact fee program is not in place and higher user fees are used to cover the costs of expansion.

The influence of *RIF* in the residential price models and *CIF* in the commercial price models merits discussion in tandem for at least two reasons. First, they are highly similar in the sense that they both fund the same underlying infrastructure projects (roads, police, fire, public buildings) and reduce the need to raise revenues for those purposes through property taxes. Second, the variables are incredibly highly correlated in both levels and changes, as communities generally create/modify both concurrently. For these reasons, each regression model includes only the respective fee paid by developers in that case, rather than both. Considering residential land, the *RIF* variable is always found to be negative, but statistical significance is never obtained. The null effect suggests the benefits associated with these programs are meaningful to developers, and may offset the majority of direct monetary costs. In fairness, the consistently negative point estimates and t-statistics near/above 1 in most cases offer at least some weak evidence that residential land prices fall as *RIF* increases, suggesting a small amount of backward shifting may be occurring. Interestingly, either scenario suggests it is reasonable to think of residential impact fees as a benefits tax, with either all or a majority of the monetary cost offset by other direct benefits to developers. While not dramatic, the effect seems somewhat less intense in urban areas than in the full sample. The point estimates and t-statistics are both larger in the full models than in the urban sample regressions, although the estimated point effects to not differ significantly. While this evidence is only suggestive, it is qualitatively consistent with the idea that the monetary costs of impact fees may be offset to the greatest extent in urban areas — consistent with work that emphasizes the potential for impact fee programs to mitigate the stringency of other land use regulations.

Turning to commercial impact fees (*CIF*), both full sample models show significant negative effects. The urban sample sees the effect

Table 8
Predicted effects of an additional $1000 of impact fees on land values.

Variable	Residential land			Commercial land		
	% Δ in constant quality value	Δ in mean parcel value	Δ in value per acre	% Δ in constant quality value	Δ in mean parcel value	Δ in value per acre
SIF	0.26% decrease	−$207	−$643*	0.53% increase	$897	$375
RIF	No significant effect	No significant effect	No significant effect	Not applicable	Not applicable	Not applicable
CIF	Not applicable	Not applicable	Not applicable	0.39% decrease	−$660	−$276
WSIF	0.83% decrease	−$662	−$2056	No significant effect	No significant effect	No significant effect

* Predicted price effects are calculated using mean values for *PLR* and *PLC* from Table 3 and coefficient point estimates from the full sample first-differenced and random trend models, averaging where a statistically significant relationship was obtained in either. 'No significant effect' is reported when neither model achieved statistical significance. The change in value per acres uses the average lot size for residentially zoned parcels (14,041 square feet, or 0.322 acres) and for commercially zoned parcels (104,254 square feet, or 2.393 acres).

weaken and lose statistical significance. Recall that an important anticipated difference between the residential and commercial development cases was that many communities actively seek to restrict residential development, but there is much less evidence to support the idea that commercial development is discouraged. In fact, a commonly described phenomenon is that communities are generally found to aggressively compete for new commercial development (Anderson and Wassmer, 2000). With little potential for positive effects on the regulatory review of new development, only the reduction in future property taxes and enhanced level of service provision remain. The results suggest the benefits from these factors mitigate the size of the effect but are not large enough to fully offset the monetary costs of the impact fees.

7. Conclusions

Development impact fee programs are increasingly used by local governments to manage economic growth. While a large number of studies have investigated their effects on housing prices, only a few have empirically examined their effects on the value of undeveloped land. The disagreements between the findings of these papers, the lack of attention given to school impact fees as a category worth separate consideration, and the underlying importance of capitalization effects of impact fees all motivate this study.

The results suggest that development impact fee programs do in fact influence market prices for undeveloped land. The paper explores the determinants of constant quality prices for residentially and commercially zoned land in 61 Florida counties between 1994 and 2009. In doing so, it documents the intense early 2000's run-up and rapid post-2006 decline in constant quality land prices in Florida. More importantly, the causal effects of various types of development impact fees on land prices are found to be nuanced. Several margins ignored by previous studies are shown to be relevant. In particular, we investigate relationships with both residentially and commercially zoned land; a distinction that proves to be very meaningful when considering school and water/sewer impact fee programs.

Water/sewer impact fees seem to have significantly different effects than impact fees covering public services otherwise funded through property taxes, and to have stronger effects on residentially zoned parcels than on commercially zoned parcels. Impact fee programs for services otherwise funded through property tax revenue are found to have a stronger negative effect on commercially zoned parcel values than on their residential counterparts, providing interesting indirect evidence that development impact fee programs interact significantly with the preexisting regulatory environment governing local development decisions.

The most important result from this investigation is that school impact fees are found to increase the value of commercially zoned land, while at the same time lowering the value of residentially zoned parcels. The relevance of this finding extends to more general questions regarding alternative methods of local education finance, as communities with school impact fees are placing a smaller burden on commercial property owners than otherwise similar communities with school fees. Determining whether this shift is a desirable or undesirable outcome goes beyond the scope of this study. While this study supports many of the conclusions of the new view of impact fees, it also motivates further investigation. Impact fees in Florida fall largely under the control of counties, rather than municipalities. Since these roles are reversed in most other states, it is worth noting the competition for development between municipal governments could be fiercer than competition between counties, since municipalities are closer substitutes for one another, and that this may in turn influence patterns of impact fee usage as well as their effects. Finally, Florida experienced a tremendous amount of population growth and economic development over the investigated period, leading the state to adopt a facilities concurrency requirement that limited development if infrastructure was not already in place to serve new facilities. For all these reasons, it would be interesting to see if impact fees have similar effects in other environments.

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